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Liquidity provision: lessons from a natural experiment

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***Keywords**:* liquidity, investment, default risk, arrears

JEL classification: G31; G32; G38; E51

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Vicente J. Bermejo† José M. Abad‡

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1 Introduction

In a recession, where should the government inject liquidity to foster investment and economic growth? To which extent does relaxing firms' financial constraints increase investment? Does this relation depend on firms' growth opportunities, debt maturity, or market conditions? The goal of this paper is to answer these questions with a clean causal identification strategy. We exploit a natural experiment that occurred in the biggest liquidity injection to the corporate sector in Spanish history. In particular, we evaluate the effectiveness of a liquidity injection program conducted by the Spanish government through the Fund for Financing Payments to Suppliers (FFPS). The program was introduced to expand economic activity and to overcome the strong recession that Spain was suffering. Spain was undergoing a strong credit crunch in 2012 and the government injected almost 30bn euros to alleviate firms' credit constraints and stimulate economic growth.

The crisis represented a negative shock to the supply of external finance for firms and this induced a decline of corporate investment (Duchin, Ozbas, and Sensoy, 2010). In this setting, it is of great importance to determine the best way to channel liquidity into the economy to foster investment. Prior research has shown that reduced bank liquidity causes a reduction of credit supply to firms (Ivashina and Scharfstein (2010), Santos (2010) or Iyer, Peydró, da Rocha-Lopes, and Schoar (2013)). In an attempt to alleviate banks' liquidity constraints, in 2009 the Spanish government created the Fund for Orderly Bank Restructuring (FROB), a program designed to bailout and reconstruct the Spanish financial system. After several bailouts, Spain received almost 39bn euros for bank recapitalization from the European Financial Stability Facility in 2012. Bank recapitalization and the effects of monetary policy have been widely studied (Ashcraft, McAndrews, and Skeie (2011), or Diamond and Rajan (2011)), and precautionary hoarding and reluctance of banks to lend during a crisis have been evidenced. This was the case in Spain, where the credit crunch was especially severe and despite the large liquidity injection that Spanish banks received, access to finance was reported as the most pressing problem by almost 30% of the firms interviewed in a study by the European Central Bank (2014).

It is in this setting that the Spanish government introduced the FFPS program as an alternative and direct channel of liquidity to firms. Substantial literature has studied the effect of public spending on the real economy, and in particular on private investment, but results are far from being conclusive and have never been focused in recessionary periods (Barro (1981), Blanchard and Perotti (2002) or Kim and Nguyen (2014)). The case of Spain seems an ideal setting to study the potential impact of unorthodox stimulus policies during a recession when firms experience a serious shortage of credit supply.

We find that the plan was successful in stimulating investment. In particular, we find strong empirical evidence of a positive and significant relationship between liquidity and investment, which we claim is evidence of the effectiveness of the plan in alleviating the financial constrains caused by the credit crunch. Firms dedicated on average 4% of the cash received (1.1bn euros) to increase long-term investment.[1] This effect is stronger for firms with lower default risk and higher investment opportunities. Firms with higher default risk and lower investment opportunities are more prone to repay financial debt. On average, firms use 8% of cash transfers to repay financial debt.

The large unexpected liquidity shock conducted by the Spanish government (through the FFPS) in 2012 affected over 60,000 firms. In the five years prior to this shock, Territorial Administrations (both regional and local governments) had been accumulating arrears owed to suppliers. The volume of arrears was around 30bn euros, a figure as big as 3% of Spanish GDP. In February and March 2012, two laws were ratified by Parliament to set up the FFPS. The first appearance in the news of this measure was in mid-January 2012. All payments to suppliers were done in May/July 2012 through a cash transfer managed by the Spanish Official Credit Institute (ICO).

Our empirical strategy relies on the fact that the announcement and occurrence of the liquidity shock is confined to the short period between January and July 2012. Therefore, in December 2011 this shock was completely unexpected by any firm, and by December 2012 all firms had received the cash at least five months before. We use end of year financial data of the firms and have information from December 2007 up to December 2013. We use two methodologies, a DID approach that exploits heterogeneity in the size of the liquidity received by firms and a DID using as control group some firms that were paid a year later due to the plan's exogenous disbursement implementation. For both methodologies we use matching techniques to make the groups more comparable, although in the second methodology we show that firms are already very similar on observables.

[1] Our estimates are relative to a control group, so these numbers must be interpreted as an increase in investment relative to our control group. This does not necessarily imply a net increase in investment if the control group reduces investment.

Suppliers that worked for groups of municipalities (*mancomunidades*) that authorities had overlooked in the laws passed in 2012 received the payment of their arrears a year later. These suppliers were paid in a second phase, together with other suppliers whose invoices were also not adequately processed in 2012. In total, more than 7,000 firms (representing arrears amounting to around 1bn euros) were paid in this second phase in 2013. We use this event as a refinement to contrast our main findings. We use the firms in phase 2 as our control group and study the impact of the liquidity shock of 2012 on the firms in phase 1. The advantage of using firms in phase 2 as our control group, is their resemblance in their characteristics to those in phase 1, and that they receive the shock a year later for exogenous reasons. By using these firms, we also control for potential endogeneity that arises from the specificities of firms that work for the public sector. In addition, we conduct our analysis with and without a matching strategy since the initial resemblance is not perfect and to avoid any biases originated from omitted variables.

Our study also contributes to the long-standing debate on the impact of firm's financial constraints on investment. There has traditionally been broad interest in the economic and financial literature on how financial frictions affect investment (Fazzari, Hubbard, and Petersen (1988), Kaplan and Zingales (1997), Rauh (2006), Chen and Chen (2012) or Banerjee and Duflo (2014)). However, there is still no clear evidence on this relationship. For example, several papers have used data from the repatriation of foreign earnings under the American Jobs Creation Act to study the impact of changes in financial constraints on several corporate variables. Using the same data, while Blouin and Krull (2009) and Dharmapala, Foley, and Forbes (2011) find no effect on investment, Faulkender and Petersen (2012) find a positive and significant effect on corporate investment. In another influential paper, Rauh (2006) tries to identify the dependence of corporate investment on firm financial constraints. However, his work has been criticized due to his empirical specification: Rauh (2006) employs a regression discontinuity design, exploiting sharply nonlinear funding rules for defined benefit pension plans, and according to Bakke and Whited (2012), his results seem to arise from the use of a small fraction of the sample observations that have specific characteristics.

Our paper adds to the existing estimates of the effect of cash flows on investment through the use of a unique data set and a clean causal identification strategy. Correct identification of the causal effect of cash flows on investment is a challenge because both variables are co-determined in equilibrium. However, the natural experiment allows us to correctly disentangle the causality of the liquidity injection on investment. Spain is an ideal laboratory to test this puzzle because of the severe financial constraints that firms suffered during the Great Recession, as documented by Bentolila, Jansen, Jiménez, and Ruano (2013), Jimenez, Ongena, Peydro, and Saurina (2014) or Bermejo, Campos, and Abad (2015). Jimenez, Ongena, Peydro, and Saurina (2014) and Bentolila, Jansen, Jiménez, and Ruano (2013) use Spanish data on loan applications and grants from the Credit Register of the Banco de España (CIR) to disentangle the effects of credit supply and credit demand. Both papers show evidence in favor of a credit supply shock. The former finds that lower GDP growth caused a reduction in loan granting. They claim that this is especially relevant for a country like Spain, where most firms are bank dependent and bank substitution is difficult for constrained firms. The latter finds that the strong decrease of credit supply in Spain had negative effects on the real economy (they focus in the labor market effect). Interestingly, the FFPS program was precisely designed to alleviate firms' financial constraints, reduce corporate indebtedness, and foster economic growth. Therefore, it is a unique setting to study the impact of a liquidity shock on financially constrained firms.

Our data also allows us to determine whether the relation between investment and financial constraints depends on firms' characteristics. This has important policy implications, as government interventions could have different economic impact if they are channeled to different types of firms. We focus our analysis in the vast literature that analyzes the relationship between capital structure, growth opportunities and firm investment. Modigliani and Miller (1958) state that, under certain assumptions, the capital structure of the firm is irrelevant and that any firm with positive net present value investment opportunities would obtain funding to undertake them. Subsequently, many papers have stressed a negative relationship between leverage and investment when these assumptions do not hold. Myers (1977), for example, shows that with sufficiently high leverage, profitable projects can go unfunded because of the debt overhang created by prior debt financing. This effect has been commonly called the "underinvestment" problem of debt financing and implies that debt reduces the value of firms with growth opportunities. On the other hand, Jensen (1986)) or Stulz (1990) highlight the positive aspects of debt on investment, especially for low-growth firms, since debt can limit managerial discretion over free cash flows and avoid what has been called the "over-investment" problem. In the same vein, in the literature on cash windfalls, Blanchard, Lopez-de Silanes, and Shleifer (1994) show that firms do increase investment when they receive a cash windfall, by investing it in unattractive projects to avoid having outsiders with claims on this cash. It is clear that debt has a desirable moderating effect on investment when growth opportunities are low and "overinvestment" is plausible. However, debt and capital market imperfections can also have a negative effect on investment when interesting investment opportunities arise. Our research design allows us to better understand the impact of leverage and growth opportunities on the sensitivity of investment to liquidity.

Disentangling the effect of leverage and growth opportunities from the causal relation between liquidity and investment is challenging because liquidity, growth opportunities, leverage, and cash are jointly co-determined. By exploiting the unexpectedness of the liquidity shock received by the firms in 2012, and measuring growth opportunities and leverage prior to the shock, we observe their differential impact on the sensitivity of investment to liquidity. Moreover, we avoid additional sources of potential endogeneity that will be discussed later by exploiting the data from phase 2. In particular, we find that more leveraged firms use the liquidity received to repay debt, and that the firms that are more likely to invest are those with lower debt and greater growth opportunities. Banerjee and Duflo (2014) use variation in a targeted lending program to estimate whether firms are credit constrained. Contrary to our findings, they state that only constrained firms will use cash to expand production while unconstrained firms would use it as a substitute for other borrowing. However, they study firms in a unique industry (manufacturing), in a developing country (India), and in a setting with very different market conditions. We are aware that our results are specific for recessionary environments where credit supply shortage affects the corporate sector.

Our paper is also closely related to papers that study the differential effect of liquidity risk on short and long-term investment, and their impact on economic growth along the business cycle. Procyclicality theories argue that in a credit crunch, constrained firms are more concerned about the liquidity risk of long-term investments and reduce these investments in favor of more liquid short-term investments. Long-term investment has higher liquidity risk and thus firms with higher liquidity constraints are likely to reduce long-term investments. This effect is stronger in recessions, when liquidity is expected to be scarce. Aghion, Askenazy, Berman, Cette, and Eymard (2012) show that R&D investment is countercyclical without credit constraints, but it becomes procyclical as firms face tighter credit constraints.

In our analysis, we focus on long-term investment. Long-term investment enhances productivity growth more than short-term investment (Aghion, Angeletos, Banerjee, and Manova, 2010), it increases long-term economic growth and it is key to recover from a financial crisis (Garicano and Steinwender, 2014). We find that less indebted firms with higher growth opportunities exhibit a greater propensity to invest when they receive the liquidity injection. Our results are in line with those of Garicano and Steinwender (2014) who introduce a novel measure of credit shocks by observing the change from long-term investments to short-term investments of financially constrained firms. They find that firms prefer short-term investments that yield short-term cash flows since they want to mitigate the risk of being liquidated due to lack of access to cash. Our paper complements their paper: we empirically show a significant and different reaction of firms with heterogeneous probabilities of default when credit constraints are alleviated. We measure whether there is a significant reaction to a liquidity shock and study what firms actually do with the cash. As documented by Garicano and Steinwender (2014), reducing long-term investment impedes recovery from the financial crisis and reduces long-term economic growth. From a policy point of view, our results are key to determine which firms should the government target with a liquidity injection to increase long-term investment and foster economic growth.

The rest of the paper is organized as follows. In Section 2 we provide background information on the institutional setting in which the shock takes place. Section 3 describes the data used for the analysis and the construction of some relevant variables. The empirical strategy and summary statistics are shown in Section 4. Section 5 reports the results and Section 6 concludes.

2 Institutional Setting

The Spanish economy suffered a strong credit crunch originated by the financial crisis that burst in 2008 (Bentolila, Jansen, Jiménez, and Ruano (2013), Jimenez, Ongena, Peydro, and Saurina (2014) and Bermejo, Campos, and Abad (2015)). The financial crisis had a substantive impact on the Spanish private sector, leading to higher unemployment and depressed domestic demand (Campos and Reggio, 2015). The public sector was not left unscathed. Spain's public administrations, particularly at the sub-national level, experienced funding problems in the capital markets, just like local banks, and they also delayed payments to suppliers. The result was that, as of December 2011, the commercial debt accumulated by regional and local governments amounted almost to 30bn euros (almost 3% of GDP). This situation was creating a vicious circle: while mitigating the financial constraints of regional and local governments, it was augmenting the financial constraints that firms were already experiencing and hindering their recovery.

Therefore, aiming to address the liquidity problems faced by suppliers of regional and local governments, the Spanish government set up a new State-owned vehicle, the FFPS, through two Royal Decrees passed in 2012, February 24 and March 9.

On the asset side, the FFPS made payments directly to the suppliers of regional and local governments, subrogating itself in their position as claimants against these territorial administrations. As a result, commercial debt previously held by suppliers turned into financial debt in the hands of the FFPS. Interestingly, while participation by the 8,000 Spanish local authorities was mandatory, participation by the 17 regions was voluntary; and actually 3 of them (Basque Country, Galicia and Navarra) decided not to participate. Payments were made on three different dates: on May 28, 9.3bn euros were transferred directly to the suppliers of the 8,000 local governments; on June 25, 17.7bn euros were transferred directly to the suppliers of the 14 participating regions; and finally, on July 30, 0.3bn euros were transferred to the suppliers of local governments that had been left behind in the May payment. Overall, in just three bank transfers made in three different dates within a period of just two months, the ICO (the FFPS' paying agent) injected an amount of cash worth 27.3bn euros in the real economy.

Importantly, funding provided by the FFPS to the regional and local governments was guaranteed through the retention of their share of State tax receipts. Funding costs for regional and local governments equaled the Spanish Treasury's funding cost plus a maximum margin of 115 basis points to which a maximum mediation margin of 30 basis points was also added. These were quite favorable conditions compared to what regional and local governments could actually get by themselves in the capital markets. In order to avoid moral hazard, regional and local governments were required to submit a fiscal adjustment program to the Central Government. While regional and local governments complying with this requirement enjoyed funding with a maturity of 10 years with a 2-year interest-only grace period, funding provided to regional and local governments failing to meet this requirement was deducted from their share of State tax receipts over a 5-year period.

On the liability side, the FFPS gathered funds from a 30bn euros (maximum up to 35bn euros) syndicated loan granted by a pool of most of the Spanish banks. Given the State-owned nature of the FFPS, the syndicated loan was guaranteed by the State, making it attractive for participating banks. At the same time, however, all FFPS' liabilities became part of the central Government debt.

2.1 The second phase

In February 2013, another Royal Decree Law was ratified resulting in a new round (phase 2) of the FFPS. It was approved to pay the arrears to the suppliers of certain groups of municipalities (*mancomunidades*), a different sub-national entity that authorities had left behind in the laws passed in 2012, as well as claims which did not qualify in the 2012 payments due to different political reasons. Again, ICO transferred around 1bn euros to suppliers of regional and local governments.

The important fact for our analysis, is that the reason why some firms participated in this new phase was a matter of the slack of the laws passed in the first phase (they did not include *mancomunidades*) and political issues independent of the characteristics of the suppliers. In fact, not only were firms in both phases very similar in characteristics, but many of the suppliers in phase 2 also participated in phase 1. However, we conduct a matching procedure since we do find that firms that exclusively received funds in phase 2 are smaller from those of phase 1. Importantly, while payments by the FFPS extended over a 3-year window (2012-14), data exploited was restricted to the first 2 years (2012-13) since we need a window after the shock to capture the consequences of the liquidity injection.

Data from regions and municipalities is heterogeneous: this data shows significant heterogeneity in the payment behavior and financial strength of different regions and municipalities. This can lead to an endogenous relation of the suppliers that contract with different administrations, and thus must be taken care of. In our main analysis, we include geographical fixed effects to account for this heterogeneity, and in some cases we also control for the financial health of regions and municipalities.

3 Data and Sample

In this section we describe the data. All our data has annual frequency. Moreover, we also explain the construction of some variables used for our analysis.

We exploit a data set constructed by the Spanish Official Credit Institute (ICO). The ICO data set includes anonymous firm information from different phases of the FFPS and exhaustive firm-level data from the Iberian Balance Sheet Analysis System (SABI),[2]. Initially, in the first phase, the ICO data set includes anonymous information for firms accounting for 48.2% of all suppliers that benefited from the FFPS (64,879 out of 134,568) and almost 70% of the funds injected (19bn euros out of 27.3bn euros).[3] The data set includes information on the number and amount of unpaid bills that each firm has with each regional and local government, the amounts seized by the government due to unpaid taxes and social contributions and the dates in which the payments took place. The difference between the amount of unpaid bills and the seized amount equals the cash the firm effectively receives.

Interestingly, the ICO data set matches the information from the FFPS to SABI, a database with a coverage of more than 1.25 million firms in Spain. SABI data includes corporate accounting information, sector, number of employees, cash flow information and investment information. ICO's data set does not include information on 46,564 self-employed individuals (34.6% of suppliers and 1.5% of funds), nor on 23,125 firms (17.2% of suppliers and 29% of funds) that were not available in SABI.

Regarding the data from phase 2, a total of 1.14bn euros were injected to 5,070 firms. The ICO data set includes 1,848 firms, from which 1,201 are firms that already received funds in phase 1 (total amount of 259mn euros and average bill of 216,000 euros), and 647 are firms that only receive funds in phase 2 (total amount of roughly 80mn euros and average bill of 120,000 euros).

ICO obtained all the credit rating and probability of default data from a special financial strength indicator module available through SABI and provided by ModeFinance.[4] This data is an assessment of the creditworthiness of a company and it

[2]SABI data is provided by INFORMA D&B in collaboration with Bureau Van Dijk

[3]Information on self-employed individuals and firms not covered in SABI (mainly financial firms and very small companies) is lost.

[4]ModeFinance is a data vendor that creates and develops a credit risk assessment methodology called MORE (Multi Objective Rating Evaluation)

is based on a snapshot of the financial health of the company. These ratings are also provided on an annual frequency.

We obtain data on aggregate amounts of arrears and accounting information of counties and regions from the Spanish Ministry of Economy database.

Finally, we obtain from the Spanish Tax Agency the dates of each unpaid invoice. This information is useful to account for the unexpectedness of the liquidity shock.

In our analysis, we exclude financial firms, which means that a total of 156 firms are dropped from the FFPS sample. Moreover, we also drop firms that have no information on total assets.[5] We restrict our sample of treated and untreated observations to those that have observations on all the matching covariates in the four years of our analysis.[6] Matching covariates are the same for all our regressions, so the sample is homogenous and results are comparable. By following this approach, we are aware that we are creating a survival bias, but we avoid an entry/exit bias whose consequences are far more unpredictable.

3.1 Our dependent variables: measuring corporate investment and short-term financial debt

We study the effect of the liquidity shock on investment and short-term financial debt. Each of these dependent variables is measured in a similar way.

We follow Asker, Farre-Mensa, and Ljungqvist (2014) and measure corporate investment as the annual increase in gross fixed assets (gross property, plant and equipment) scaled by beginning-of-year total assets. As noted by Asker, Farre-Mensa, and Ljungqvist (2014), by using this measure, we are capturing increase in assets due to both capital expenditures (CAPEX) and mergers and acquisitions (M&A). Our study is primarily focused on private firms which usually do not pay their acquisitions with stocks (due to their reduced size), so this measure seems to be the most appropriate to accurately measure corporate investment. As mentioned in Section 1, we focus on long term investment since it enhances productivity growth more than short-term investment (Aghion, Angeletos, Banerjee, and Manova, 2010), it increases

[5]This implies that roughly 10.000 additional firms are dropped.
[6]Matching procedure is described in Section 4.1.

long-term economic growth and it is key to recover from a financial crisis (Garicano and Steinwender, 2014). Thus, investment for any firm i is:

$$Investment_{it} = (Fixed\,assets_{it} - Fixed\,assets_{it-1}) * 100/Total\ Assets_{it-1} \qquad (1)$$

In a similar vein, in the case of short-term financial debt, we measure our variable of interest as the annual difference in short-term financial debt scaled by beginning-of-year total assets. Again, we multiply by 100 to scale coefficients, in order to interpret coefficients of regressors in percentage terms.

3.2 Measuring the liquidity shock by firm

All the invoices with different local and regional governments are aggregated at the firm level. Therefore, we have the total amount of arrears that each firm is paid. Information on seized amounts by the central government are also reported in our database. Seized amounts are due to debts that firms had with the central government. These seized amounts are deducted from the total amount of arrears that are owed to the firm. Our measure of the liquidity shock is the total amount of arrears minus the total amount seized by the government. It is therefore a measure of the effective amount of euros transferred from ICO to the firm. We normalize the size of the liquidity shock by the firms' total assets in 2011. We normalize by the value in 2011 since it is the year prior to the realization of the shock and we don't want our measure of the liquidity shock to be affected by the shock itself (which happens in 2012). Thus, the liquidity shock for any firm i is:

$$Liquidity\ shock_i = (Total\ arrears_i - Seized\,amounts_i)/Total\ Assets\ in\ 2011_i \qquad (2)$$

3.3 Measuring default risk and investment opportunities

We disentangle the differential effect of default risk and investment opportunities on the relation between investment and the liquidity shock.

Faulkender and Petersen (2006) find that credit ratings exogenously affect a firm's access to financing. Our measures of credit ratings are firm-year probabilities of default.

These probabilities are ranked from 0 to 100, with 100 being the highest probability of default.[7] Moreover, we also proxy credit ratings by computing adjusted Altman Z-scores and leverage, results are unchanged.[8] We divide the sample at the median to classify firms as having high or low default risk. We use values for 2011 to make sure they are exogenous to the liquidity shock. Several papers, such as Almeida, Campello, and Weisbach (2004), Campello, Graham, and Harvey (2010) or Chang, Dasgupta, Wong, and Yao (2014) have used credit ratings as proxies for financial constraints.

Traditionally, investment opportunities have been measured using either Tobin's q (ratio of the firm's market value to the book value of its assets) or sales growth. The majority of the firms in our sample are not traded on the stock exchange. In Spain, barely 200 firms are traded, so we use sales growth to proxy for investment opportunities. This measure has been profusely used in the literature, for example by Billett, King, and Mauer (2007), Bloom, Bond, and Van Reenen (2007), Michaely and Roberts (2012) or Asker, Farre-Mensa, and Ljungqvist (2014). For each firm, we calculate the average sales growth for the two years previous to the shock (2010 and 2011). Subsequently, for each industry, we divide the sample at the median to classify firms as having high or low two-year sales growth.

4 Empirical Strategy and Summary Statistics

To analyze the consequences of the liquidity shock on investment and short-term financial debt, we use two differences-in-differences (DID) testing procedures. Matching variables, controls, rules to fix outliers and regression techniques are the same for both DID approaches and both variables of interest. In this way, results are made comparable.

We exploit the data from the FFPS that describes the repayment of arrears that Territorial Administrations had been accumulating. Given the specificities of firms that work for the public sector, it is difficult to decide on an appropriate control group to analyze the effect of this liquidity shock on investment. To avoid unobserved heterogeneity generated by these specificities, we restrict our analysis to firms that

[7] Probabilities of default are provided by ModeFinance, as previously mentioned

[8] Altman Z-score is measured following Altman (1968).

participated in the FFPS plan.[9] We exploit the heterogeneity in the size of the liquidity shock and use as treated firms those in the top tercile and as control group the firms in the lowest tercile. However, we find differences in firm characteristics among these two groups and therefore follow a matching procedure to control for these differences. Still, firms in the top tercile have a higher exposure to the public sector and we are concerned about the potential endogeneity that this can cause. To solve this, we take advantage of the plan's plausibly exogenous disbursement implementation and run another DID procedure using as control group some firms that were paid a year later. These firms are similar on all observables except in size, we correct this by matching firms in phase 2 with firms of similar size from phase 1.

4.1 Methodology 1: analyzing the heterogeneity in the size of the liquidity shock

Our first empirical strategy uses a DID methodology that exploits heterogeneity in the size of the liquidity injection and the time difference before and after the shock.

To construct the first difference, we separate firms (only firms with government arrears that participate in the first phase of the FFPS) in three quantiles according to the size of the liquidity shock they receive.[10] The first difference exploits heterogeneity in the size of the shock that the firms are exposed to. For that purpose, we drop the firms in the middle quantile in order to better gauge the effect of receiving a big liquidity shock versus the effect of receiving a smaller liquidity shock. The treated group will be formed by the firms exposed to the big liquidity shock (top quantile), and the control group will be composed by the group of firms that receive a smaller liquidity shock (bottom quantile).

There are significant differences in observables among the treated and control firms. Since both groups of firms appear to be different on several dimensions, they are likely to differ along unobservable dimensions too. Including control variables in a linear regression framework might not adequately control for unobservable heterogeneity between both quantiles (e.g., Irani and Oesch (2013)). Rosenbaum and Rubin (1983) propose propensity score matching as a method to reduce the bias

[9] In an extended version of this paper we also use firms randomly downloaded from SABI.

[10] Liquidity shock is scaled by assets in 2011, as noted in section 3.

originated by the estimation of treatment effects with observational non-random data sets. In order to achieve objective causal inference, we make use of matching techniques to try to approximate to randomized trial. To control for the potential endogeneity that non random data sets can cause, we use a matching approach to improve the resemblance of firms receiving a high and low liquidity shock.

To avoid endogeneity or spurious correlations it is important that our treated and control group are similar in all characteristics (observable and unobservable) that can affect investment (or the variables of interest analyzed in each case). As shown in Table 1, this is not the case. Table 1 shows means and standard deviations of a list of variables for the top and bottom quantiles (columns 1 and 2). Columns 3 and 4 in Table 1 report the means and standard deviations of the matched groups, both for the treated and control group. Table 2 develops t-tests to evaluate whether the differences of means for the unmatched and matched groups are significant. Column 1 reports the differences of the unmatched groups and column 2 reports the differences of the matched groups.

We adopt nearest-neighbor propensity score matching, each firm in the top tercile (treated firms) is matched to a unique firm from the bottom tercile (control firms). We choose a single match and allow for replacement (the same control firm can be used more than once as a match). We are more concerned on minimizing the bias at the cost of larger variance, since our sample is sufficiently large to be less concerned about variance (Abadie and Imbens (2002)). Moreover, to avoid biased coefficients, we set a caliper of 0.01.[11] This implies that some treated firms might not be matched if they do not have a control firm within the caliper chosen. That is the reason why we observe less firms after the matching is conducted in columns 3 and 4 of Table 1.

We match the treated and control group in size (measured by total assets), the growth rate of sales (proxy for growth opportunities), probabilities of default, corporate investment[12], profitability (measured by EBIT[13] to lagged assets) and industrial classification. We restrict the number of covariates since there exists a trade-off between the plausibility of the unconfoundedness assumption and common support (Black and Smith (2004)). According to Sianesi (2004), we must focus on covariates that simultaneously affect the treatment status (receiving a high liquidity shock) and the outcome variable (corporate investment). We have chosen these

[11] A caliper sets a maximum distance of the propensity score for each treatment and its control.
[12] Measured as described in Section 3.1.
[13] Earnings before interest and tax.

covariates since they have been proven to be determinants of firm investment decisions and are significantly different among firms in the top and bottom tercile groups. Once a match is formed, it is kept for the following years. We ensure that all potential matches have data on all the covariates for the whole sample.[14]

We conduct the matching prior to the realization of the liquidity shock to make sure that our matching procedure is exogenous to any effects caused by the shock. We know that all variables included in the matching model must be unaffected by the treatment (the liquidity injection of 2012), and thus we carry out the matching by using the values of the covariates in 2010 and 2011. It is necessary that the treated and control groups follow parallel trends prior to the realization of the shock. We report the summary statistics and t-test results of 2011 in the appendix. The fact that our groups are comparable in 2010 and 2011 is evidence that our matching is robust and correctly specified.

Finally, the second difference is the time dimension, before and after the liquidity shock. Since we have yearly information on company financials by the end of the year, we define the period before the shock as 2010-2011, and the period after the shock as 2012-2013.

This allows us to estimate the differences-in-differences effect of a liquidity shock on investment: the difference between suppliers that receive a high versus a low liquidity shock (matched) and the difference between the period before and the period after the shock.

Our analysis does not only report results using the matched groups. We carry out baseline regressions to evaluate the data before the matching is done. These regressions are useful to compare raw results to those that arise from the matched groups and to better understand the effects of the techniques we apply. Our baseline equation is as follows:

$$y_{it} = POST_{(t \geq 2012)} + \sigma LiquidityShock_i \times POST_{(t \geq 2012)} + Firm_i + \beta X_{it} + \varepsilon_{it} \qquad (3)$$

where y_{it} is our variable of interest (corporate investment or short-term financial debt); $POST_{(t \geq 2012)}$ is a dummy variable (structural break) that takes value 1 for 2012 and 2013

[14]As reported in Section 3, if a firm does not have observations on all the matching covariates in the four years of our analysis, the firm is dropped and not used to form the matched groups.

and zero for years 2010 and 2011; $LiquidityShock_i$ is a continuous variable that captures the size of the liquidity shock;[15] $LiquidityShock_i \times POST_{(t \geq 2012)}$ is an interaction term; $Firm_i$ is a firm fixed effect and X_{it} is a vector of controls.

Controls are the same in all regressions and include total assets, capital structure (liabilities to equity), a bankruptcy dummy,[16] an interaction between the bankruptcy dummy and the capital structure variable, sales to lagged assets, return on assets, growth rate of return on assets, cash, probability of default, growth rate of sales, EBIT to lagged assets, short-term debt to long-term debt and a dummy for the firm's age.[17] All controls are measured prior to the shock. Lagged values are used for all years except for 2013, in which the value of 2011 is used.[18]

We compute an analogous regression in which instead of having a continuous measure of the liquidity shock, we use two groups (high and low) that will be used in our main DID methodology. We create a dummy that takes value 1 for the high liquidity group (top quantile or treated group) and zero for the bottom quantile.

Our main DID methodology is based in the following specification:

$$y_{it} = POST_{(t \geq 2012)} + \delta Grouphigh_{\{\ell_i \in L_H\}} \times POST_{(t \geq 2012)} + Firm_i + \beta X_{it} + \varepsilon_{it} \qquad (4)$$

where $POST_{(year \geq 2012)}$ is analogous to that of equation (3); $Grouphigh_{\{\ell_i \in L_H\}}$ is an indicator of whether liquidity ℓ in firm i belongs to a group of high liquidity recipients (those in the top tercile); $Grouphigh_{\{\ell_i \in L_H\}} \times POST_{(t \geq 2012)}$ is an interaction term and our variable of interest; $Firm_i$ is a firm fixed effect and X_{it} is the vector of controls. The coefficient of interest is therefore δ, which indicates whether firms that receive a higher liquidity shock (top tercile and treated firms), invest more than firms that receive

[15] It's construction has been described in Section 3.

[16] This dummy takes value 1 when the firm has negative equity.

[17] We construct three age bin classes corresponding to firm's created after 2005 (young), 1995-2005 (mid), and pre-1995 (old). This dummy is colinear with the firm fixed effect except when the firm changes age bin.

[18] Alternative specifications have been used in which no controls are employed or in which controls are lagged values for all years including 2012. Results are unchanged. If controls from 2012 or 2013 are used, there is a risk that they are affected by the treatment. We are not interested in the mechanism in which the liquidity shock affects investment through other variables, so in our main methodology we avoid including control variables from 2012 or 2013. If post-treatment controls were added, then we would have to decompose the effect of the treatment to learn what part of the effect of the liquidity shock on investment goes directly through the shock, and what part affects investment through other control variables.

a lower liquidity shock (bottom tercile and control firms) after the realization of the shock.

Our DID methodology is adjusted to allow for an analysis within groups of default risk and growth opportunities. Groups are always created by separating firms in the sample in two quantiles above and below the median.[19] These groups are included in the regressions by interacting the dummies of the groups within our main specification. As an example, we report how the specification changes when we include default risk:[20]

$$\begin{aligned} y_{it} = & \sum_{j=Low,High} (\omega_j POST_{(t\geq 2012)} \times PDj_{\{PD_i \in PDj\}} \\ & + \gamma_j Grouphigh_{\{\ell_i \in L_H\}} \times POST_{(t\geq 2012)} \times PDj_{\{PD_i \in PDj\}}) \\ & + Firm_i + \beta X_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

where all variables are analogous to those in equation (4), except for $(PDj_{\{PD_i \in PD_j\}})$. $(PDlow_{\{PD_i \in PDlow\}})$ is equal to one for the firms with default risk below the median and zero otherwise, and $(PDhigh_{\{PD_i \in PDhigh\}})$ is equal to one for firms with probabilities of default above the median and zero otherwise.

The specification is as follows when we interact the groups of default risk and growth opportunities at the same time:

$$\begin{aligned} y_{it} = & \sum_{j=Low,High} \sum_{k=Low,High} (\rho_{jk} POST_{(t\geq 2012)} \times PDj_{\{PD_i \in PDj\}} \times Growthk_{\{Growth_i \in Growthk\}} \\ & + \lambda_{jk} Grouphigh_{\{\ell_i \in L_H\}} \times POST_{(t\geq 2012)} \times PDj_{\{PD_i \in PDj\}} \times Growthk_{\{Growth_i \in Growthk\}}) \\ & + Firm_i + \beta X_{it} + \varepsilon_{it} \end{aligned} \tag{6}$$

where all variables are analogous to those in equation (5), and $Growthk_{\{Growth_i \in Growthk\}}$ takes different values according to whether firm k belongs to the group with high or low growth opportunities.

As commented earlier, the size of the liquidity shock depends on the firm's exposure to local/regional governments. Thus, our methodology is exposed to potential endogeneity due to omitted variables if there are unobserved characteristics related to the size of the liquidity shock that affect investment (or the corresponding variable of

[19] Section 3 explains how groups of default risk and growth opportunities are created.

[20] The specification is analogous for growth opportunities.

interest) and are not captured by the matching procedure or the controls. A bigger amount of unpaid arrears might not only be correlated with size, financial constraints or industrial effects; but also with the "quality" of the governments that a firm works with or simply with the exposure of the firm to public institutions. We try to control for this potential endogeneity by including two sets of controls. To control for firms that work for "lower quality" municipalities (firms that work with municipalities with a lot of debt and that are worst payers), we construct the following measure per firm: $Quality = \sum_{i=1}^{n}(weight_i \times municipalitydebt_i)$ where i stands for municipality, n for the number of municipalities that a firm has unpaid invoices with, weight measures the percentage weight of unpaid amount in invoices with municipality i respect to all unpaid invoices, and municipality debt is measured as debt to income of municipality i. We also include as a control variable the number of municipalities that the firms works with. Still, it is impossible to assert that our identification strategy is completely clean of potential endogeneity. We overcome this weakness by taking advantage of a refinement described in Section 4.2.

4.2 Methodology 2: analizing the heterogeneity in the disbursement implementation

Our DID methodology described in Section 4.1 is exposed to potential endogeneity caused by the heterogeneity in the exposure of firms to local and regional authorities. The ideal experiment would compare firms that have the same exposure to the public sector. We try to overcome this fragility by exploiting the plan's plausibly exogenous disbursement implementation. The specific characteristics of this setting are described in Section 2.1.

Arrears owed to *mancomunidades* were paid a year later due to slack of the laws passed in phase 1. These *mancomunidades* are not concentrated in specific regions of Spain, in fact they are spread out and exist in all regional administrations of the country. Moreover, the industrial distribution of firms that work for *mancomunidades* is similar to those that appear in phase 1. Therefore, this second phase can be exploited as a refinement to measure whether there are significant differences on investment among the firms that participated in the first phase (received the liquidity shock in mid-2012), relative to those that participated in the second phase (received the liquidity shock in mid-2013). By exploiting this refinement, we control for potential endogeneity that arises from the specificities of firms that work for the public sector.

However, the drawbacks of this methodology are the amount of firms that exclusively receive the shock in phase 2 and the time spam after the shock. Since we use year end corporate data (December), firms only had several months to respond to the liquidity shock. They receive the money in May-July 2012, and we have financial data of the firms from December 2012. The information from December 2013 cannot be used in this analysis: the refinement would not be sufficiently clean since the firms in the second phase received the liquidity shock in August 2013.

We use firms in phase 1 as our treated firms and firms that only participate in phase 2 as our control group. We drop the firms that appear both in phase 1 and phase 2, since we want our control firms to participate exclusively in phase 2.[21] Firms in phase 1 and 2 are very similar on average, except for size. Since we have many more firms in the first phase, we match each firm in phase 2 with a peer firm from phase 1 to have common support, drop outliers, and improve the resemblance of the groups to better approximate to random trial.

Again, we follow a differences in differences testing procedure. However, in this case we measure the causal effect on investment for firms receiving the liquidity shock in 2012, and compare them to firms that do not receive the shock in 2012. Now, both groups have exposure to the public sector. To this end, we need both groups to be comparable. Our treated group are those firms in phase 1 that receive the cash in mid-2012. Our control group are those firms in phase 2 that receive the cash a year later. As reported in Table 3, both groups of firms appear to be very similar in all dimensions except for the size of the liquidity shock and total assets. Firms in phase 2 have less exposure to the public sector, but are bigger on average. As in our DID analysis, to control for the potential endogeneity that non random data sets can cause, we use a matching approach to create control-matched groups. We use a somewhat unusual procedure, since we have only 647 firms that can be used as controls, and more than 60.000 firms that are treated (firms that receive the shock in phase 1). We use all the firms in phase 2 (controls) and find a nearest neighbor for each control in the treated sample.

To avoid endogeneity or spurious correlations, it is important that our two groups

[21]The refinement is not as clean if our control firms receive cash also in phase 1. In this methodology we are particularly interested in achieving a clean identification.

are similar in all characteristics (observable and unobservable) that can affect investment and debt. Table 3 shows means and standard deviations of a list of variables for the two phases (columns 1 and 2) prior to the shock (2011). We match both groups in the size of the liquidity shock, firm size (measured by total assets) and industry.

We follow the same criteria as in our main specification and adopt nearest-neighbor propensity score matching (Rosenbaum and Rubin (1983), Dehejia and Wahba (1999), Dehejia and Wahba (2002)). Each firm (for each of the two phases) that does not receive the liquidity shock (belongs to phase 2) is matched to a unique firm from phase 1 that receives the shock (treated firms). We choose a single match and allow for replacement (the same treated firm can be used more than once as a match). Once a match is formed, it is kept for the following year, we ensure that all potential matches have data on all the covariates for the whole sample (if not the firm is dropped from our sample). The means and standard deviations of the matched groups are listed in columns 3 and 4 of Table 3. We conduct the matching prior to the realization of the liquidity shock to make sure that our matching procedure is exogenous to any effects caused by the shock. We know that all variables included in the matching model must be unaffected by the treatment (liquidity shock), and thus we carry out the matching in 2011 (the year before the shock is realized).

Baseline equation:

$$y_{it} = \kappa POST_{(t=2012)} + \eta Phase1_{\{i \in Ph1\}} \times POST_{(t=2012)} + Firm_i + \beta X_{it} + \varepsilon_{it} \quad (7)$$

where $Phase1_{\{i \in Ph1\}}$ is a dummy variable that takes value one for firms that participate in phase 1 and zero for firms that participate in phase 2 (this variable can also take a continuous value, being zero for firms in phase 2 and continuous in the amount of the shock received by the firm in phase 1); $POST_{(t=2012)}$ is a dummy variable (structural break) that takes value 1 for 2012 and zero in year 2011; $Phase1_{\{i \in Ph1\}} \times I_{(t=2012)}$ is an interaction term and X_{it} is a vector of controls. The coefficient of interest is η, which indicates the effect on investment of receiving the liquidity shock in 2012 versus not having received it yet.

The baseline equation interacted with default risk dummies is:

$$\begin{aligned} y_{it} = \sum_{j=Low,High} & (\tau_j POST_{(t=2012)} \times PDj_{\{PD_i \in PDj\}} \\ & + \phi_j Phase1_{\{i \in Ph1\}} \times POST_{(t=2012)} \times PDj_{\{PD_i \in PDj\}}) + Firm_i + \beta X_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

where the notation is analogous to equation (7) but now each term is interacted with the dummies of default risk. ($PDLow_{\{PD_i \in PDLow\}}$) is equal to one for the firms with default risk below the median and zero otherwise, and ($PDHigh_{\{PD_i \in PDHigh\}}$) is equal to one for firms with probabilities of default above the median and zero otherwise.

In equation (9), we show the specification used when we interact the groups of default risk and growth opportunities at the same time:

$$\begin{aligned} y_{it} = & \sum_{j=Low,High} \sum_{k=Low,High} (\kappa_{jk} POST_{(t=2012)} \times PDj_{\{PD_i \in PDj\}} \times Growthk_{\{Growth_i \in Growth_k\}} \\ & + \mu_{jk} Phase1_{\{i \in Ph1\}} \times POST_{(t=2012)} \times PDj_{\{PD_i \in PDj\}} \times Growthk_{\{Growth_i \in Growth_k\}}) \\ & + Firm_i + \beta X_{it} + \varepsilon_{it} \end{aligned} \tag{9}$$

where all variables are analogous to those in equation (8), and $Growthk_{\{Growth_i \in Growthk\}}$ takes different values according to whether firm k belongs to the group with high or low growth opportunities.

5 Results

Tables 5 and 6 use the specifications, matching techniques and controls described in Section 4.1. Table 5 reports the effects on investment and Table 6 reports the effects on short-term financial debt. Both tables follow the same exact structure. Column 1 reports results before the matching is applied, as described in equation (3) of Section 4.1. In column 1 the liquidity shock is continuous in the amount of the liquidity shock received by the firm. Columns 2 to 5 use the matched data. Column 2 is based in the specification described in equation (4). Columns 3 and 4 report results from equation (5), where groups of default risk and growth opportunities are separately and subsequently interacted with the variables of interest. Finally, column 5 is based in the specification in equation (6), where the groups of growth opportunities and default risk are interacted simultaneously with the variables of interest. Due to space availability and for clarity of exposition, only the coefficients of interest are reported.

Table 5 reports results on investment. Column 1 confirms that the relation between investment and the continuous amount of liquidity received by the firm is positive and significant. This result suggests that 3.5% of cash transfers were devoted to increase investment.[22] Since total cash transfers were around 27bn euros, this implies that this liquidity injection generated an increase of direct long-term investment of around 0.93bn euros. However, when the binary specification for the liquidity shock is used (column 2), the significance disappears. This is because all the within group heterogeneity is lost and both groups in aggregate are not significantly different. In column 3, the average effect on treated firms is divided into two groups according to their default risk. An important result arises: the sensitivity of investment to the liquidity shock is positive and significant for firms with low default risk. For every 100 euros received from the liquidity shock, firms belonging to the low group of default risk invest on average 0.9 euros more than firms belonging to the high group.[23] In column 4 we recognize a positive response of investment to liquidity when firms have high growth opportunities, however the coefficient is not significant. In the last column we observe a positive and significant coefficient for firms with low probabilities of default and high growth opportunities. Among firms with high growth opportunities, for every 100 euros of cash received from the liquidity shock, firms that have low probabilities of default invest on average 1.4 euros more than firms with high probabilities of default.[24] Among firms with high default risk, for every 100 euros of cash received from the liquidity shock, firms that have high growth opportunities invest on average 0.6 euros more than firms with low growth opportunities.[25]

In Table 6 we observe a negative relation among the liquidity shock and the growth

[22]Holding all other variables constant, we can assume this since we control for debt, cash or sales growth.

[23]To obtain the differential impact on investment of belonging to low and high groups of default risk, we subtract the two coefficients of column 3: 0.545-(-0.353)$\approx$ 0.9. Both coefficients are significantly different. The average liquidity of both groups of default risk is not significantly different.

[24]We subtract the two coefficients of column 5 for high growth opportunities: 0.760-(-0.599)$\approx$ 1.4. Both coefficients are significantly different. The average liquidity of these two groups is not significantly different.

[25]We subtract the two coefficients of column 5 for high default risk: 0.760-(.157)$\approx$ 0.6. Both coefficients are significantly different. The average liquidity of both groups of low default risk is not significantly different.

of short-term financial debt. Most firms that receive the higher liquidity shock seem to reduce short-term financial debt more than firms that receive the lower liquidity shock. This result is significant both for the continuous specification of liquidity (column 1), as well as for the binary specification (column 2). For every 100 euros of the liquidity shock received, firms dedicate on average 8.6 euros to reduce short-term financial debt. In other words, firms dedicate on average 8.6% of cash transfers to repay financial debt. For every 100 euros, firms in the high tercile of the liquidity shock dedicate 1.3 euros more to reduce short-term financial debt than firms in the low tercile. Results are much more significant for short-term debt than for investment. All firms seem to use the liquidity received to reduce debt. However, there is heterogeneity in the sensitivity to reduce debt that depends on firm characteristics that are captured by our groups of default risk and growth opportunities. Firms with higher risk of default and lower growth opportunities exhibit higher sensitivities to reduce short-term financial debt (columns 3 and 4 respectively). For every 100 euros, firms with higher default risk dedicate 1 euro more to reduce short-term financial debt than firms with lower default risk.[26] Similarly, for every 100 euros, firms with lower growth opportunities dedicate 0.6 euros more to reduce short-term debt than firms with higher growth opportunities. In fact, these results are confirmed in column 5 when these groups are interacted.

Tables 7 and 8 show results using the methodology described in Section 4.2. In this case, we take advantage of the plan's plausibly exogenous disbursement implementation.

In Table 7 we show the results for regressions in which the dependent variable is firm investment, and Table 8 measures the effects of the liquidity shock on short-term financial debt. Column 1 uses all firms in phase 1 and phase 2, no matching is carried out, therefore there are many more firms from phase 1. Column 1 shows results for equation (7), where phase 1 takes a continuous value. It takes value zero for firms in phase 2, and it is continuous in the amount of the liquidity shock received by the firm in phase 1. These results are very similar to those obtained in column 1 of Tables 5 and 6 respectively. There are small differences in the size of the coefficients due to the definition of outliers.[27] Column 2 is analogous to column 1 but the liquidity shock is a binary variable. Column 3 shows results for equation (8). Column 4 reports results

[26] We subtract the two coefficients of column 3: -1.768-(-0.796)$\approx$ 1. Both coefficients are significantly different. The average liquidity of both groups is not significantly different.

[27] In both methodologies, any firm that has missing values for a covariate used for the matching in the sample period is dropped. Since covariates and sample periods are different in both methodologies, results are not comparable.

for the high and low group of growth opportunities. Finally, column 5 interacts both groups as described in equation (9).

Table 7 corroborates results from Table 5. Firms with lower default risk and higher growth opportunities are more sensitive to invest once they receive the liquidity shock. However, although the sign and significance of the coefficients points in the same direction, the sizes are not comparable. In this section, the control group is made of firms that have not received any liquidity since they belong to phase 2, in Section 4.1 firms in the control group had received a lower liquidity shock relative to the treated group. It is therefore expected that the size of the coefficients in this section is larger than in the previous section for columns 2, 3, 4 and 5.

Table 8 shows that firms with higher default risk are more sensitive to reduce short-term financial debt. These results are similar to those obtained in Section 4.1. On average, firms dedicate 14% of cash transfers to reduce short-term financial debt.[28] In column 3 we corroborate that firms with higher default risk exhibit a higher sensitivity to reduce short-term financial debt once they receive the liquidity shock. Due to the reduced power problem mentioned, no significance is achieved for the regression with growth opportunities (column 4). However, the magnitude of the coefficients suggests that firms with lower growth opportunities seem to reduce more short-term debt.

Power is lost in these regressions relative to those in Section 4.1, since the number of firms used is much smaller. There is a trade-off between this methodology and the methodology presented in Section 4.1. In this case, a clean causal identification is pursued at the cost of using less firms and thus having less power.[29] In the analysis in Section 4.1, full exogeneity cannot be assured. However, results are robust, significance is strong and power is not an issue since sample size is big enough. By using both methodologies and obtaining similar results, we prove that our findings are robust and strong.

[28] Again, as previously mentioned, there are small differences in the size of the coefficients due to the definition of outliers.

[29] Robust standard errors at the firm level are not shown since significance in this analysis is an issue.

6 Conclusion

In this paper we study the Spanish central government's decision to make a huge and direct liquidity injection to credit constrained firms during the banking crisis. The Spanish economy was undergoing a strong credit crunch in a severe recessionary environment. Using a unique data set and a clean causal identification strategy we find a positive and significant response of corporate investment to this unexpected governmental liquidity injection. This indicates that unorthodox stimulus policies can reactivate economic growth when the banking industry is not providing sufficient credit. Our estimates are the joint result of both the supply and demand of liquidity during the recession. The positive impact of a higher liquidity supply is moderated by the potential contemporaneous drop in liquidity demand as firms' investment opportunities vanish. Still, we find positive and significant reactions of investment to liquidity.

We also find that the impact of this policy is very different across firms. Our results show an heterogeneous reaction of firms to the liquidity shock. Firms with lower default risk and higher growth opportunities are more sensitive to increase investment, whereas firms with higher default risk, or that are highly leveraged, prefer to repay debt. From a policy perspective, given that the main objective of the governmental plan was to increase aggregate investment and to foster economic growth, our results give important insights on which are the appropriate firms to target with a public liquidity injection: firms with low default risk and high growth opportunities. It remains to be explored whether the liquidity injection also affected firms' labor policies and competitiveness.

Finally, we contribute to the debate on the sensitivity of investment to cash flows. The positive and significant response of corporate investment to the liquidity injection is evidence that firms were indeed financially constrained. We further quantify this sensitivity and find that firms invest on average 4% of the cash received. On the other hand, 13% of this liquidity is used to repay debt.

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7 Tables

Table 1 *Quality of the match for the DID analysis in 2010*

	(1) GHLiq=1	(2) GHLiq=0	(3) GHLiq=1 on sup.	(4) GHLiq=0 (M)
Liquidity shock(contin)	0.13	0.00	0.12	0.00
	(0.23)	(0.00)	(0.18)	(0.00)
Total assets	7136.30	21096.52	8261.16	12299.10
	(60799.84)	(265236.15)	(66259.14)	(92927.01)
Employees	68.55	81.73	68.08	69.71
	(615.91)	(1016.87)	(648.18)	(600.99)
Probability of default	9.33	9.55	9.45	9.21
	(18.10)	(17.49)	(18.17)	(17.03)
ST debt to LT debt	6.27	8.97	6.64	9.59
	(37.66)	(94.29)	(40.68)	(103.97)
Investment	0.55	1.21	0.43	0.47
	(22.99)	(33.51)	(21.59)	(12.96)
Sales growth	0.15	0.02	0.03	0.01
	(5.69)	(1.87)	(0.94)	(0.90)
EBIT to lagged assets	4.17	3.02	3.03	3.02
	(18.98)	(19.09)	(14.73)	(11.35)
Altman Z-score	2.23	2.10	2.17	2.12
	(1.64)	(1.34)	(1.60)	(1.32)
Cash	519.62	1166.17	592.62	721.72
	(6220.09)	(24363.40)	(6815.17)	(9480.60)
Observations	10134	10134	7854	7854

This table reports summary statistics of firm-year observations in 2010 for the sample used for the DID analysis. Firms are classified as treated firms (column 1) if GHLiq = 1, which implies that these firms are classified in the top tercile regarding the size of the liquidity shock received, or as control firms (column 2) if GHliq = 0, which implies they belong to the bottom tercile. Columns 3 and 4 report summary statistics after the matching is realized. In column 3 we classify treated firms on support and in column 4 all control matched firms. Liquidity shock (contin) is the size of the liquidity size as described in Section 3.2, total assets and employees are measured in thousands, probabilities of default are described in Section 3.3, ST debt to LT debt is the ratio of short-term debt to long-term debt (includes debt issued and financial debt), investment and sales growth are calculated as described in Section 3.1 and Section **??** respectively, EBIT lo lagged assets is earnings before interest and taxes divided by lagged total assets, Altman Z-score is measured as in Altman (1968), cash is measured in thousands and includes cash and very liquid assets. Numbers reported are cross-sectional averages and standard errors in parentheses.

Table 2 *Ttest analysis: differences of means for unmatched and matched groups in 2010*

	(1) Mean differences	(2) Mean differences (Matched)
Liquidity shock(contin)	-0.127***	-0.120***
	(-56.02)	(-58.51)
Total assets	13960.2***	4037.9**
	(5.16)	(3.14)
Employees	13.18	1.635
	(1.10)	(0.16)
Probability of default	0.215	-0.238
	(0.86)	(-0.85)
ST debt to LT debt	2.698*	2.942
	(2.21)	(1.93)
Investment	0.665	0.0374
	(1.65)	(0.13)
Sales growth	-0.129*	-0.0250
	(-2.09)	(-1.71)
EBIT to lagged assets	-1.146***	-0.0100
	(-4.29)	(-0.05)
Altman Z-score	-0.128***	-0.0446
	(-6.11)	(-1.91)
Cash	646.6*	129.1
	(2.52)	(0.95)
Observations	20268	15708

This table reports t-test results of firm-year observations in 2010 for the sample used for the DID analysis. Column 1 of this table analyzes mean differences of the unmatched sample (columns 1 and 2 of Table 1). Column 2 analyzes mean differences of the matched sample (columns 3 and 4 of Table 1). Liquidity shock (contin) is the size of the liquidity size as described in Section 3.2, total assets and employees are measured in thousands, probabilities of default are described in Section 3.3, ST debt to LT debt is the ratio of short-term debt to long-term debt (includes debt issued and financial debt), investment and sales growth are calculated as described in Section 3.1 and Section **??** respectively, EBIT lo lagged assets is earnings before interest and taxes divided by lagged total assets, Altman Z-score is measured as in Altman (1968), cash is measured in thousands and includes cash and very liquid assets. T-statistics in parentheses. * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$

Table 3 *Quality of the match for phases 1 and 2 in 2011*

	(1) Phase2	(2) Phase1	(3) Phase2 on sup.	(4) Phase1 (M)
Liquidity shock(contin)	0.02	0.05	0.02	0.02
	(0.08)	(0.11)	(0.08)	(0.08)
Total assets	26475.91	7823.03	26475.91	27393.65
	(198715.89)	(89645.75)	(198715.89)	(226550.85)
Employees	57.97	47.81	57.97	104.09
	(432.56)	(588.45)	(432.56)	(720.86)
Probability of default	16.13	13.67	16.13	14.48
	(24.28)	(21.87)	(24.28)	(23.14)
ST debt to LT debt	11.40	8.56	11.40	7.34
	(91.00)	(243.61)	(91.00)	(45.09)
Investment	-0.37	0.05	-0.37	0.45
	(10.23)	(22.74)	(10.23)	(13.73)
Sales growth	0.04	0.21	0.04	0.17
	(0.73)	(29.84)	(0.73)	(1.90)
EBIT to lagged assets	-0.04	0.98	-0.04	0.92
	(18.66)	(29.32)	(18.66)	(20.60)
Altman Z-score	1.69	1.95	1.69	1.84
	(1.77)	(1.80)	(1.77)	(1.63)
Cash	344.71	500.55	344.71	365.85
	(1713.51)	(14890.41)	(1713.51)	(1326.64)
Observations	388	39007	388	388

This table reports summary statistics of firm-year observations in 2011 for the sample used for the refinement DID analysis. Firms are classified as control firms (column 1) if they receive the money in phase 2, or as treated firms (column 2) if they belong to phase 1. Columns 3 and 4 report summary statistics after the matching is realized. In column 3 we classify control firms on support and column 4 exhibits treated matched firms. Liquidity shock (contin) is the size of the liquidity size as described in Section 3.2, total assets and employees are measured in thousands, probabilities of default are described in Section 3.3, ST debt to LT debt is the ratio of short-term debt to long-term debt (includes debt issued and financial debt), investment and sales growth are calculated as described in Section 3.1 and Section **??** respectively, EBIT lo lagged assets is earnings before interest and taxes divided by lagged total assets, Altman Z-score is measured as in Altman (1968), cash is measured in thousands and includes cash and very liquid assets. Numbers reported are cross-sectional averages and standard errors in parentheses.

Table 4 *Ttest analysis: differences of means for unmatched and matched groups in 2011*

	(1) Mean differences	(2) Mean differences (Matched)
Liquidity shock(contin)	0.0274***	0.00186
	(6.37)	(0.31)
Total assets	-18652.9	917.7
	(-1.85)	(0.06)
Employees	-10.16	46.12
	(-0.45)	(1.04)
Probability of default	-2.456*	-1.646
	(-1.98)	(-0.97)
ST debt to LT debt	-2.837	-4.055
	(-0.47)	(-0.62)
Investment	0.419	0.828
	(0.79)	(0.95)
Sales growth	0.166	0.131
	(1.06)	(1.27)
EBIT to lagged assets	1.012	0.954
	(1.06)	(0.68)
Altman Z-score	0.256**	0.150
	(2.83)	(1.22)
Cash	155.8	21.14
	(1.31)	(0.19)
Observations	39395	776

This table reports t-test results of firm-year observations in 2011 for the sample used for the DID analysis. Column 1 of this table analyzes mean differences of the unmatched sample (columns 1 and 2 of Table 3). Column 2 analyzes mean differences of the matched sample (columns 3 and 4 of Table 3). Liquidity shock (contin) is the size of the liquidity size as described in Section 3.2, total assets and employees are measured in thousands, probabilities of default are described in Section 3.3, ST debt to LT debt is the ratio of short-term debt to long-term debt (includes debt issued and financial debt), investment and sales growth are calculated as described in Section 3.1 and Section **??** respectively, EBIT to lagged assets is earnings before interest and taxes divided by lagged total assets, Altman Z-score is measured as in Altman (1968), cash is measured in thousands and includes cash and very liquid assets. T-statistics in parentheses. * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$.

Table 5 *Effects on Investment (Methodology 1).*

VARIABLES	(1) Cont-Liq	(2) Match	(3) M-FC	(4) M-GO	(5) M-FC-GO
Post	-0.902***	-0.716***			
	(0.144)	(0.157)			
Post*Liquidity shock(cont)	3.455***				
	(0.772)				
Post*GroupHigh		0.075			
		(0.227)			
Post*GHLiq*PD-low			0.545*		
			(0.299)		
Post*GHLiq*PD-high			-0.353		
			(0.465)		
Post*GHLiq*Growth-low				-0.078	
				(0.268)	
Post*GHLiq*Growth-high				0.160	
				(0.468)	
Post*GHLiq*PD-low*Growth-low					0.157
					(0.393)
Post*GHLiq*PD-high*Growth-low					-0.241
					(0.340)
Post*GHLiq*PD-low*Growth-high					0.760**
					(0.384)
Post*GHLiq*PD-high*Growth-high					-0.599
					(1.099)
Observations	47,499	37,742	37,742	37,742	37,742
R-squared	0.007	0.013	0.013	0.013	0.014
Number of firms	14,510	11,385	11,385	11,385	11,385

This table presents estimates from panel regressions explaining yearly investment for the period 2010 to 2013. Post is a dummy variable that takes value one for years 2012 and 2013. Liquidity shock (cont) is the size of the liquidity shock received by the firm scaled by total assets in 2011, GroupHigh or GHLiq is a dummy variable that takes value 1 for the firms in the highest tercile of the liquidity shock and PD-low (PD-high) and Growth-low (Growth-high) are dummy variables that take value one for the firms in the bottom (top) half of probabilities of default and growth opportunities, respectively. Other controls include total assets, capital structure (liabilities to equity), a bankruptcy dummy (this dummy takes value 1 when the firm has negative equity), an interaction between the bankruptcy dummy and the capital structure variable, sales to lagged assets, return on assets, growth rate of return on assets, cash, probability of default, growth rate of sales, EBIT to lagged assets, short-term debt to long-term debt and a dummy for the firm's age. All controls are measured prior to the shock, so lagged values are used for all years except for 2013, in which the value of 2011 is used. All regressions include firm fixed effects. Within R-squared is reported. Robust standard errors clustered at the matched-firm level and shown in parentheses. ***, ** or * indicates that the coefficient is significant at the 1%, 5% or 10% level, respectively.

Table 6 *Effects on Short-Term Financial Debt (Methodology 1).*

VARIABLES	(1) Cont-Liq	(2) Match	(3) M-FC	(4) M-GO	(5) M-FC-GO
Post	-0.985***	-0.812***			
	(0.131)	(0.156)			
Post*Liquidity shock(cont)	-8.608***				
	(1.635)				
Post*GroupHigh		-1.303***			
		(0.252)			
Post*GHLiq*PD-low			-0.796***		
			(0.256)		
Post*GHLiq*PD-high			-1.768***		
			(0.414)		
Post*GHLiq*Growth-low				-1.613***	
				(0.346)	
Post*GHLiq*Growth-high				-1.035***	
				(0.365)	
Post*GHLiq*PD-low*Growth-low					-0.585
					(0.358)
Post*GHLiq*PD-high*Growth-low					-2.290***
					(0.514)
Post*GHLiq*PD-low*Growth-high					-0.969***
					(0.360)
Post*GHLiq*PD-high*Growth-high					-1.134*
					(0.682)
Observations	44,749	35,577	35,577	35,577	35,577
R-squared	0.023	0.022	0.023	0.022	0.024
Number of firms	13,838	10,859	10,859	10,859	10,859

This table presents estimates from panel regressions explaining yearly short-term debt for the period 2010 to 2013. Post is a dummy variable that takes value one for years 2012 and 2013. Liquidity shock (cont) is the size of the liquidity shock received by the firm scaled by total assets in 2011, GroupHigh or GHLiq is a dummy variable that takes value 1 for the firms in the highest tercile of the liquidity shock and PD-low (PD-high) and Growth-low (Growth-high) are dummy variables that take value one for the firms in the bottom (top) half of probabilities of default and growth opportunities, respectively. Other controls include total assets, capital structure (liabilities to equity), a bankruptcy dummy (this dummy takes value 1 when the firm has negative equity), an interaction between the bankruptcy dummy and the capital structure variable, sales to lagged assets, return on assets, growth rate of return on assets, cash, probability of default, growth rate of sales, EBIT to lagged assets, short-term debt to long-term debt and a dummy for the firm's age. All controls are measured prior to the shock, so lagged values are used for all years except for 2013, in which the value of 2011 is used. All regressions include firm fixed effects. Within R-squared is reported. Robust standard errors clustered at the matched-firm level and shown in parentheses. ***, ** or * indicates that the coefficient is significant at the 1%, 5% or 10% level, respectively.

Table 7 *Effects on Investment (Methodology 2).*

VARIABLES	(1) Cont-Liq	(2) Match	(3) M-PD	(4) M-GO	(5) M-PD-GO
Post	-0.665***	-0.873			
	(0.105)	(1.150)			
Post*Phase1-Liquidity(cont)	3.229***				
	(1.128)				
Post*Phase1		1.538			
		(1.570)			
Post*Phase1*PD-low			4.689*		
			(2.438)		
Post*Phase1*PD-high			-0.799		
			(2.052)		
Post*Phase1*Growth-low				-1.289	
				(2.291)	
Post*Phase1*Growth-high				4.135*	
				(2.160)	
Post*Phase1*PD-low*Growth-low					-1.660
					(4.163)
Post*Phase1*PD-high*Growth-low					-1.062
					(2.752)
Post*Phase1*PD-low*Growth-high					7.876***
					(3.028)
Post*Phase1*PD-high*Growth-high					-0.695
					(3.171)
Observations	44,580	879	879	879	879
R-squared	0.008	0.067	0.078	0.076	0.089
Number of firms	25,497	502	502	502	502

This table presents estimates from panel regressions explaining yearly investment for the period 2011 to 2012. Post is a dummy variable that takes value one for 2012. $Phase1 - Liquidity(cont)$ is the size of the liquidity shock received by the firm scaled by total assets in 2011, $Phase1$ is a dummy variable that takes value 1 for the firms that participate in phase 1 and zero for firms that participate in phase 2, and PD-low (PD-high) and Growth-low (Growth-high) are dummy variables that take value one for the firms in the bottom (top) half of probabilities of default and growth opportunities, respectively. Other controls include total assets, capital structure (liabilities to equity), a bankruptcy dummy (this dummy takes value 1 when the firm has negative equity), an interaction between the bankruptcy dummy and the capital structure variable, sales to lagged assets, return on assets, growth rate of return on assets, cash, probability of default, growth rate of sales, EBIT to lagged assets, short-term debt to long-term debt and a dummy for the firm's age. All controls are measured prior to the shock, so lagged values of the variables are used for all years. All regressions include firm fixed effects. Within R-squared is reported. Robust standard errors clustered at the matched-firm level and shown in parentheses. ***, ** or * indicates that the coefficient is significant at the 1%, 5% or 10% level, respectively.

Table 8 *Effects on Short-Term Financial Debt (Methodology 2).*

VARIABLES	(1) Cont-Liq	(2) Match	(3) M-PD	(4) M-GO	(5) M-PD-GO
Post	-0.998***	1.226			
	(0.145)	(1.301)			
Post*Phase1-Liquidity(cont)	-14.184***				
	(1.593)				
Post*Phase1		-2.208			
		(1.764)			
Post*Phase1*PD-low			0.283		
			(2.772)		
Post*Phase1*PD-high			-3.989*		
			(2.304)		
Post*Phase1*Growth-low				-3.250	
				(2.596)	
Post*Phase1*Growth-high				-1.241	
				(2.431)	
Post*Phase1*PD-low*Growth-low					-1.231
					(4.827)
Post*Phase1*PD-high*Growth-low					-4.033
					(3.105)
Post*Phase1*PD-low*Growth-high					1.012
					(3.434)
Post*Phase1*PD-high*Growth-high					-3.925
					(3.594)
Observations	42,484	840	840	840	840
R-squared	0.060	0.476	0.479	0.477	0.479
Number of firms	24,171	476	476	476	476

This table presents estimates from panel regressions explaining yearly short-term financial debt for the period 2011 to 2012. Post is a dummy variable that takes value one for 2012. Phase1-Liquidity (cont) is the size of the liquidity shock received by the firm scaled by total assets in 2011, Phase1 is a dummy variable that takes value 1 for the firms that participate in phase 1 and zero for firms that participate in phase 2, and PD-low (PD-high) and Growth-low (Growth-high) are dummy variables that take value one for the firms in the bottom (top) half of probabilities of default and growth opportunities, respectively. Other controls include total assets, capital structure (liabilities to equity), a bankruptcy dummy (this dummy takes value 1 when the firm has negative equity), an interaction between the bankruptcy dummy and the capital structure variable, sales to lagged assets, return on assets, growth rate of return on assets, cash, probability of default, growth rate of sales, EBIT to lagged assets, short-term debt to long-term debt and a dummy for the firm's age. All controls are measured prior to the shock, so lagged values of the variables are used for all years. All regressions include firm fixed effects. Within R-squared is reported. Robust standard errors clustered at the matched-firm level and shown in parentheses. ***, ** or * indicates that the coefficient is significant at the 1%, 5% or 10% level, respectively.

8 Appendix

8.1 Alternative methodology: flexible time model

An extended version of this paper makes use of a flexible model with year fixed effects instead of PRE and POST dummies (Mora and Reggio (2013)). This is useful to compare whether the two years before and after the shock are significantly different among each other or can be grouped together. We use 2010 as our baseline year and omit it.

8.2 Random download

We base the download on the CIFs (firm fiscal identification code) of the firms. CIFs are constructed by 9 characters, first character is a letter that indicates the legal type of the firm, the following two numbers indicate the region of the headquarters of the firm, the next five numbers depend on the time when the firm was registered in the Spanish Official Registry, and the last number is a control digit. To construct the random sample, we follow the subsequent steps:

1. Download all the CIFs that exist in SABI.
2. Eliminate all the CIFs of firms that participate in the FFPP.
3. Segment the remaining sample according to the legal types of firms.
4. For each legal type, keep all firms whose penultimate number is a one.
5. Calculate the percentage of the different legal types of firms that appear in the FFPS database.
6. Randomly download from each legal type of firm group as many firms as needed in order to have similar percentages as those observed for the FFPS database.
7. For some specific types, there are not enough firms of a certain legal type in my random groups. Our solution is to randomly download other firms whose penultimate number is not a one.

8.3 Analysis of the quality of the DID match for 2011

Table 9 *Quality of the match for the DID analysis in 2011*

	(1) GHLiq=1	(2) GHLiq=0	(3) GHLiq=1 on sup.	(4) GHLiq=0 (M)
Liquidity shock(contin)	0.13	0.00	0.12	0.00
	(0.23)	(0.00)	(0.18)	(0.00)
Total assets	7253.02	21263.17	8427.23	12368.68
	(62463.07)	(270868.76)	(68978.29)	(95951.87)
Employees	66.07	82.77	66.25	69.51
	(595.45)	(1035.55)	(632.51)	(584.94)
Probability of default	11.97	11.29	11.59	11.46
	(20.39)	(19.26)	(19.96)	(19.59)
ST debt to LT debt	5.99	8.76	6.15	9.35
	(38.15)	(107.28)	(39.49)	(119.36)
Investment	-0.60	0.11	-0.47	-0.35
	(9.91)	(20.55)	(9.90)	(11.35)
Sales growth	0.04	0.40	-0.01	0.01
	(1.28)	(29.13)	(0.42)	(0.58)
EBIT to lagged assets	1.33	1.60	1.31	1.42
	(16.60)	(14.23)	(14.78)	(11.37)
Altman Z-score	2.05	2.02	2.03	2.02
	(1.75)	(1.34)	(1.69)	(1.34)
Cash	466.90	1135.99	535.72	686.30
	(6593.61)	(29271.79)	(7380.04)	(8752.10)
Observations	10134	10134	7854	7854

This table reports summary statistics of firm-year observations in 2011 for the sample used for the DID analysis. Matching is done in 2010 as described in Section 4.1. Firms are classified as treated firms (column 1) if GHLiq = 1, which implies that these firms are classified in the top tercile regarding the size of the liquidity shock received, or as control firms (column 2) if GHliq = 0, which implies they belong to the bottom tercile. Columns 3 and 4 report summary statistics after the matching is realized. In column 3 we classify treated firms on support and in column 4 all control matched firms. Liquidity shock (contin) is the size of the liquidity size as described in Section 3.2, total assets and employees are measured in thousands, probabilities of default are described in Section 3.3, ST debt to LT debt is the ratio of short-term debt to long-term debt (includes debt issued and financial debt), investment and sales growth are calculated as described in Section 3.1 and Section **??** respectively, EBIT lo lagged assets is earnings before interest and taxes divided by lagged total assets, Altman Z-score is measured as in Altman (1968), cash is measured in thousands and includes cash and very liquid assets. Numbers reported are cross-sectional averages and standard errors in parentheses.

Table 10 *Ttest for the DID analysis in 2011*

	(1) Mean differences	(2) Mean differences (Matched)
Liquidity shock(contin)	-0.127***	-0.120***
	(-56.02)	(-58.51)
Total assets	14010.2***	3941.4**
	(5.07)	(2.96)
Employees	16.70	3.256
	(1.39)	(0.33)
Probability of default	-0.679*	-0.128
	(-2.44)	(-0.40)
ST debt to LT debt	2.777*	3.206
	(2.01)	(1.86)
Investment	0.717**	0.123
	(3.16)	(0.72)
Sales growth	0.364	0.0247**
	(1.25)	(3.05)
EBIT to lagged assets	0.270	0.110
	(1.24)	(0.52)
Altman Z-score	-0.0344	-0.00704
	(-1.57)	(-0.29)
Cash	669.1*	150.6
	(2.18)	(1.13)
Observations	20268	15708

This table reports t-test results of firm-year observations in 2011 for the sample used for the DID analysis. Matching is done in 2010 as described in Section 4.1. Column 1 of this table analyzes mean differences of the unmatched sample (columns 1 and 2 of Table 1). Column 2 analyzes mean differences of the matched sample (columns 3 and 4 of Table 9). Liquidity shock (contin) is the size of the liquidity size as described in Section 3.2, total assets and employees are measured in thousands, probabilities of default are described in Section 3.3, ST debt to LT debt is the ratio of short-term debt to long-term debt (includes debt issued and financial debt), investment and sales growth are calculated as described in Section 3.1 and Section **??** respectively, EBIT lo lagged assets is earnings before interest and taxes divided by lagged total assets, Altman Z-score is measured as in Altman (1968), cash is measured in thousands and includes cash and very liquid assets. T-statistics in parentheses. * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$