CLEAR CONSCIENCE NEVER FEARS MIDNIGHT KNOCKING: THE EFFECT OF EARNINGS MANIPULATION ON THE APPLICATION OF PAYCHECK PROTECTION PROGRAM DURING THE COVID-19

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_____ (Signed)

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ABSTRACT

This paper examines the real consequences of earnings management through the lens of public funds application. Utilizing the Paycheck Protection Program (PPP) during the Covid-19 pandemic as a laboratory, I document that firms with higher earnings management prior to the outbreak of Covid-19 are less likely to apply for the PPP loans, suggesting that firms tend to forgo "low-hanging fruit" funding opportunities to pre-empt potential public outcry over government funds flowing to disreputable firms. I further find that the identified effect is more pronounced for firms receiving greater public attention and when the loans are under tighter scrutiny. Finally, I find that firms with higher earnings management are less likely to repay PPP loans after the Small Business Administration (SBA) called for returning the loans if borrowers cannot make a good-faith certification, probably because returning behaviour may expose firms to heightened public scrutiny. Overall, my findings shed novel light on the role of financial reporting in capital allocation during unexpected challenging times.

Keywords: Covid-19; Paycheck Protection Program (PPP); Earnings management; Public scrutiny; Capital allocation

JEL Classification: G28; G38; M41

I. INTRODUCTION

The Covid-19 pandemic is the most serious economic crisis since World War II (OECD, 2020).[1] The United States is no exception. In the first few months of the crisis, tens of millions of people lost their jobs,[2] and the unemployment rate reached 14.8% in April 2020—the highest rate since data collection began in 1948.[3] In response, the U.S. Congress and the federal government quickly passed and signed into law the Coronavirus Aid, Relief, and Economic Security (CARES) Act on March 27, 2020. A central piece of the CARES Act is the Paycheck Protection Program (PPP), which was aimed at keeping workers employed by providing low-interest or even forgivable loans to employers. However, a puzzling phenomenon is that, although half of the public firms are eligible for the PPP program, only about one-third of those eligible public firms eventually choose to borrow. Thus, an interesting question arises as to what factors prevent those eligible public firms from not borrowing the PPP loans, which are widely deemed "low-hanging fruit" funds during the crisis period. In this paper, I investigate the role of earnings management in shaping firms' borrowing decisions.

I conjecture that firms with higher earnings management are less likely to borrow the PPP loans for the following reasons. First, the PPP loans are designed to support small businesses to cover employee payroll, whereas the listed companies are generally perceived by the public to be not entitled to the program.[4] As such, listed firms must trade off the costs and benefits in making borrowing decisions. To the extent that earnings management is detrimental to corporate reputation (e.g., Zahra, Priem and Rasheed 2005; Roychowdhury 2006; Martínez-Ferrero, Banerjee, and García-Sánchez 2016), borrowing behaviour of such firms is likely to

[1] https://www.oecd.org/coronavirus/policy-responses/the-territorial-impact-of-covid-19-managing-the-crisis-across-levels-of-government-d3e314e1/
[2] See https://www.cbpp.org/sites/default/files/8-13-20pov.pdf
[3] See Congressional Research Service Report (August 20, 2021) at https://sgp.fas.org/crs/misc/R46554.pdf
[4] See Fortune, *PPP: Dozens of public companies kept millions of dollars in small-business loans* (July 5, 2020) (online at https://fortune.com/2020/07/07/ppp-loans-public-companies-small-businesses-sba-paycheck-protection-program/)

provoke public attention and regulatory scrutiny. Second, because PPP loans are of public interest, regulators promise to investigate on certification of public borrowers. Financial numbers are under strict review because they are important in identifying eligible firms and confirming maximum loan amount. Because earnings management is a typical red flag of misstatement in financial numbers (Huang et al. 2020), firms with higher earnings management do not expose their opaque financial report to regulators and thus have less likelihood to borrow the "lower-hanging fruit".

It is inherently challenging to test the factors behind a firm's borrowing decisions for at least two reasons. First and foremost, in the case of commercial loans, the received loan amounts are jointly determined by demand and supply. Thus, it is difficult to distinguish between borrowers' incentives and lenders' considerations in determining the loans. Second, a general lack of transparency in lenders' decision-making process makes it difficult to pin down the impact of any firm-level characteristics on the borrowing outcomes.

The PPP provides a unique setting that enables me to overcome the above limitations. First, since the loans are fully guaranteed by the government, participating banks have little exposure to credit risk in relation to the loans. Consequently, PPP loans are granted on a "first-come, first-serve" basis, in which borrowers' incentives dominate in the course of borrowing. In other words, the PPP setting enables me to isolate borrowers' characteristics from lenders' considerations in the lending process because participating banks have little incentives to screen borrowers (Cororanton and Rosen 2021). Second, the eligibility criteria of PPP are clearly defined so that I can precisely identify a group of eligible firms, among which some choose to borrow while others do not. On top of this, following the exogenous coronavirus outbreak, the federal government rushed to provide urgent financial assistance to business owners to countervail the negative economic consequences of Covid-19. Hence, it is unlikely that firms adopt discretionary accounting choices in anticipation of future crisis as well as fund

opportunities. Thus, the PPP program provides me an ideal setting to identify the causal effect of earnings management on the application of public funds.

I investigate the impact of earnings management on the likelihood of borrowing PPP loans using a sample of eligible listed firms. Focusing on listed firms provides at least two advantages for my study. First, compared with their privately-owned counterparts, listed firms subject to greater reputational costs and public scrutiny. This is particularly true in the case of PPP wherein only less than 40% of eligible listed firms borrowed relative to over 80% of private firms (Cororaton and Rosen 2021). Given a general finding that earnings manipulation is detrimental to corporate reputation, I would expect the impact of earnings management on borrowing decision to be more noticeable for listed firms. Second, listed firm sample allows me to obtain accounting and employee data to identify eligible borrowers and then conduct regression analyses. As listed firms are under same financial reporting standards and similar supervision, earnings management among listed firms is more comparable than that among private firms.

In line with my prediction, the results show that firms with higher earnings management are associated with a lower likelihood of borrowing PPP loans. This effect is not only statistically significant, but also economically meaningful. Specifically, a one standard deviation increase in absolute discretionary accruals leads to a 2.7-3.1 percent decrease in the likelihood of borrowing. Overall, my results support my hypothesis that potential reputational concerns, arising from higher earnings management, disincentivize firms from borrowing public funds.

To ensure the robustness of the results, I carry out a battery of sensitivity analyses by using alternative measurements of PPP loans and discretionary accruals, and using non-accruals-based financial reporting quality measures such as financial statement readability and restatement probability. First, I conjecture that firms with lower financial reporting readability

are less likely to borrow PPP loans because firms most likely to have managed earnings have lower readability in their financial reports (Lo, Ramos, and Rogo 2017). Second, Amiram et al. (2015) find that if distribution of leading digits of firms' financial statements numbers deviates from Benford's Law, then these firms will have higher likelihood of committing material misstatements in following fiscal year. Therefore, I conjecture that firms with firms with higher FSD_Score, the restatement probability measurements developed according to Benford's Law, are less likely to borrow PPP loans. My results are consistent when replacing with alternative measurements of earnings manipulation.

One may concern that PPP-borrowing and non-borrowing firms may not be comparable. The observed heterogeneity could further confound my inferences. To mitigate this concern, I perform analyses based on matched samples to ensure that borrowing and non-borrowing firms have similar firm characteristics. I employ multiple matching techniques, including entropy balancing matching, coarsened exact matching, propensity score matching, and nearest matching, and obtain results consistent with those from the baseline test.

I next examine whether the baseline result varies with the strength of public attention and scrutiny risks. If I find evidence that the negative impact of higher earnings management on the borrowing likelihood is exacerbated when public attention and scrutiny risks are higher, then the endogeneity concern should be further mitigated (Jiang 2017).[5] I measure public attention using the issuance of SEC comment letters (Cassell, Dreher, and Myers 2013), occurrence of legal cases (Adhikari, Agrawal, and Malm 2019) and negative media sentiment (Gantchev and Giannetti 2021) prior to the outbreak of Covid-19. I find that the negative impact of higher earnings management on borrowing likelihood is more pronounced for firms with

[5] Jiang (2017) argues that cross-sectional variation tests help mitigate endogeneity concerns when mechanisms of endogeneity are known.

higher public attention. This is probably because high public visibility exposes borrowing firms to higher risks, thus leading to greater reputational concerns.

To measure scrutiny risk, I utilize a unique feature of the PPP setting, in which different purposes of application are subject to different levels of scrutiny. Since PPP loans are designed to cover payroll costs, rent, mortgage interest and utilities bills, if a firm borrows mainly for those purposes, then PPP loans can be forgivable. Nevertheless, if a firm applies for PPP loans because of other reasons, they are likely to face higher scrutiny risks after the loans are granted because they need to offer tailored supporting documents awaiting tailored investigation from SBA. Thus, I partition my sample into two groups according to whether their loans are forgivable. The negative effect of higher earnings management on borrowing likelihood remains significantly negative for the subgroup with higher scrutiny risk, while is muted for the subgroup with lower scrutiny risk. Besides, since borrowers with loans greater than $2 million are subject to review by SBA for compliance with program requirements, those firms are expected to have higher scrutiny risk. Indeed, I find that my baseline relation is stronger for firms with PPP loans which are greater than 2 million dollars.

Finally, I conduct two further analyses to substantiate my main inferences. I first test whether PPP loans can achieve their objectives by comparing the changes in employee number and financial performance between PPP borrowers and eligible non-borrowers. My results show that PPP borrowers lay off less employees and exhibit better financial performance relative to the non-borrowing peers. Additionally, due to widespread public discontent that publicly traded firms should not be entitled to the emergency program, SBA strengthened the requirement on good-faith certification and requested borrowers who cannot certify in good faith to repay the loans in full by May 14, 2020. This provides me with an opportunity to test whether firms' earnings management plays any role in their decision to return the loans. Interestingly, I find that firms with higher earnings management are less likely to return their

loans than firms with higher-quality financial statements. One possible explanation is that returning behaviour of misbehaving firms may alert the public about their financial reporting weakness. As such, to safeguard themselves from public scrutiny, misbehaving firms choose not to return the funds.

My study makes the following contributions. First, my paper is related to several concurrent studies on PPP. By studying the geographic distribution of funds, Granja, Makridis, Yannelis, and Zwick (2020) find a low correlation between regional PPP funding and employment shock severity. Chetty, Friedman, Hendren, and Stepner (2020) and Autor et al. (2020) document evidence consistent with PPP loans boosting employment rate. Several other studies investigate the determinants of obtaining PPP loans. For example, there is a consensus that lending relationships increases the likelihood of receiving PPP funds and loan size (Amiram and Rabetti 2020; Li and Strahan 2021; Duchin et al. 2022). However, Berger et al. (2020) show that relationship borrowers obtain worse loan terms, such as higher interest rates, on their non-PPP loans, following the onset of the Covid-19 crisis. In addition, Erel and Liebersohn (2020) find that FinTech substitute for traditional bank financing in the provision of PPP loans. Cororaton and Rosen (2020) find that public PPP borrowers tend to be smaller, have less cash, have higher leverage and fewer investment opportunities. To the best of my understanding, my paper is the first to examine how firms' financial reporting practices affect their PPP borrowing and subsequent returning decisions.

My study is also related to a growing literature on the real effects of financial reporting. This stream of literature focuses primarily on the effects of financial reporting on investing and financing decisions made by firms (Shakespeare 2020). The overall evidence suggests that financial accounting can improve investment efficiency and affect financing decision (e.g., initial public offerings (IPO), seasoned equity offerings (SEO), mergers and acquisitions) by reducing information asymmetry and improving monitoring (e.g., Shivakumar 2000; Sletten,

Ertimur, Sunder, and Weber 2018; Levi and Segal 2015; Roychowdhury, Shroff and Verdi 2019). Relatively little is known about how financial reporting quality affects firms' borrowing decisions, especially in implicit costs channel.

My study contributes to emerging literature on corporate subsidy as well because forgivable PPP loans can be considered a corporate subsidy offered by federal government to small businesses. Existing papers on corporate subsidy focus on the impact of corporate subsidy, relatively less papers explore the determinants of subsidy grants. In particular, no study to date has examined the influence of earnings management on firms' application of corporate subsidy. One possible reason is that existing archival data cannot distinguish subsidy grants and subsidy application. For example, GoodjobFirst, the commonly used dataset in corporate subsidy literatures can only identify the firms who get granted but cannot identify firms who apply but get declined (Raghunandan 2021). My study seeks to contribute to this stream of literature using the unique setting that all PPP applications are served with "first come, first serve" principle.

The rest of the paper proceeds as follows. Section 2 discusses institutional background concerning PPP loans. Section 3 discussed related literature and develops testable hypothesis. Section 4 describes the sample, data and variables. Section 5 presents the empirical results. Section 6 concludes.

II.INSTITUTIONAL BACKGROUND

In March 2020, COVID-19 accelerated to spread across the U.S. The negative economic impact followed, such as the plummet of employment rate and the crash in stock market. For example, The stock market triggered level 1 market wide circuit breakers during the opening hour on March 9,12, 16, and 18 separately. Before the four times on March 2020, the circuit-breakers have only been triggered once from its creation in 1987. During the March 2020, S&P

500 dropped 12.56% and S&P 600, whose composites are small cap public companies dropped 22.88%. In additional, not seasonally adjusted initial claims of unemployment insurance raised to nearly 600 million in April 2020, six times the number last year. In order to tackle with the dramatic economic shock, the Congress quickly signed into law the CARES Act on March 27, 2020. The CARES Act offers more than $2.2 trillion of emergency assistance and health care response for individuals and businesses. PPP is one of enactments in the CARES Act, taking part of $349 billion. The primary objective of PPP loans is to help small businesses "maintain the payroll, hire back employee who may have been laid off, and cover applicable overhead".

PPP program provides fully-guaranteed and forgivable loans to eligible small businesses on a "first-come, first-serve" basis. PPP lenders, including federally insured depository banks, federally insured credit unions, and Farm Credit System institutions, are allowed to process PPP loans. Firms are eligible for PPP loans if they meet any of the following requirements: (1) the small business has no more than 500 employees; (2) the small business meets the SBA employee-based or revenue-based size standard corresponding to its primary industry;[6] and (3) any single business entity that is assigned a NAICS code beginning with 72 (including hotels and restaurants) and that employs not more than 500 employees per physical location. Unlike commercial loan lenders, the PPP lenders faced extremely low credit risk because the loans are fully guaranteed by Small Business Administration (Duchin and Hckney 2021). As such, it is unlikely that PPP loan applications by eligible borrowers are rejected.[7]

PPP loans are attractive for several reasons. First, the loans are 100% forgivable if: (1) at least of 75 percent of the loan proceeds cover payroll costs over an 8-week or 24-week covered period; and (2) the borrowers maintain their employee and compensation levels. Second, even

[6] See SBA's Table of size standards (Online available at https://www.sba.gov/document/support-table-size-standards)

[7] I manually checked corporate filings and websites and did not find any case in which the firm applied for PPP loans but turned out to be declined because of banks' screening.

if not forgivable, the loan contract terms are favourable to borrowers. PPP loans carried a 1% interest rate. Both principal and interest payments were deferred ten months after the end of the 8-week or 24-week cover period. In addition, there are no fees associated with the loan, and no collateral or guarantees are required.

On April 3, 2020, the PPP program started disbursing funds. Because of the strong demand, the initial $349 billion were exhausted within two weeks. On April 24. Congress injected additional $310 billion for the PPP program, and SBA began accepting new applications since April 27. The second round of PPP program closed to new loan applications on August 8, 2020. The whole PPP program had distributed 79.67 percent ($525 billion) of total fund ($659 billion), leaving approximately $134 billion unused. Figure 1 lists the dates and amounts of public firms' borrowing.

During the disbursement of the PPP program, nearly half of public firms were eligible for the program. However, only one third of those firms decided on borrowing the loans (Cororanton and Rosen 2021), owing to the widespread discontent that public firms have much more sources to finance themselves in capital markets compared with unlisted small businesses and thus should not crowd out the funding opportunities for the latter.

To respond to public criticism, on April 23, the SBA clarified the good-faith certification for PPP loan applications. In particular, the SBA highlighted that "borrowers must certify in good faith that their PPP loan request is necessary" and "public companies should be prepared to demonstrate to SBA, upon request, the basis for its certification". Meanwhile, SBA required that any borrowers who repay the loan in full by May 14, 2020 will be deemed to have made the good faith certification. Consequently, more than 100 public firms returned their PPP loans as of August 8th, 2020.

III. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Literature Review

PPP program has drawn widespread attention from researchers. One strand of literature evaluates economic consequences of PPP loans. There is agreement in the literature that PPP program lowers unemployment during the pandemic. For instance, Autor et al. (2020) find that PPP-eligible firms experience less employment falls relative to others. Barraza et al. (2020) show that areas with more bank branches that issued SBA backed loans in 2019 experience smaller increases in unemployment following the PPP program. Hubbard and Strain (2020) document that PPP program improves employment, financial health, and survival rate of small businesses. Apart from employment, some studies find that PPP program bolsters firms' liquidity and alleviates the shortfall (Chodorow-Reich, Darmouni, Luck, and Plosser 2021). Notwithstanding the above benefits, some studies document evidence that the costs outweigh the benefits for PPP program. For example, Granja et al. (2020) show that PPP first-round funds flow disproportionately into districts hit less by the pandemic. Duchin and Hackney (2022) find that PPP funds go to firms in battleground states and Republican states, suggesting that quid-quo-pro politics, rather than economic considerations, influence the allocation of PPP funds.

Another stream of literature pays attention to the factors that drive public firms to borrow from the PPP program. For instance, Cororaton and Rosen (2021) show that smaller firms with less cash, higher leverage, and fewer investment opportunities are more likely to borrow. Besides, several studies reveal that bank relationships play a crucial role in the application. Amiram and Rabetti (2020) find that firms with existing banking relationship receive PPP loans earlier than other eligible applicants. In a similar vein, Li and Strahan (2021) and Duchin et al. (2022) find that firms with personal ties to banks are more likely to obtain PPP loans. Additionally, Erel and Liebersohn (2020) suggest that FinTech substitutes for

traditional bank lending in the case of PPP program. Relatively few studies focus on the factors that prevent firms from borrowing PPP loans. One exception is Balyuk, Prabhala, and Puri (2021), which shows that the perceived costs of SBA audit deter public firms to access the PPP loans. My paper contributes to this line of literature by documenting novel evidence that firms' financial reporting quality can affect their PPP borrowing decisions.

Hypothesis Development

Firms face a trade-off between benefits and costs when choosing to borrow from public funds. In the context of PPP program, the benefit is apparent that PPP is a low-interest loan with potential to be forgiven if the borrower satisfies the given criteria. The PPP loans have an interest rate of 1% while SBA 7(a) loans, SBA's most common loan program which includes financial help for businesses with special requirements, have interest rate from 5.75% to 8.25%.[8] In addition, PPP loans will be fully forgiven if the funds are used for designated purposes, such as payroll costs, interest on mortgages, rent, and utilities. Furthermore, because PPP loans are fully guaranteed by SBA, banks approve and make deposits in a quick manner, further minimizing the transaction costs of borrowing. When it comes to the costs, the most important ones include reputational harm and negative signalling (Cororaton and Rosen 2021). To the extent that public firms have much more financing sources to help themselves get through the difficult times compared with their private counterparts, accessing an emergency program, which is intended to support small businesses, will inevitably damage their public image and provoke public outcry. The perceived reputational costs would be magnified when the public firm engages in disreputable activities. Using survey evidence, Colonnelli, Gormsen and McQuade (2021) confirm that public support for corporate bailout decreases in response to bad corporate behaviour. Earnings management has adverse impact on the quality of reported earnings since these will not be as they are supposed to be. As a consequence, firms

[8] See https://www.nav.com/blog/sba-loan-rates-74401/

that overly pursue earnings management will be deemed to be dishonest in financial reporting practices. In line with this reasoning, prior studies show that discretional accounting practices exert a negative impact on corporate reputation (e.g., Fombrun et al. 2000; Roychowdhury 2006; Martínez-Ferrero et al. 2016). Given the above arguments, firms with higher earnings management may suffer greater loss in corporate reputation if they borrow from the PPP program.

On top of this, prior studies consistently document that firms adopt earnings management mainly to avoid reporting losses and earnings declines, which tend to decrease the confidence of investors and lenders (e.g., Burgstahler and Dichev 1997; Dechow and Skinner 2000; Dechow et al. 2010). A firm who seeks emergent financial assistance through the PPP program can be interpreted as a negative signal that the firm has financial health problems (Cororaton and Rosen 2021). This negative signal is particularly relevant for firms involved in earnings management because it can raise a suspicion about the firms' previously reported earnings. Taken together, I formulate my hypothesis as follows:

> ***Hypothesis:*** *Firms with higher earnings management are less likely to borrow from the PPP program.*

However, the hypothesis has tensions. Some factors related to PPP loans may induce firms to borrow regardless of risks brought from public pressure and scrutiny. First, the financial benefits of PPP loans are concrete for firms, especially in the tough pandemic period. For example, Cororanton and Rosen (2021) find that firms with financial constraint have higher likelihood of borrowing PPP loans. Firms may out-weigth financial benefits than implicit costs related to public pressure and scrutiny risks concerning with PPP loans. Second, firms with more earnings management have higher cost of debt (Francis et al. 2005). These firms have more difficulties in borrowing external money and thus rely more on PPP loans for survival

and business operation. Therefore, casual effects of earnings management on firms' PPP borrowing decision is an empirical question.

IV. SAMPLE, DATA, AND RESEARCH DESIGN

In this section, I discuss: (1) how to identify eligible public firms for the PPP loans, (2) how to identify public PPP borrowers and returners, (3) how to construct the final sample for testing the hypothesis, and (4) research design as well as measurements of key variables.

Eligible Public Firms

I start with identifying all eligible public firms, regardless of whether they applied for the PPP loans. I focus on firms headquartered in the US because the PPP is intended to assist US companies. Because the information on total assets, cost of goods sold, revenue, and number of employees[9] is essential in determining the eligibility of borrowing, I drop firms without such information in their 10K filings issued from 31 March, 2019 to 31 March, 2020, prior to the initiation of the PPP program. I also drop firms with less than five employees. Further, I delete firms without issuing 8-K/10-Q/10-K filings from March 1st, 2020 to August, 8th, 2020 because SEC EDGAR files are needed to identify PPP borrowers. This procedure results in a sample of 3,985 public firms.

According to the CARES Act issued on 27 March, 2020, a firm is eligible for the PPP loans if it meets any requirement of the following three: (1) with no more than 500 employees; or (2) meeting the SBA employee-based or revenue-based size standard corresponding to its primary industry; or (3) operating in accommodation and food industries whose NAICS 2-digit codes are 72 and employees per physical location are no more than 500. The first criteria (1) and (3) are self-explanatory. For the second criterion, I extract the Table of Small Business

[9] For most of industries, size standards are the average annual receipts calculated from revenue and cost of goods solde or the average employement of a firm. For some special industries, size standards are total assets (eg. NAICS codes 522110, 522120, 522130, 522190, and 522210). The detailed calculation can be found in 13 CFR § 121.104 and 13 CFR § 121.106.

Size Standards Matched to North American Industry Classification System Codes from the SBA official website.[10] SBA Size Standard Table regulates size standards in millions of dollars or size standards in the number of employees for every six-digit NAICS industry.[11]

Among the 3,985 public firms in Compustat, 1,907 (47.85 percent) satisfy at least one of the three eligibility requirements. Specifically, 1,334 (69.95 percent), 1,647 (89.37 percent) and 67(3.51 percent) satisfy the criterion one, criterion two, and criterion three, respectively.

Public Borrowers and Returners

I next collect information on firms who were granted the PPP loans from four sources: (1) FactSquared Data (https://factba.se/sba-loans); (2) SEC filings issued from 27 March, 2020 to 31 August 2020; (3) SBA PPP loans All Data (https://ppp-loan.info/), and (4) data from other scholars.[12]

Specifically, I start with the FactSquared data, sourced from 8-K filings from April 3rd, 2020 to August 8th, 2020. The data include information on borrowing firms, loan amount, and whether a firm returned the loan. There are 440 loan entries (409 firms) matched with my eligible firm sample.

However, some firms may not disclose the receipt of the PPP loans in their 8-K filings. Rather, they disclose the PPP-related information in 10-Q or 10-K filings as "subsequent events". Thus, I supplement the FactSquared data using the SEC Full Text Search. I filter results with keywords as "PPP", "Paycheck Protection Loan", or "SBA loan", SEC-type as "8-K,10-K,10-Q", and time between 27 March, 2020 and 30 June, 2020. I next manually check

[10] https://www.sba.gov/document/support--table-size-standards
[11] For firms with only 2-5 digit NAICS industry code, I use the medium number of matched size standards in SBA Table In untabulated robustness check, I delete those firms. It caused little difference in identifying eligible firms.
[12] I am grateful to Daniel Rabetti at Tel Aviv University for sharing data with me.

each document and extract PPP-related information. The loan entries are therefore expanded to 585 and the number of firms are expanded to 570.

The above steps hinge on firms' voluntary disclosures. However, according to the U.S. Open Government Initiatives, SBA must publicize detailed information about all approved PPP loans. To avoid loss of observations due to firms' nondisclosure, I manually check the SBA website and gather additional PPP borrowers that are not revealed by their disclosures. After manual checking, my sample is expanded to include 844 loan entries (740 firms).

Finally, I compare my sample with that used in Amiram and Rabetti (2020). I include 55 additional entries from their data, ending up with a sample of 895 loan entries (777 unique firms). Finally, I aggregate loan-level data into firm-level data. 627 firms are kept with valid gvkey. I delete 18 financial service firms (NAICS 2-digit code is 52), 135 firms with insufficient data for calculating control variables, and one firm without loan amount information. The final sample consists of 1,201 eligible firms, where 473 firms are the PPP borrowers. The sample selection is demonstrated in Table 1.

[Insert Table 1 here]

Research Design

To test the main hypothesis, I estimate the following Logistic model:

$$Prob\left(Borrow_{i,j,c}\right) = \alpha + \beta EM_i + \gamma CONTROL_i + \eta_c + \eta_j + \epsilon_{i,j,c} \quad (1)$$

where, for firm *i* in industry *j* with headquartered in state *c*, $Borrow_{i,j,c}$ is an indicator variable that equals one if the firm receive a PPP loan and zero otherwise. EM_i is my variable of interest. Following prior studies (e.g., Dechow, Ge, and Schrand 2010; Lo et al. 2017), I use two commonly used proxies to measure earnings management. My first measure is based on the modified Jones Model (Dechow, Sloan and Sweeney 1995). The model is as follows:

$$\left(\frac{TotalAcc_t}{AT_{t-1}}\right) = \alpha_1\left(\frac{1}{AT_{t-1}}\right) + \alpha_2\left(\frac{\Delta REV_t - \Delta REC_t}{AT_{t-1}}\right) + \alpha_3\left(\frac{PPE_t}{AT_{t-1}}\right) \quad (2)$$

Where $TotalAcc_t$ are total operating accruals, AT_{t-1} is total at the end of year t-1, ΔREV_t is the change in revenues from year t-1 to t, ΔREC_t is the change of accounts receivables, and PPE_t is gross property, plant and equipment. I estimate the model in cross-section by firm using quarterly financial statements from 2015 to 2019. The absolute value of residuals from this estimation forms the discretionary accruals ($DACC\_MJ_t$).

My second measure of earnings management is from the performance-matched modified Jones model developed by Kothari, Leone, and Wasley (2005). Specifically, I estimate the following model:

$$\left(\frac{TotalAcc_t}{AT_{t-1}}\right) = \alpha_1\left(\frac{1}{AT_{t-1}}\right) + \alpha_2\left(\frac{\Delta REV_t}{AT_{t-1}}\right) + \alpha_3\left(\frac{PPE_t}{AT_{t-1}}\right) + \alpha_4\left(\frac{ROA_t}{AT_{t-1}}\right) \quad (3)$$

Eq.(3) extends Eq.(2) by including $\mathrm{ROA_t}$, return of assets in period *t*. The absolute value of residuals forms the discretional accruals ($DACC\_KWL_t$)

In robustness check, I also employ several alternative measures of earnings management by estimating the model in cross-section by industry and year using quarterly financial statements (*DACC2Q_MJ* and *DACC2Q_KWL*) and yearly financial statements (*DACC2Y_MJ* and *DACC2Y_KWL*), separately. The results are qualitatively unchanged.

$CONTROL_i$ is a set of firm characteristics that affect the probability of firms to apply for the PPP loans (e.g., Amiram and Rabetti 2020; Cororanton and Rosen 2021; Duchin et al. 2022). I include size and employee numbers because PPP borrowers are smaller and have fewer employees compared to eligible non-PPP firms (Cororanton and Rosen 2021; Duchin et al. 2022). I control for profitability, market-to-book ratio, cash-to-asset ratio, and leverage because firms' financial health is associated with their likelihood of borrowing PPP loans (Cororanton and Rosen 2021). In addition, older firms are more likely to borrow according to prior

literatures (Amiram and Rabetti 2020; Li and Strahan 2021). All control variables are computed using data as of the 4th calendar quarter of 2019. The variable η_c represents state-level fixed effects based on the ZIP code disclosed in SEC files in the fourth calendar quarter of 2019. The variable η_j represents industry-level fixed effects based on two-digit NAICS industry codes. The standard error is clustered by state because the influence of the COVID-19 pandemic is correlated with geographic proximity (e.g., Jia et al. 2020). If my hypothesis is supported, β in Eq. (1) should be significantly negative.

Table 2 provides the descriptive statistics for variables used in the main regression. We winsorize continuous variables at the top and bottom 1 percent. On average, 39.4% of eligible firms borrow the PPP loans in my sample. The mean total asset is $673.367 million. 74.4% of eligible firms experience a loss in the fourth quarter of 2019. In addition, the mean of absolute discretional accruals is 0.067 for performance-matched Jones model and 0.054 for the modified Jones model, respectively. My summary statistics are largely comparable with those in prior studies (e.g., Amiram and Rabetti 2020; Cororanton and Rosen 2021; Duchin et al. 2022). However, as we can see, the standard deviation of size and employee are relatively large. It shows variations among observations. In order to mitigate the variation, I utilize several matching method in robustness check.

[Insert Table 2]

V. EMPIRICAL RESULTS

Baseline Results

Table 3 reports the results of estimating model (1). Columns (1) and (2) report the results with *DACC_KWL* and *DACC_MJ* as the independent variables, respectively. In column (1), the coefficient on *DACC_KWL* is significantly negative (coefficient = -2.849, *t*-statistic =

-2.28). Similarly, the coefficient on *DACC_MJ* in column (2) is also negative and significant (coefficient=-2.479, *t*-statistic =-2.49). In terms of economic magnitude, one standard deviation increase in *DACC_KWL* (*DACC_MJ*) leads to a 3.1 percent (2.7 percent) decrease in the likelihood of borrowing relative to its sample mean, which is economically meaningful. Together, these results suggest that firms with higher earnings management have a lower likelihood of borrowing the PPP loans, which is consistent with my hypothesis.

Regarding the control variables, I find that the PPP borrowers tend to be smaller (negative coefficients on *Ln(Asset)* and *Employee*), older (a positive coefficient on *Ln(Firm Age)*), and less profitable (a negative coefficient on *Dummy_loss*). In addition, firms with higher cash-to-asset ratio and firms with lower leverage are less likely to borrow from the PPP program. These results are largely consistent with those of Cororanton and Rosen (2021).

[Insert Table 3]

Robustness Checks

I perform a series of robustness checks to ensure that my main results are insensitive to alternative measurements and model specifications. In Table 4, Panel A, I replace the dummy dependent variable with a continuous variable *Ln(Loan amount)*, measured as the amount of PPP loans a firm has borrowed. Because the loan amount is a non-negative number, I use a Tobit regression model. My main finding continues to hold. Specially, the coefficient on *DACC_KWL* and *DACC_MJ* are -13.266 (*t*-statistics=-2.52) and -13.506 (*t*-statistics=-2.58) separately, suggesting that firms with higher earnings management tend to borrow less from the PPP program.

In Panel B, I estimate *DACC2_KWL* and *DACC2_MJ* with industry-level accrual models instead of firm-specific accrual models. In columns (1) and (2), I use the data from the fourth quarter of 2009 to calculate the quarterly discretional accruals. In columns (3) and (4), I

use the yearly-end financial reports of 2009 to calculate the yearly discretional accruals. The coefficients on quarterly *DACC2_KWL* and *DACC2_MJ* are -1.298 (*t*-statistics=-1.70) and -2.708 (*t*-statistics=-2.86), respectively. The coefficients on yearly *DACC2_KWL* and *DACC2_MJ* are -0.836 (*t*-statistics=-2.60) and -0.957 (*t*-statistics=-3.33), respectively. overall, my finding is robust to alternative measures of discretionary accruals.

In Panel C, I expand to test non-accrual based financial reporting quality. In column (1), I use *Bog Index*, a measure of readability developed by Bonsall et al. (2017). The Bog Index ranges from 0 to 1, with a higher value indicating a lower level of readability. In column (2), I measure readability using the logarithm of the gross 10-K file size available on the SEC's EDGAR website. Loughran and McDonald (2014) argue that the size of 10-K outperforms other text-based readability measurements because it does not require document parsing and is easy to replicate. I find that the coefficient on *Bog-Index* is -2.110 (*t*-statistics=-2.85) and the coefficient on *Size of 10K* is -0.042 (*t*-statistics=-2.42), suggesting that firms with less readable financial reports are less likely to borrow PPP loans. In column (3), I use *FSD_SCORE*, a measure of restatement probabilities developed by Amiram et al. (2015). The *FSD_SCORE* is the mean absolute deviation between the empirical distribution of leading digits contained in all firms' financial statements and Benford's Law. Amiram et al. (2015) find that *FSD_SCORE* can be used as leading indicator to identify misstatements. I find that the coefficient on *FSD_SCORE* is -37.847 (*t*-statistics=-2.50), suggesting a negative association between restatement probabilities and application of PPP loans.

Taken together, these results bolster my confidence in finding a negative relationship between financial reporting quality and likelihood of borrowing PPP loans.

[Insert Table 4]

Matched Sample Analysis

To mitigate the concern that my results are confounded by observed differences in firm characteristics between the borrowers and non-borrowers, I repeat my main test using matched samples.

First, I use entropy balancing matching to re-weight the non-borrower group in order to ensure comparability of the borrowers and non-borrowers following Hainmueller (2012). The advantage of the entropy balancing method is that it helps achieve better matching outcomes without exerting too many arbitrary matching criteria and keeping the completely full sample of the control group unchanged (McMullin and Schonberger 2020).[13] Table 5, Panel A shows that the mean of the control variables between borrowers and non-borrowers are exactly balanced, and the variance and skewness of both groups are balanced to their best. Table 5, Panel B reports the regression results of model (1) using the re-weighted sample. The coefficients on *DACC_KWL* and *DACC_MJ* remain significant and negative (*t*-statistics = -2.63 and -2.17, respectively).

Second, I perform tests using coarsened exact matching (CEM) to construct the test sample (Blackwell, Iacus, King, and Porro 2009). I cut the sample into 397 strata according to control variables and perform a one-to-one match. Panel C of Table 5 shows that the differences in control variables, except for Market to Book ratio, between borrowers and non-borrowers diminish after matching. Table 5, Panel D shows that coefficient on *DACC_KWL* is -4.736 (*t*-statistics = -2.40) and on *DACC_MJ* is -3.430 (*t*-statistics = -2.04), consistent with the baseline regression results.

Third, in order to mitigate concerns of size variations in a further step, I perform tests using more intuitive matching principle. In panel E column (1) and (2), I perform tests using nearest matching. Specifically, for each borrower, I choose one non-borrower with closest size

[13] I also use propensity-score-matched sample and my results continue to hold. To save space, the results are untabulated but available upon request.

in the same 2-digit NAICS industry without replacement. The coefficients on *DACC_KWL* is -2.84 (*t*-statistics= -2.15) and on *DACC_MJ* is -2.694 (*t*-statistics = -2.58). In panel E column (3) and (4), I only include observations that fullfill the criterial one (less than 500 employees) and rerun the main analysis. The coefficients on *DACC_KWL* is -2.965 (*t*-statistics= -2.20) and on *DACC_MJ* is -2.618 (*t*-statistics = -2.64). In conclusion, after controlling the size variations, the baseline results are still significant.

[Insert Table 5]

Impact Threshold for a Confounding Variable

While matching method addresses observable selection bias, "selection bias due to unobservables" are still unsolved (Tucker 2010). Even though I argue that COVID-19 and the corresponding PPP loans are "surprise" to firms' management, I cannot rule out possibility that firms' earnings management activities and application decisions are endogenously determined by other omitted variables. Following Larcker and Rusticus (2010), I use impact threshold for a confounding variable to release the concern. In untabulated table, I find that the ITCV value is 0.135[14], meaning an omitted variable would have to possess an average correlation of at least 0.135 with both *DACC_KWL* (the independent variable) and borrowing decision (the dependent variable) for the estimated nonzero relationship between the two actually not be different from zero. However, when checking the correlation of our control variables, only *Ln(Asset)* possess the sizable effects. In addition, the ITCV test shows that 26.57% (319) of cases would have to be due to unobservable variables to invalidate the inference using *DACC_KWL*. If we use *DACC_MJ*, the ITCV value is 0.142 and the case ratio is 28.64%, quite similar to the one using *DACC_KWL*. Since it is hard to imagine an omitted variable with a correlation effects greater than size and it is not quite possible that nearly one quarters of cases

are misclassified due to unobservables, I conclude that omitted variables will not shake my baseline analysis concretely.

Cross-sectional Tests

In this section, I investigate whether the effect of earnings manipulation on the probability of borrowing the PPP loans varies cross-sectionally. These cross-sectional tests could help me understand why those eligible firms do not apply for the PPP loans. Specifically, I consider the moderating effect of public attention and scrutiny risk associated with PPP borrowers.

I first examine the moderating effect of public attention on the baseline relation. I expect that public attention plays an important role in constraining a firm's PPP application incentive when the firm has a poor record of earnings management, because high public visibility exposes misbehaving firms to higher litigation and reputational risks.

I measure public attention in several ways. First, I use *Dummy_comment letter*, defined as 1 if a firm received a SEC comment letter in the last three years (i.e., from February 2017 to February 2020), and 0 otherwise. Since a comment letter is an important means used by the SEC to discipline firms with suspected misconduct behaviour (Cassell, Dreher, and Myers 2013; Heese, Khan, and Ramanna 2017), firms receiving comment letters will look more concerning in the public eyes. Second, I measure public attention with the incidence of legal cases. Firms experiencing lawsuits are expected to have higher public scrutiny (Adhikari, Agrawal, and Malm 2019). Specifically, I define an indicator variable, *Dummy_legal case*, which takes the value of 1 if the firm was a defendant of any legal cases in the last three years (i.e., from February 2017 and February 2020), and otherwise 0. Third, I capture public attention using negative media sentiment. Prior literature suggests that negative media sentiment can easily catch public attention (Gantchev and Giannetti. 2021). I define a dummy variable,

Dummy_news sentiment to measure public attention, which equals1 if the average news sentiment from the last three month (i.e., from November 2019 to February 2020) is positive, and 0 otherwise. News sentiment measurement is obtained from Refinitive News Analytics dataset.

Panel A of Table 6 reports the cross-sectional results of regulator attention. In column (1) and column (2) of Panel A, I find that the coefficients on *DACC_KWL* are negative and significant in the subsample of firms receiving comment letters over the past three years (coefficients= -9.188, *t*-statistics =-3.20) but are insignificant for firms that did not receive comment letters during the same period (coefficients = -2.669, *t*-statistics =-1.57). The difference of coefficients on *DACC_KWL* is significant in 10 percent level (p-value=0.0617 in row test based on seeming unrelated regression procedures). In column (3) and column (4) of Panel A, I find similar results with *DACC_MJ* as proxy for earnings quality (coefficients difference as 0.1481). It is consistent with our expectation that our main results are manifested in firms with higher regulator attention.

Panel B reports the cross-sectional results of judiciary attention. Column (1) shows result of main regression using firms that were defendants of any legal cases in the last three years and column (2) using firms that do not involve in any legal cases in the last three years. In column (1) and column (2), the coefficients on *DACC_KWL* are -21.735 (*t*-statistics =-3.20) and -0.513 (*t*-statistics =-0.25) separately. The difference of coefficients are significant in 1 percent level (p-value<0.001). In column (3) and column (4), the results replicate using *DACC_MJ* with a coefficients difference as 0.0421. These results show that our main results are pronounced in firms with higher judiciary attention.

Panel C reports the cross-sectional results of public attention. Column (1) runs main regression using firms whose average news sentiment from the last three months (i.e., from

November 2019 to February 2020) is positive and column (2) using firms whose average news sentiment is negative. I use 3 months instead of 3 years in news sentiment test because timeliness is important for news coverage. I find that coefficients on *DACC_KWL* for firms with negative public image is -4.396 (*t*-statistics = -2.58) while coefficients on *DACC_KWL* for firms with positive image is 0.705 (*t*-statistics = 0.42). The difference is significant in 5 percent level (p-value=0.035). In column (3) and Column (4), results hold if I replace *DACC_KWL* into *DACC_MJ*. Results in Panel C imply that baseline results are more pronounced in firms with negative image. Overall, the results in Table 6 support the notion that the effect of earnings quality on the borrowing decision of PPP loans is stronger in firms with higher public attention from regulators, legal authority, and mass public.

[Insert Table 6]

Next, I examine whether the effect of earnings management on the probability of borrowing PPP loans varies with scrutiny risks in relation to the PPP loans. According to SBA regulation, PPP loans can be forgiven if firms use at least 75% of the loan for payroll, rent, mortgage interest, and utilities.[15] When assessing the applications, SBA requires firms to provide credential materials of payroll costs. Because the payroll information is easy to track, SBA does not require additional information in the following forgiveness applications. However, when firms apply for the PPP loans for other purposes, they need to describe their usages in the application forms and face higher level of scrutiny after they are granted the loans[16].

[15] On June 5, 2020, the proportion for payroll was reduced to 60%.

[16] In Borrower Application Form, borrowers need to explain the "other" purpose in details. In addition, applicant must certify by initialling that "I understand that if the funds are knowingly used for unauthorized purposes, the federal government may hold me legally liable, such as for charges of fraud." As long as firms offer concrete materials to show that the money for "other" purpose is necessary for their business operation, they are still considered as stating "in good faith" and get granted. See Application Form in https://www.sba.gov/document/sba-form-2483-ppp-first-draw-borrower-application-form

Given the above institutional background, I measure the scrutiny risk using an indicator variable that equals 1 if a PPP loan is settled by full forgiveness, and 0 otherwise. I delete firms whose loans are returned because those loans entries are not available in SBA dataset so I cannot obtain forgiveness status of them. Then I separate the sample into two groups according to their forgiveness situation. In Panel A of Table 7, I find that, for the subsample of firms whose PPP loan is settled by full self-payment, the coefficients on absolute discretional accruals are negative and significant (coefficients=-5.413, *t*-statistics=-1.91 using *DACC_KWL*; coefficients=-3.268, *t*-statistics=-2.10 using *DACC_MJ*), whereas for the subsample of firms whose PPP loan is settled by full forgiveness, the coefficients are insignificant (coefficients=-1.877, *t*-statistics=-1.36 using DACC_KWL; coefficients=-1.690, *t*-statistics=-1.26 using *DACC_MJ*). This result is consistent with the negative effect of higher earnings management on borrowing being more pronounced in firms whose loans are used for other purposes.

On May 13, 2020, SBA updated the FAQ and stated that "borrowers with loans greater than $2 million will be subject to review by SBA for compliance with program requirements". SBA required those PPP borrowers to fill up SBA Form 3509 to provide supplemental financial information afterwards. Therefore, PPP borrowers with their loan amount greater than $2 million face higher scrutiny risk. Thus, I further measure the scrutiny risk using an alternative indicator variable, which takes value of 1 if the amount of awarded PPP loans is larger than or equal to 2 million dollars, and 0 otherwise. In Panel B of Table 7, I find that my results are stronger in firms with PPP loans which are greater than 2 million dollars. Altogether, the results of Table 7 provide support to the notion that the negative effect of higher earnings management on the borrowing decision of PPP loans is more conspicuous when borrowers face intensified scrutiny risks.

[Insert Table 7]

Further Analysis

The preceding results confirm evidence consistent with my hypothesis that firms with poorer record of earnings management tend to avoid applying for PPP loans. In this section, I further explore two issues. First, I test whether the PPP program has achieved its stated objectives. Since PPP loans are aimed at minimizing unemployment and financial uncertainties caused by the pandemic, I investigate the impact of PPP loans on employment rate and financial performance. I measure the effectiveness of PPP loans using change of cash ratio, number of employees, market value, and return of assets from 2020 fiscal year to 2019 fiscal year end. Table 8 reports the comparison of changes between PPP borrowers and non-borrowers. I find that PPP borrowers lay off less employees, and have higher market value, ROA and cash-to-asset ratio than non-borrowers during the COVID-19 pandemic, which reaffirm the findings of prior literature that PPP loans succeed in keeping employment and improving firm's financial performance (e.g., Hubbard and Strain 2020; Duchin and Hackney 2021). My results also suggest negative economic consequences of poor financial reporting quality, especially during the crisis period. In the normal time, higher performances are possibly rewarded with higher market valuation, even if there is evidence of earnings management to achieve the results (Myers, Myers, and Skinner 2007). However, during the unexpected COVID-19 crisis, firms with higher earnings management have to forgive good funding opportunities because of potential scrutiny risks and reputation losses from previous earnings manipulation.

[Insert Table 8]

As discussed in the institutional background, many public firm borrowers rushed to obtain PPP loans immediately following the implementation of the program. However, a few firms chose to return their loans after more details about the program solidified and public outcry intensified. This unique background offers a good opportunity to study the impact of financial reporting quality on returning decisions of the PPP borrowers. To this end, I focus on

firms that are awarded PPP loans, and define an indicator variable (*Dummy_return*) that equals 1 for returners and 0 otherwise. In my sample, 85 firms (17.97 percent of the PPP borrowers) eventually repaid their loan in full after they received it. Panel A of Table 9 reports the results using Logit model. The dependent variable is *Dummy_return*. I find that firms with poorer financial reporting quality are less likely to return the PPP loans. The coefficient on *DACC_MJ* is -6.478 (*t*-statistics= -2.72). I find similar results when the independent variable is *DACC_KWL*, though the significance is marginal (-1.37). In Panel B Table 9, I use bivariate Probit model to account for that a firm's decision to return the loan depends on its borrowing decision in the very beginning. The results of the second stage show that the coefficients on *DACC_KWL* and *DACC_MJ* are significant and negative (*t*-statistics =-2.11 and -3.72, respectively). This is probably because returning PPP loans may cast doubt on a firm's eligibility to borrow, thus triggering greater public attention. Therefore, firms with higher earnings management choose not to return the loans to avoid alerting the public and regulators about their poor financial reporting practices. However, I admit that litigation risks may not be the only factor when firms consider on returning decision. One alternative explanation will be self-selection. The cautious firms have already chosen no-borrowing, so only firms that plan to use the fund applied for the loan regardless of the risks brought from earnings management.

[Insert Table 9]

V CONCLUSION

Nearly half of US public firms were eligible for the PPP in 2020, but only one third of those eligible firms choose to get the "free" money. One critical reason is that firms with higher earnings management qualities have concerns of reputation loss and possible investigation if they expose themselves to the public and government through the application. In this paper, I

use public firms' application of Paycheck Protection Program (PPP) as a setting to investigate the real consequences of financial reporting quality through the lens of public funds application. Proxied by absolute discretional accruals, we find that eligible public firms with higher earnings management are less likely to borrow the PPP loans than other eligible public firms. In cross-sectional tests, we find that the negative associations are more pronounced when firms received comment letters recently, when firms engaged legal cases as defendant recently, when firms have negative public image recently. In addition, we find that the negative associations are more pronounced when firms allocate the PPP grant to discretional usages and when borrowing amount triggers SBA's investigation. Overall, I offer evidence that earnings management play an interesting "self-discipline" role in the application of corporate subsidy.

This paper contributes to real effect of earnings management and contemporaneous studies of the PPP. First, because the PPP loans are unanticipated by firms and offer attractive and low credit-risk fund opportunities for broad eligible firms, it offers a great setting to test real effect of earnings management on firm's funding decision towards government subsidies. Second, this paper contributes to discussion on determinants and effects of public firms' application of PPP loans, a heated topic in both public media and academic literatures.

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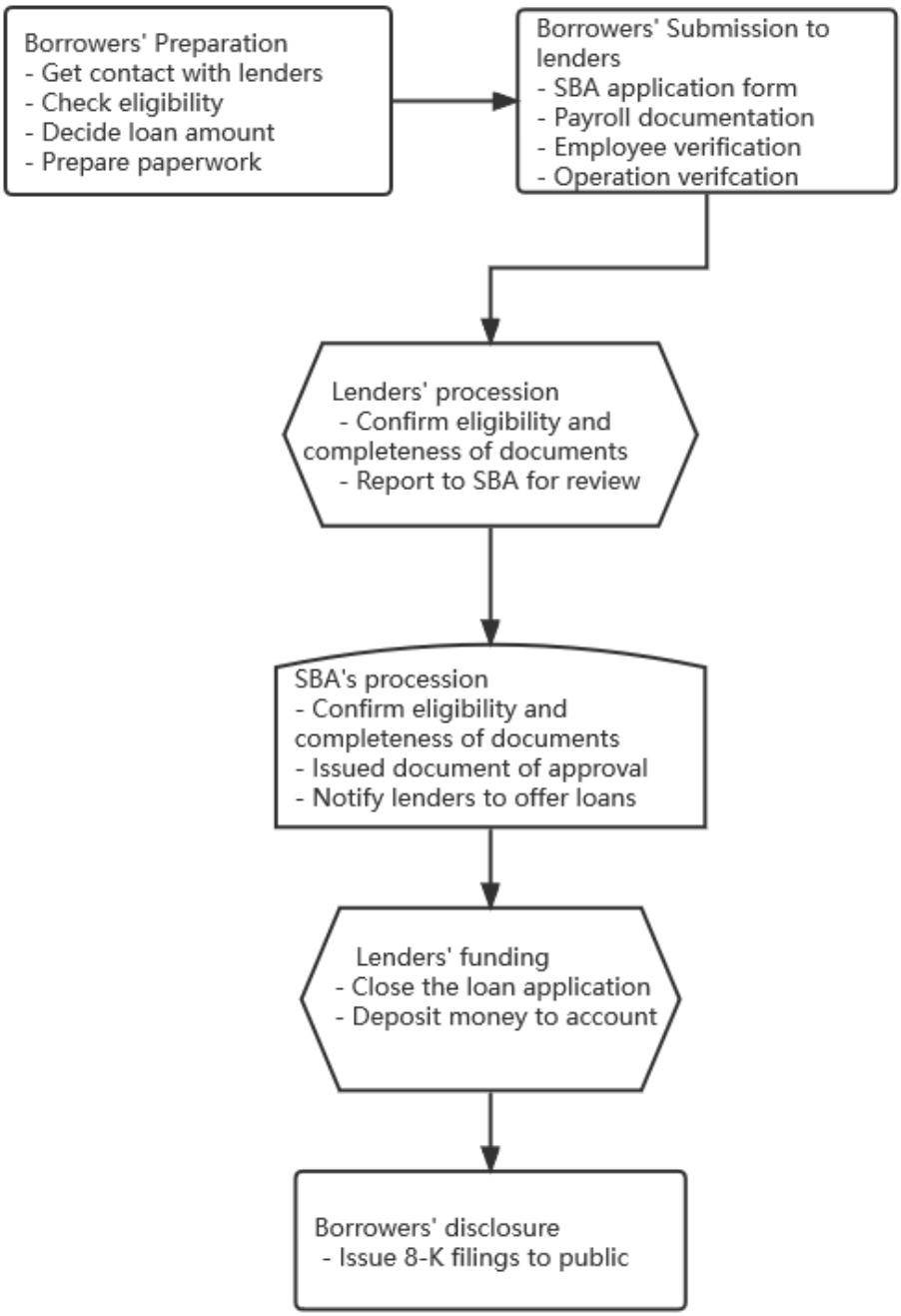
Appendix A: Variable Definition

Variables	Descriptions	Source
Dependent Variables		
Dummy_borrow	Dummy indicator, defined as 1 if firm borrowed PPP loans, and 0 otherwise.	Hand Collection
Dummy_return	Dummy indicator, defined as 1 if firm repaid PPP loans in full before 31 August 2020, and 0 otherwise.	Hand Collection
Loan amount	Logarithm of amount of PPP loans received from borrowers.	Hand Collection
Independent Variables		
DACC_KWL	Absolute value of discretionary accruals estimated by performance matched modified Jones model (Kothari et al. 2005). The accruals are estimated using quarterly financial reporting whose fiscal quarter end is between October 2019 to December 2019. Benchmark is previous 12 quarters accruals of the same firm.	Compustat
DACC_MJ	Absolute value of discretionary accruals estimated by modified Jones model (Dechow et al. 1995). The accruals are estimated using quarterly financial reporting whose fiscal quarter end is between October 2019 to December 2019. Benchmark is previous 12 quarters accruals of the same firm.	Compustat
DACC2Q_KWL	Absolute value of discretionary accruals estimated by performance matched modified Jones model (Kothari et al. 2005). The accruals are estimated using quarterly financial reporting whose fiscal quarter end is between October 2019 to December 2019. Benchmark is accruals of firms in same industries and same period.	Compustat
DACC2Q_MJ	Absolute value of discretionary accruals estimated by modified Jones model (Dechow et al. 1995). The accruals are estimated using quarterly financial reporting whose fiscal quarter end is between October 2019 to December 2019. Benchmark is accruals of firms in same industries and same period.	Compustat
DACC2Y_KWL	Absolute value of discretionary accruals estimated by performance matched modified Jones model (Kothari et al. 2005). The accruals are estimated using annual financial reporting whose fiscal year end is between October 2019 to December 2019. Benchmark is accruals of firms in same industries and same period.	Compustat
DACC2Y_MJ	Absolute value of discretionary accruals estimated by modified Jones model (Dechow et al. 1995). The accruals are estimated using annual financial reporting whose fiscal year end is between October 2019 to December 2019. Benchmark is accruals of firms in same industries and same period.	Compustat
Bog Index	Readability indication created by Bonsall et al. (2017). The formula is based on several plain English factors such as sentence length, passive voice, weak verbs, overused words, complex words, and jargon. Higher	Bonsall et al. (2017)

	values of the index imply lower readability. In order to have same scale. The Bog Index (range from 0 to 100) is divided by 100.	
Size of 10K	The natural logarithm of gross 10-K file size bytes available on the SEC's EDGAR Website.	SEC EDGAR
FSD_SCORE	The mean absolute deviation between the empirical distribution of leading digits contained in all firms' financial statements and Benford's Law	Amiram et al. (2015)
Control Variables		
Cash ratio	Cash Ratio , defined as OANCFQ divided ATQ in Compustat Fundq dataset	Compustat
Debt ratio	Debt Ratio, defined as (DLTTQ+DLCQ)/ATQ in Compustat Fundq dataset	Compustat
Dummy_loss	Dummy indicator, defined as 1 if firm has negative ROA, and 0 otherwise.	Compustat
Employee (in thousands)	Employee numbers at the 2019 fiscal year end. EMP from Compustat Funda dataset.	Compustat
Ln(Firm Age)	The natural logarithm of Firm Age. Firm Age is number of years a company has been included in Compustat database.	Compustat
Ln(Asset)	The natural logarithm of Total Asset. Total Asset is ATQ from Compustat Fundq dataset.	Compustat
M/B	Market to Book ratio, calculated as CSHOQ*PRCCQ/CEQQ in Compustat Fundq dataset.	Compustat
ROA	Return of total asset, defined as NIY divided ATQ in Compustat Fundq dataset.	Compustat
Partition Variables		
Dummy_comment letter	Dummy indicator, defined as 1 if firm had received SEC comment letter during February 2017 to February 2020, and 0 otherwise. Comment letter data is from Audit Analytics Comment Letter dataset	Audit Analytics
Dummy_legal case	Dummy indicator, defined as 1 if firm had been defendant of legal case during February 2017 to February 2020. Legal case data is from Audit Analytics Legal Case and Legal Parties dataset.	Audit Analytics
Dummy_news sentiment	Dummy indicator, defined as 1 if average news sentiment from November 2019 to February 2020 is positive, and 0 otherwise. News sentiment is from Refinitive News Analytics dataset.	Refinitive News Analytics
Dummy_forgiven	Dummy indicator, defined as 1 if PPP loan is settled by full forgiveness, and as 0 if PPP loan is settled by full payment by borrowers. Settlement Status is from SBA All data.	Hand Collection
Dummy_2million	Dummy indicator, defined as 1 if amount of PPP loans is larger than or equal to 2 million dollars, and 0 otherwise. Amount of PPP loans is from manual collected PPP loans data.	Hand Collection
Additional Variables		
Difference of Cash Ratio	Cash Ratio of 2020 fiscal year end subtracts Cash Ratio of 2019 fiscal year end.	Compustat

Difference of Employee	Employee of 2020 fiscal year end subtracts Employee of 2019 fiscal year end.	Compustat
Difference of Market Value	Market Value of 2020 fiscal year end subtracts Market Value of 2019 fiscal year end.	Compustat
Difference of ROA	ROA of 2020 fiscal year end subtracts ROA of 2019 fiscal year end.	Compustat

Appendix B: Process of PPP loans Applying



Appendix C: Example of PPP loans disclosure

Here is PPP loans disclosure in quarterly report of Zivo Bioscience, Inc. (CIK 0001101026) (https://www.sec.gov/Archives/edgar/data/0001101026/000107878220000312/0001078782-20-000312-index.html)

Paycheck Protection Program Loan

On May 7, 2020, The "Company received $121,700 in loan funding from the Paycheck Protection Program (the "PPP") established pursuant to the recently enacted Coronavirus Aid, Relief, and Economic Security Act of 2020 (the "CARES Act") and administered by the U.S. Small Business Administration ("SBA"). The unsecured loan (the "PPP Loan") is evidenced by a promissory note of the Company, dated April 29, 2020 (the "Note") in the principal amount of $121,700 with Comerica Bank (the "Bank"), the lender.

Under the terms of the Note and the PPP Loan, interest accrues on the outstanding principal at the rate of 1.0% per annum. The term of the Note is two years, though it may be payable sooner in connection with an event of default under the Note. To the extent the loan amount is not forgiven under the PPP, the Company will be obligated to make equal monthly payments of principal and interest beginning on the date that is seven months from the date of the Note, until the maturity date.

The CARES Act and the PPP provide a mechanism for forgiveness of up to the full amount borrowed. Under the PPP, the Company may apply for forgiveness for all or a part of the PPP Loan. The amount of loan proceeds eligible for forgiveness is based on a formula that takes into account a number of factors, including: (i) the amount of loan proceeds that are used by the Company during the eight-week period after the loan origination date for certain specified purposes including payroll costs, interest on certain mortgage obligations, rent payments on certain leases, and certain qualified utility payments, provided that at least 75% of the loan amount is used for eligible payroll costs; (ii) the Company maintaining or rehiring employees, and maintaining salaries at certain levels; and (iii) other factors established by the SBA. Subject to the other requirements and limitations on loan forgiveness, only that portion of the loan proceeds spent on payroll and other eligible costs during the covered eight-week period will qualify for forgiveness. Although the Company currently intends to use the entire amount of the PPP Loan for qualifying expenses, no assurance is provided that the Company will obtain forgiveness of the PPP Loan in whole or in part.

Here is PPP loans disclosure in 8-K filings of TRANS-LUX CORPORATION (CIK 0000099106) (https://www.sec.gov/Archives/edgar/data/99106/000151316220000091/form8k.htm)

Item 2.03 Creation of a Direct Financial Obligation or an Obligation under an Off-Balance Sheet Arrangement of a Registrant

On April 23, 2020, Trans-Lux Corporation (the "Company" and "Borrower") entered into that certain loan note (the "Loan Note") with Enterprise Bank and Trust ("Enterprise") as lender under the Coronavirus Aid, Relief, and Economic Security Act ("CARES ACT") of the Small Business Administration of the United States of America ("SBA"), dated as of April 20, 2020.

Under the Loan Note, the Borrower borrowed $810,800 from Lender under the Payment Protection Program included in the SBA's CARES ACT. The Loan Note proceeds are available to be used to pay for payroll costs, including salaries, commissions, and similar compensation, group health care benefits, and paid leave; rent; utilities; and interest on certain other outstanding debt. The Loan Note has a term of two years.

Interest under the Loan Note accrues at a rate per annum of 1.00%, with the first payment of principal and interest due on November 20, 2020.

According to the terms of the PPP and current guidance from the SBA and U.S. Department of Treasury, all or a portion of loans under the program may be forgiven if the Loan Note proceeds are used for permitted expenses, as outlined in the CARES Act and related regulations, including 75% of the Loan Note proceeds being used for payroll related costs. The amount that will be forgiven will be calculated in part with reference to the Company's full time headcount during the eight-week period following the funding of the Loan Note. The SBA and U.S. Department of Treasury may continue to update guidance on the calculation of loan forgiveness, which updated guidance could affect the amount of the Loan Note proceeds that could be forgiven.

The foregoing description of the Loan Note is included to provide information regarding its terms. It does not purport to be a complete description and is qualified in its entirety by reference to the full text of the Loan Note, which is filed as Exhibit 10.1 hereto and is incorporated herein by reference.

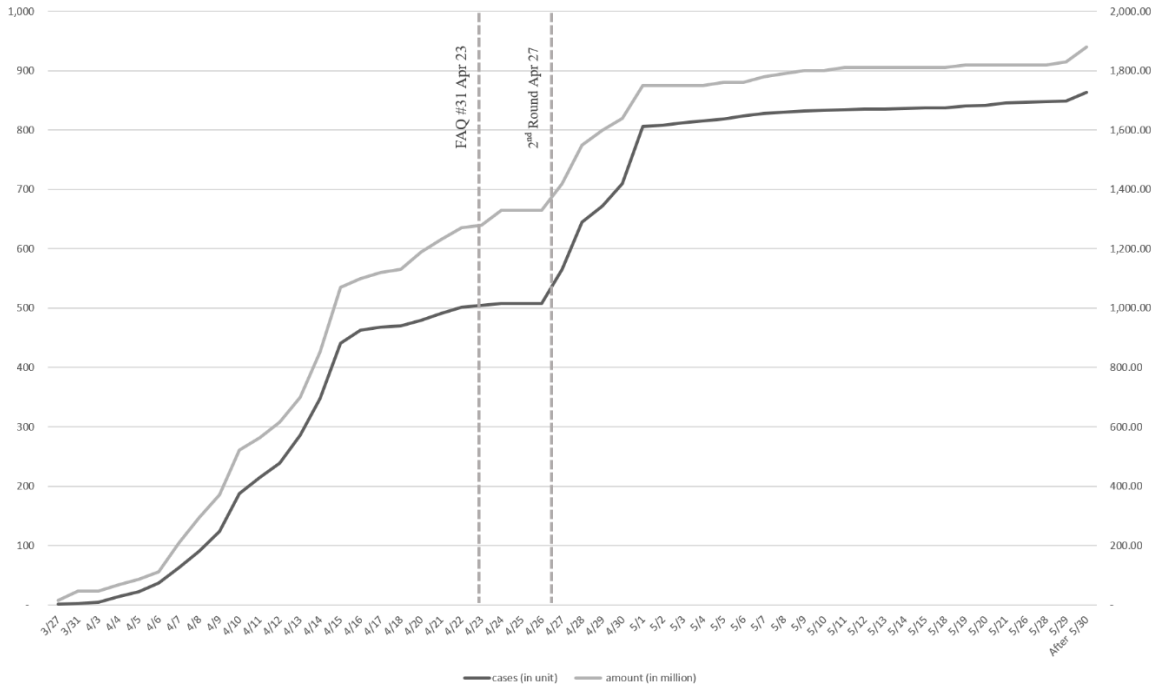


Figure 1
Date Distribution of Cases and Amounts of Public Firms Borrowing

Figure 1 plots the date distribution of borrowing. The black line is the accumulated cases of receipts of public firms PPP loan applications. The grey line is the accumulated amounts (in million) of receipts of public firms PPP loan applications. The two dash lines are the date that SBA issued FAQ #31 which explains "good faith" in applying loans for public firms and the date that second round PPP loans started. For brevity, I oppress the borrowing cases from May 30 to August 8 into one data point.

Table 1 Sample selection

Description	No. of eligible firms	No. of borrowers
Eligible public firms	**1,907**	**627**
Delete: firms in financial service industry	(318)	(18)
Delete: firms without sufficient data for calculating variables in main analysis	(383)	(135)
Delete: firms in industries without any borrower	(4)	(0)
Delete: no specific loan number	(1)	(1)
Final Sample: Eligible public firms for main analysis	**1,201**	**473**

Table 2 Descriptive statistics

This table reports summary statistics for the variables used in main analyses. My sample is comprised of firms which are included in Compustat dataset and are eligible for PPP loans. All continuous variables lower than 1% or higher than 99% are winsorized. Definitions for all variables are provide in Appendix A.

Variables	N	Mean	SD	P25	P50	P75
Dummy_borrow	1,201	0.394	0.489	0.000	0.000	1.000
Asset (in million)	1,201	673.366	2,049.301	28.295	108.526	355.756
Market value (in million)	1,201	821.750	2,088.907	32.473	151.243	616.972
Firm age	1,201	15.411	13.244	6.000	10.000	23.000
ROA	1,201	-0.435	0.793	-0.548	-0.180	0.004
M/B	1,201	4.619	7.457	0.837	2.20	5.141
Dummy_loss	1,201	0.744	0.437	0.000	1.000	1.000
Cash ratio	1,201	0.281	0.272	0.057	0.187	0.434
Debt ratio	1,201	0.333	0.554	0.043	0.168	0.412
Employee (in thousands)	1,201	1.745	1.241	0.041	0.122	0.352
DACC_KWL	1,201	0.067	0.114	0.014	0.034	0.072
DACC_MJ	1,201	0.054	0.089	0.099	0.026	0.055

Table 3 Main Test: Effect of earnings management on likelihood of borrowing

This table presents the results from regressing earnings management on whether to borrow PPP loans. Absolute value of discretionary accruals are calculated from firm-level performance matched Jones model in column (1) and firm-level modified Jones model in column (2). Continuous variables are winsorized at the 1% and 99% levels and are defined in the Variable Appendix A. Constants are omitted to be reported because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

		(1)	(2)
Dependent variable	***Predicted Signs***	***Dummy_borrow***	
DACC_KWL	-	-2.849**	
		(-2.28)	
DACC_MJ	-		-2.479**
			(-2.49)
Ln(Asset)	-	-0.725***	-0.719***
		(-7.46)	(-7.07)
Ln(Firm Age)	+	0.391***	0.388***
		(5.12)	(5.05)
Dummy_loss	+	0.566**	0.563**
		(2.35)	(2.32)
ROA	?	0.147	0.152
		(0.61)	(0.67)
M/B	?	-0.016	-0.016
		(-1.38)	(-1.37)
Cash Ratio	-	-1.394***	-1.393***
		(-8.40)	(-8.64)
Debt Ratio	+	0.293*	0.279*
		(1.89)	(1.84)
Employee	-	-0.173***	-0.172***
		(-2.62)	(-2.63)
No. of Observations		1,201	1,201
Pseudo R-squared		0.283	0.283
Industry Fixed Effect		Yes	Yes
State Fixed Effect		Yes	Yes
SE Clustered by State		Yes	Yes

Table 4 Robustness Tests

This table presents the robustness check results of baseline results. In panel A, I replace dummy variable of borrowing into continuous variable of loan amount and change the model into Tobit model. Discretionary accruals are calculated from firm-level performance matched Jones model in column (1) and firm-level modified Jones model in column (2). In panel B, I change accrual model into industry-level performance matched Jones model and industry-level modified Jones model. In column (1) and (2), I use 2019 fourth calendar quarter to calculate the quarterly discretional accruals. In column (3) and (4), I use 2019 fiscal year financial report to calculate the yearly discretional accruals. In panel C, I replace absolute discretionary accruals into other financial reporting quality indicators. In column (1), *Bog Index* is a measure of readability created by Bonsall et al. (2017). In column (2), Size of 10K is the natural logarithm of gross 10-K file size available on the SEC's EDGAR Web site suggested as a measure of annual report readability by Loughran and McDonald (2014). In column (3), FSD_Score is the mean absolute deviation between the empirical distribution of leading digits contained in all firms' financial statements and Benford's Law. Continuous variables are winsorized at the 1% and 99% levels and are defined in the Variable Appendix A. Constants are omitted to be reported because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Panel A: Alternative Model (Tobit Model)

		(1)	(2)
Dependent Variable	**Predicted Signs**	*Ln(Loan amount)*	
DACC_KWL	-	-13.266**	
		(-2.52)	
DACC_MJ	-		-13.506***
			(-2.58)
Ln(Asset)	-	-3.955***	-3.955***
		(-6.39)	(-6.22)
Ln(Firm Age)	+	2.435***	2.414***
		(5.23)	(5.20)
Dummy_loss	+	3.622**	3.588**
		(2.32)	(2.30)
ROA	?	0.716	0.683
		(0.65)	(0.64)
M/B	?	-0.084	-0.085
		(-1.23)	(-1.22)
Cash Ratio	-	-8.057***	-8.088***
		(-7.52)	(-7.64)
Debt Ratio	+	0.106	0.083
		(0.15)	(0.12)
Employee	-	-1.221***	-1.215***
		(-3.78)	(-3.81)
No. of Observations		1,201	1,201
Adjusted R-squared		0.091	0.091
Industry Fixed Effect		Yes	Yes
State Fixed Effect		Yes	Yes
SE Clustered by State		Yes	Yes

Panel B: Alternative Independent Variables: Discretional Accrual Estimated in Industry Model

		(1)	(2)	(3)	(4)
		Quarterly Data		Yearly Data	
Dependent Variable	**Predicted Signs**	*Dummy_borrow*			
DACC2Q_KWL	-	-1.298*			
		(-1.70)			
DACC2Q_MJ	-		-2.708***		
			(-2.86)		
DACC2Y_KWL	-			-0.836***	
				(-2.60)	
DACC2Y_MJ	-				-0.957***
					(-3.33)
Ln(Asset)	-	-0.709***	-0.728***	-0.737***	-0.747***
		(-6.88)	(-7.33)	(-6.81)	(-6.83)
Ln(Firm Age)	+	0.394***	0.398***	0.359***	0.357***
		(5.14)	(5.09)	(3.32)	(3.53)
Dummy_loss	+	0.559**	0.557**	0.728***	0.729***
		(2.34)	(2.22)	(3.05)	(3.03)
ROA	?	0.144	0.125	0.264	0.274
		(0.62)	(0.51)	(1.06)	(1.11)
M/B	?	-0.016	-0.017	-0.008	-0.008
		(-1.42)	(-1.41)	(-1.15)	(-1.16)
Cash Ratio	-	-1.359***	-1.418***	-1.496***	-1.553***
		(-8.09)	(-9.02)	(-7.26)	(-8.06)
Debt Ratio	+	0.253	0.282*	0.246	0.283
		(1.62)	(1.90)	(1.28)	(1.49)
Employee	-	-0.171***	-0.173***	-0.246***	-0.247***
		(-2.69)	(-2.66)	(-2.74)	(-2.68)
No. of Observations		1,201	1,201	1,167	1,167
Pseudo R-squared		0.282	0.285	0.290	0.292
Industry Fixed Effect		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
SE Clustered by State		Yes	Yes	Yes	Yes

Panel C: Alternative Independent Variables: Non-accrual Financial Reporting Quality

		(1)	(2)	(3)
Dependent Variable	**Predicted Signs**	*Dummy_borrow*		
Bog Index	-	-2.110***		
		(-2.85)		
Size of 10K	-		-0.042**	
			(-2.42)	
FSD_Score	-			-37.847**
				(-2.50)
Ln(Asset)	-	-0.648***	-0.643***	-0.785***
		(-7.96)	(-8.60)	(-8.10)
Ln(Firm Age)	+	0.222***	0.305***	0.377***
		(2.82)	(3.94)	(5.16)
Dummy_loss	+	0.710***	0.686***	0.667***
		(2.85)	(3.22)	(3.03)
ROA	?	0.280	0.219	0.270
		(1.27)	(1.05)	(1.22)
M/B	?	-0.015	-0.018	-0.020*
		(-1.34)	(-1.56)	(-1.77)
Cash Ratio	-	-1.263***	-1.537***	-1.407***
		(-6.65)	(-7.50)	(-7.09)
Debt Ratio	+	0.160	0.175	0.102
		(0.84)	(0.83)	(0.54)
Employee	-	-0.186***	-0.155***	-0.149***
		(-3.01)	(-3.62)	(-3.16)
No. of Observations		1,223	1,261	1,349
Pseudo R-squared		0.298	0.298	0.303
Industry Fixed Effect		Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes
SE Clustered by State		Yes	Yes	Yes

Table 5 Alternative Matching Samples

This table presents baseline results using several sample matching methods. In panel A, I use entropy balancing method to reweight control group so that treatment group and control group have similar summary statistics. In panel B, I show the effect of earnings management on likelihood of borrowing using entropy balancing method. In panel C, I use coarsen exact matching (CEM) method to get comparable control group and treatment group. In panel D, I show the effect of earnings management on likelihood of borrowing using CEM sample. In panel E column (1) and (2), I show the main analysis using 1:1 nearest size match in same industry. In Panel E, column (3) and (4), I show the main analysis using observations only fulfilling criteria 1. Continuous variables are winsorized at the 1% and 99% levels and are defined in the Variable Appendix A. In panel B, panel D, and panel E, constants are omitted to be reported because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Panel A: Borrowers vs Non-borrowers, After Entropy Balancing

	Treat			**Control**		
	mean	**variance**	**skewness**	**mean**	**variance**	**skewness**
Ln(Asset)	3.517	2.374	-0.00979	3.519	4.239	-0.035
Ln(Firm Age)	2.645	0.5812	-0.1455	2.645	0.6575	-0.1197
Dummy_loss	0.7967	0.1623	-1.475	0.7965	0.1623	-1.473
ROA	-0.5963	0.9962	-2.55	-0.596	0.9629	-2.458
M/B	4.059	56.99	3.494	4.058	51.91	4.081
Cash Ratio	0.2452	0.0604	1.09	0.2452	0.06387	1.256
Debt Ratio	0.4253	0.5426	3.65	0.4254	0.3571	2.195
Employee	0.2203	0.5233	10.09	0.2337	1.019	20.56

Panel B: Regression using Entropy Balancing Method

		(1)	(2)
Dependent Variable	**Predicted Signs**	*Dummy_borrow*	
DACC_KWL	-	-3.019***	
		(-2.63)	
DACC_MJ	-		-2.305**
			(-2.17)
No. of Observations		1,201	1,201
Pseudo R-squared		0.084	0.081
Control Variable		Yes	Yes
Industry Fixed Effect		Yes	Yes
State Fixed Effect		Yes	Yes
SE Clustered by State		Yes	Yes

Panel C: Borrowers vs Non-borrowers, After CEM matching

Variables	**Non-borrower**	**Mean**	**Borrower**	**Mean**	**MeanDiff**
Ln(Asset)	204	4.077	204	4.032	0.045
Ln(Firm Age)	204	2.517	204	2.502	0.015
ROA	204	5.248	204	4.396	0.852
M/B	204	0.721	204	0.833	-0.113***
Dummy_loss	204	0.312	204	0.298	0.014
Cash Ratio	204	1.068	204	0.274	0.794
Debt Ratio	204	4.077	204	4.032	0.045
Employee	204	2.517	204	2.502	0.015

Panel D: Regression using CEM matching

Dependent Variable	**Predicted Signs**	(1) *Dummy_borrow*	(2) *Dummy_borrow*
DACC_KWL	-	-4.736**	
		(-2.40)	
DACC_MJ	-		-3.430**
			(-2.04)
No. of Observations		386	386
Pseudo R-squared		0.130	0.125
Control Variable		Yes	Yes
Industry Fixed Effect		Yes	Yes
State Fixed Effect		Yes	Yes
SE Clustered by State		Yes	Yes

Panel E: Regression using Alternative matching method

Dependent Variable	**Predicted Signs**	(1) *Dummy_borrow*	(2) *Dummy_borrow*	(3) *Dummy_borrow*	(4) *Dummy_borrow*
DACC_KWL	-	-2.840**		-2.965**	
		(-2.15)		(-2.20)	
DACC_MJ	-		-2.694**		-2.618**
			(-2.58)		(-2.64)
No. of Observations		750	750	1,063	1,063
Pseudo R-squared		0.140	0.140	0.286	0.285
Control Variable		Yes	Yes	Yes	Yes
Industry Fixed Effect		Yes	Yes	Yes	Yes
State Fixed Effect		Yes	Yes	Yes	Yes
SE Clustered by State		Yes	Yes	Yes	Yes
Matching principle		Same 2-digit industry, closest size		Criterial 1 (SBA Size Standard)	

Table 6 Cross-sectional Test: Public pressure

This table presents cross-sectional results of scrutiny risk from public pressure. In panel A, I partition sample into firms that have received SEC comment letter during 3 years before 2020 March and firms that haven't received such comment letter. In panel B, I partition sample into firms that have been defendant of legal case during 3 years before 2020 March and firms that haven't been defendant during the same period. In panel C, I partition sample into firms that have positive news sentiment during 3 months before 2020 March and firms that have negative news sentiment during the same period. Continuous variables are winsorized at the 1% and 99% levels and are defined in the Variable Appendix A. Constant are omitted to be reported because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Panel A: Cross-sectional tests: Regulatory Attention

	(1)	(2)	(3)	(4)
Partition Criteria	*Comment letter*			
	Yes	No	Yes	No
DACC_KWL	-9.188***	-2.669		
	(-3.20)	(-1.57)		
DACC_MJ			-6.182**	-2.084**
			(-2.43)	(-2.04)
No. of Observations	220	919	220	919
Pseudo R-squared	0.378	0.273	0.359	0.272
Control Variables	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
SE Clustered by State	Yes	Yes	Yes	Yes

Panel B: Cross-sectional tests: Legal Attention				
	(1)	(2)	(3)	(4)
Partition Criteria		*Legal Case*		
	Yes	No	Yes	No
DACC_KWL	-21.735***	-0.513		
	(-4.68)	(-0.25)		
DACC_MJ			-11.723**	-0.756
			(-2.53)	(-0.56)
No. of Observations	233	938	233	938
Pseudo R-squared	0.450	0.300	0.450	0.300
Control Variables	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
SE Clustered by State	Yes	Yes	Yes	Yes

Panel C: Cross-sectional tests: Public Attention				
	(1)	(2)	(3)	(4)
Partition Criteria		*News Sentiment*		
	Positive	Negative	Positive	Negative
DACC_KWL	0.705	-4.396***		
	(0.42)	(-2.58)		
DACC_MJ			-1.771	-2.375**
			(-0.85)	(-2.21)
No. of Observations	592	589	592	589
Pseudo R-squared	0.326	0.293	0.326	0.293
Control Variables	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
SE Clustered by State	Yes	Yes	Yes	Yes

Table 7 Cross-sectional Test: PPP loans characters

This table presents cross-sectional results of scrutiny risks from structure of PPP loans. In panel A, I partition sample into whether PPP loans are forgiven. In panel B, I partition sample according to whether firms PPP loans. Continuous variables are winsorized at the 1% and 99% levels and are defined in the Variable Appendix A. Constant are omitted to be reported because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Panel A: Cross-sectional tests: Loan Settlement Method

	(1)	(2)	(3)	(4)
Partition Criteria	*Loan Settlement*			
	Exemption	Self-paid	Exemption	Self-paid
DACC_KWL	-1.877	-5.413*		
	(-1.36)	(-1.91)		
DACC_MJ			-1.690	-3.268**
			(-1.26)	(-2.10)
No. of Observations	990	711	990	711
Pseudo R-squared	0.288	0.443	0.288	0.437
Control Variables	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
SE Clustered by State	Yes	Yes	Yes	Yes

Panel B: Cross-sectional tests: Amount Threshold

	(1)	(2)	(3)	(4)
Partition Criteria	*Amount Threshold*			
	>=2 million	<2 million	>=2 million	<2 million
DACC_KWL	-4.486**	-2.363*		
	(-2.54)	(-1.76)		
DACC_MJ			-3.359**	-1.974
			(-1.96)	(-1.64)
No. of Observations	805	1,113	805	1,113
Pseudo R-squared	0.240	0.326	0.238	0.325
Control Variables	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
SE Clustered by State	Yes	Yes	Yes	Yes

Table 8 Ex Post Benefits of PPP loans

This table reports summary statistics for the difference of employee number, market value, ROA, and cash ratio from 2019 fiscal year end to 2020 fiscal year end. All continuous variables lower than 1% or higher than 99% are winsorized.

Variables	Non-borrower	Mean	Borrower	Mean	MeanDiff
Difference of Employee	683	-0.153	456	-0.014	-0.138***
Difference of Market Value	688	0.361	459	0.456	-0.095*
Difference of ROA	688	0.059	459	0.143	-0.084**
Difference of Cash Ratio	684	0.044	457	0.082	-0.038***

Table 9 Additional Test: Effect of earnings management on likelihood of return

This table presents the results from regressing earnings management on whether to return PPP loans. Absolute value of discretionary accruals are calculated from firm-level performance matched Jones model in column (1) and firm-level modified Jones model in column (2). In panel A, I use logit model and in panel B I use bivariate probit model. Continuous variables are winsorized at the 1% and 99% levels and are defined in the Variable Appendix A. Constant are omitted to be reported because of fixed effects. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using a two-tailed t-test.

Panel A: Return Result

		(1)	(2)
Dependent Variable	**Predicted Signs**	*Dummy_return*	
DACC_KWL	-	-5.015	
		(-1.37)	
DACC_MJ	-		-6.478***
			(-2.72)
Ln(Asset)	+	0.600***	0.587**
		(2.64)	(2.57)
Ln(Firm Age)	?	0.028	-0.001
		(0.14)	(-0.01)
Dummy_loss	?	-1.292***	-1.321***
		(-2.79)	(-2.82)
ROA	?	-0.169	-0.168
		(-0.52)	(-0.59)
M/B	+	0.038**	0.038**
		(2.39)	(2.48)
Cash Ratio	+	1.753***	1.754***
		(2.78)	(2.79)
Debt Ratio	?	-0.502	-0.555
		(-1.18)	(-1.25)
Employee	+	0.890*	0.877*
		(1.67)	(1.66)
No. of Observations		416	416
Pseudo R-squared		0.264	0.268
Industry Fixed Effect		Yes	Yes
State Fixed Effect		Yes	Yes
SE Clustered by State		Yes	Yes

Panel B: Biprobit Results

Dependent Variable	**Predicted Signs**	(1) *Dummy_return*	(2) *Dummy_return*
DACC_KWL	-	-2.622**	
		(-2.11)	
DACC_MJ	-		-3.763***
			(-3.72)
Ln(Asset)	?	-0.027	-0.069
		(-0.42)	(-0.98)
Ln(Firm Age)	?	0.133*	0.149*
		(1.87)	(1.86)
Dummy_loss	?	-0.175	-0.179
		(-0.98)	(-0.94)
ROA	?	-0.012	0.015
		(-0.11)	(0.13)
M/B	?	0.007	0.007
		(1.14)	(1.14)
Cash Ratio	?	0.139	0.114
		(0.81)	(0.49)
Debt Ratio	?	-0.167	-0.175
		(-1.22)	(-1.12)
Employee	?	-0.075**	-0.065**
		(-2.44)	(-2.08)
No. of Observations		1,201	1,201
Industry Fixed Effect		Yes	Yes
State Fixed Effect		Yes	Yes
SE Clustered by State		Yes	Yes