# Central Bank Intervention and Bank Liquidity: Evidence from the Paycheck Protection Program

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**Abstract**

How do banks use external funding sources when faced with an unexpected liquidity shock? This paper uses loan-level transactions from the Paycheck Protection Program (PPP) to understand how a bank's decision to borrow reserves from the discount window (DW) affected its lending behavior during the COVID-19 crisis. Implementation of the PPP can be seen as an exogenous shock to the liquidity demand for banks, independent of their financial conditions. By exploiting this independence, I find a causal relationship between use of DW and the number of PPP loans extended by large banks but not small banks. While both types used the DW in the absence of a long-term funding source, usage of the DW almost doubled PPP lending for large banks. After the establishment of a long-term funding source, however, this effect was reduced to 69% due to substitution away from the DW. These findings suggest that in the presence of an unexpected liquidity shock, the DW plays a critical role in extending short-term liquidity to the banking sector.

**Keywords:** Liquidity, Paycheck Protection Program, Discount Window
**JEL Code:** E58, E65, G01, G21, G28

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# 1 Introduction

The discount window (DW), operated by the Federal Reserve, has always been central to financial stability. Banks that cannot obtain liquidity from other sources use the DW as a lender-of-last-resort. Until recently, there has not been enough data to show how important the window was in ensuring that the liquidity needs of banks are met.[1] The implementation of the Paycheck Protection Program (PPP) during the COVID-19 Epidemic gives us a natural experiment to observe the liquidity-provision services of the DW. PPP loans demanded can be seen as a conditionally exogenous shock to the liquidity needs of banks independent of their financial health. Therefore, by using loan-level data, we can estimate the impact of the DW on the banking sector by observing its effect on bank lending.

This paper finds evidence that banks used the DW as a temporary liquidity source and to expand the number of loans they can originate early in the program. Using a recently released set of DW data, I find a strong correlation between a bank's daily PPP lending and its propensity to use the DW. An event study approach finds that all banks use the DW as a temporary measure of liquidity while waiting for a long-term liquidity source. Furthermore, a cross-sectional analysis finds a positive causal effect of DW usage on the quantity of PPP lending done by large banks, defined as assets greater than $600 million. The point estimate for small banks was large but had no statistical significance. Large banks that borrowed from the DW during the early stages of the PPP program extended almost twice as many loans as their non-borrowing counterparts. This effect was strongest before the establishment of a long-term funding source but retained significance even after long-term funding was available. Conditional on usage, a higher quantity borrowed from the DW also increased the quantity of PPP loans extended.

Does the DW play an economically significant role? Prior to COVID, discount window borrowing averaged about one to two billion dollars every quarter. In the second quarter of 2020, overnight borrowing from the window increased by three orders of magnitude, reaching a level of around $927 billion (38% of aggregate reserves). On April 3, 2020, submissions for PPP loans officially began, allowing small businesses to request loans from eligible financial institutions. Phase 1 of the PPP program lasted from April 3 to April 16 and distributed $349 billion to small businesses. Phase 2 of the program began on April 27 after an additional $320 billion in funding was approved. During Phase 1, banks borrowed a total of $220 billion in overnight funding from the DW.[2]

[1] Discount window data was only publicly released after the enactment of the Dodd-Frank Act in 2010. Since then, there has not been a major incident until the COVID-19 Epidemic.

[2] Since banks can borrow the same amount for multiple days, these values have been converted to overnight-equivalent

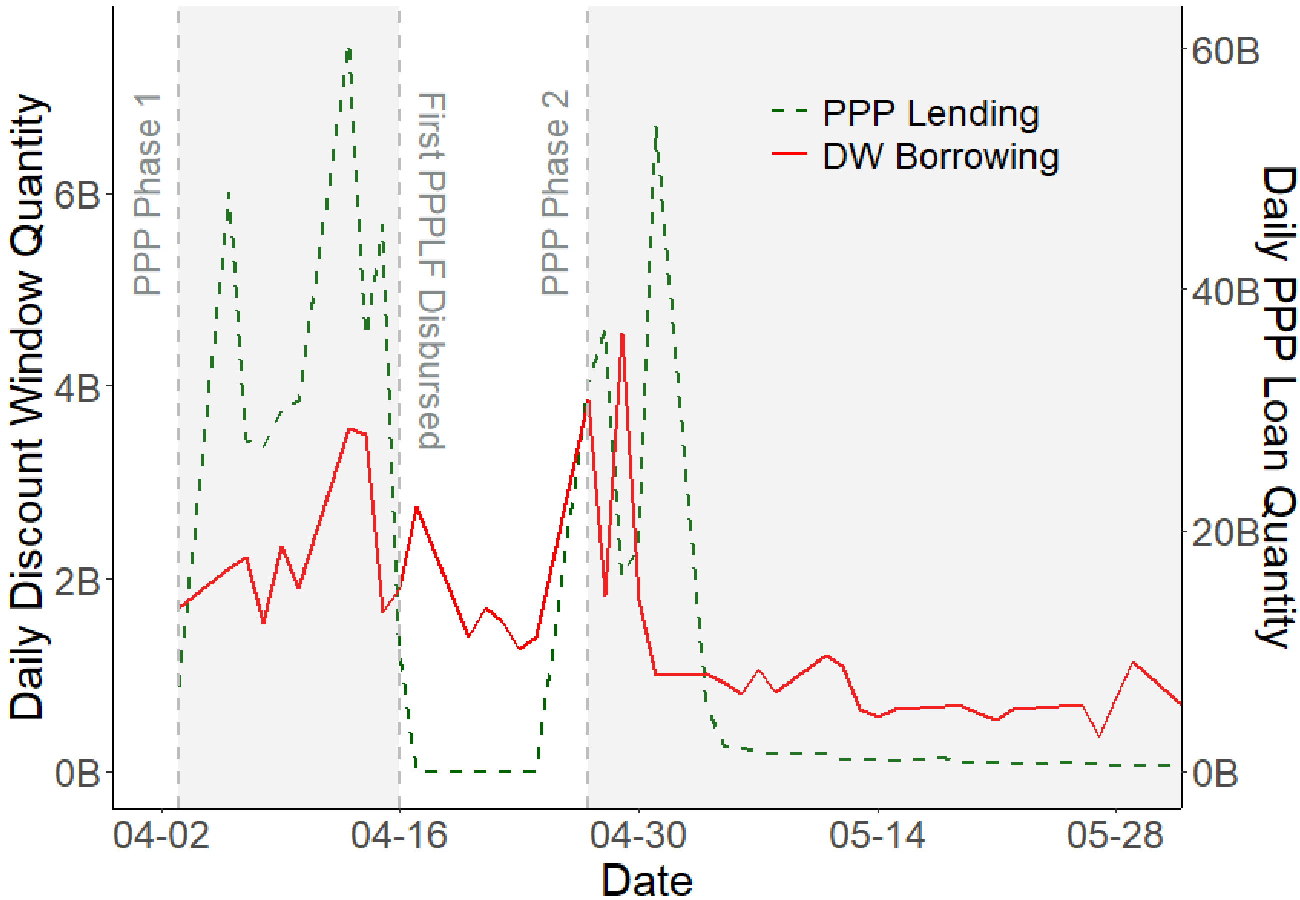


**Figure 1:** Plot of the DW Borrowing and PPP Lending at the aggregate level after the PPP program has begun until mid-May. The green dashed line represents the aggregate amount of PPP loans lent out on that day, with scaling on the right y-axis. The red line corresponds to the aggregate amount of DW borrowing on that day, with scaling on the left y-axis. Vertical dashed lines signify important events. PPP phases are shaded in gray. Values of the DW borrowing quantity have not been converted to overnight borrowing, so magnitudes are smaller. Weekends are dropped since DW is closed on weekends. An alternate version with the weekends included is shown in Figure A.1.

Figure 1 plots the aggregate level of DW borrowing and PPP lending for the period of April and May when the majority of PPP loans were distributed. As the figure shows, large increases in PPP lending are strongly correlated with large increases in DW borrowing. The correlation is strong during Phase 1, before funds from the PPPLF were distributed, and weaker in Phase 2 when banks had access to long-term liquidity and loan demand was more stable. As Phase 1 of the PPP program ended unexpectedly due to an announcement from the SBA, the timing of the

rates. When looking at just the total quantity of borrowing (without the conversion), Phase 1 borrowing was only $22.4 billion (implying an average loan length of 10 days). Total borrowing for the second quarter of 2020 reached $74 billion.

PPP program was not related to the choice of banks to use the DW.[3]

My first analysis explores whether banks increase their likelihood of borrowing from the DW when they lend more PPP loans. Using a linear probability model, I regress an indicator variable of DW usage on reserve-adjusted PPP lending at the bank-day level, with controls for bank characteristics and Fed district and date fixed effects. Since banks of different asset class hold different levels of reserves, the reserve-adjustment is necessary to not over-weigh the impact of large banks in the regression. I find that a 10 percentage point (pp) increase in reserve-adjusted PPP lending is correlated with an 18% higher chance of borrowing from the DW in the pooled sample. When looking at large versus small banks (∼\$600M cut-off), the results differ depending on how the regression is specified. The pooled sample with an interaction term between size and PPP lending shows a significant positive correlation for large banks. When looking at subgroups, however, the coefficient of interest is significant for small banks.[4] This probability is negatively correlated with measures of a bank's financial stability and has no correlation with the impact of COVID.

I then look to the question of why banks are borrowing from the DW. If banks only used the DW as a temporary source of liquidity before they can get long-term funding, then they should use it while waiting for funds from the PPPLF to arrive. To test this hypothesis, I construct an event study design, taking the period while banks wait for PPPLF funds as a treatment. I then estimate a two-way fixed effects model and find that on average, large banks increase their DW borrowing probability by 2.6-3%, while small banks only increase their borrowing by 1.1-1.3%. This effect persists for up to three weeks in the case of large banks, and only about one and a half weeks for small banks. After receiving funds from the PPPLF, both sets of banks decrease their use of the DW, lending support to the conjecture that banks are using it as a stopgap measure of liquidity.

Given that there is evidence that banks used the DW for liquidity purposes, did DW borrowing expand the amount of PPP lending done by banks? In the tertiary analysis, I perform a cross-sectional regression using the aggregated lending by banks during April and May. There are two main endogeneity concerns that must be resolved to establish a causal relationship between DW

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[3] The SBA posted a statement on its website on April 16, 2020, saying that it is currently unable to accept new PPP applications based on currently available funding. A joint statement by Secretary of the Treasury, Steven Mnuchin, and Administrator of the SBA, Jovita Carranza, was made on April 15 to urge the Senate to appropriate additional funding for the program.

[4] The main analysis is done using Federal District fixed effects to account for different scrutiny levels of each district to window usage. A robustness check replacing district by bank fixed effects finds that a 10 pp increase in PPP lending is correlated with a 4.8% higher chance of borrowing from the DW for large banks and no effect for small banks. This result is robust to Poisson and Logistic regressions.

usage and PPP lending. The first source of endogeneity comes from heterogeneous balance sheet cost and liquidity constraints for each bank. Banks that are highly constrained in their reserves could simultaneously tap into the DW for funds and decrease the amount of PPP loans that they extend, which would negatively bias the true relationship if left uncontrolled. Since bank characteristics can only be observed quarterly, daily fluctuations in liquidity constraints cannot be captured. The second source of endogeneity comes from the fact that banks can choose the number of loans they originate on a given day. Therefore, the decision of loan origination and DW borrowing is likely jointly decided, resulting in simultaneity bias.

To solve these endogeneity problems, I use the previous familiarity of each bank with the DW as an instrument, an approach similar to Anbil et al. [2021]. The instrument is constructed by aggregating all DW borrowing by a bank since 2010 and dividing it by the reserve quantity reported in the Call Reports. The instrument fulfills the relevancy condition due to a bank's propensity to use the DW again if they have already used it in the past and captures how familiar a bank is with posting collateral and withdrawing funds from the window. Banks that want to use the DW have to submit forms to determine their eligibility, as well as post collaterals to the DW before funds can be advanced. These logistical constraints can make it difficult for banks to borrow from the DW without having prior experience. Once the fixed cost is paid, however, borrowing from the DW only requires a call to the local Federal Reserve branch. This makes it so banks who have previously used the DW face a lower marginal cost of using the DW once again.

The primary assumption for this instrument to be valid is that familiarity with the DW only affects the amount of PPP lending done through its effect on a bank's current likelihood to use the window again. Although previous DW usage might affect a bank's propensity to use other sources of external funding, I control for these alternative sources. The exclusion restriction can also be violated from unobserved bank-specific risk tolerance, which could affect their decision to use the DW and their decision to extend risky loans. PPP loans are a special case, however, as they carry zero weight when calculating risk-weighted regulatory ratios. As a result, any unobserved risk factors should be orthogonal to the number of PPP loans a bank chooses to extend since PPP loans are riskless. Using a two-stage least squares approach, I find that DW usage increased PPP lending from large banks by 91% during Phase 1 of the PPP program, but had little to no effect on small banks. At the intensive margin, an increase in DW borrowing by one standard deviation during Phase 1 increased PPP lending by 43.6%. These effects hold when the sample is extended to the end of May, but are weaker due to substitution towards long-term funding provided by the PPPLF.

One explanation for the differences in small bank behavior could be that small banks face greater stigma than large banks when accessing the DW. From Berger et al. [2014], small banks that borrowed from the 2008 Term Auction Facility were generally weak as compared to their counterparts while large banks were not. This implies that when accessing central bank lending facilities, smaller banks give off a stronger negative signal of asset quality and are subsequently more averse to using them. Another possible reason why small banks aren't as affected by the DW is that the fixed costs for small banks are not worth the marginal benefit. Since banks only obtain 1-5% of the origination fee for PPP loans, banks that have high PPP demand from businesses obtain greater benefits from lending. If the fixed cost of borrowing from the DW is large, either from logistical or informational frictions, then small banks might not find it worth their resources. Additionally, smaller banks hold more liquid assets as a share of their portfolio and do not need as much external funding as large banks. This can be seen through the DW data, as only 23% of small banks have previously borrowed from the DW as compared to the 63% of large banks.

This paper shows the importance of the DW during liquidity crises. When banks face any liquidity crisis, either through exogenous demand shocks or an increase in interest rates, they should be aware of the options avaiable. If banks are more willing to obtain external liquidity through the discount window, they can drastically reduce the risk of bankruptcy. Currently, due to the rapid interest rate increase, many banks are facing an unrealized loss due to the fall in bond prices. Borrowing from the DW during this time could alleviate the consequences of a possible bank run and ensure the stability of the banking sector.

## 1.1 Related Literature

This paper contributes to a growing literature on examining the effects of liquidity facilities on the PPP program. Lopez and Spiegel [2021] and Anbil et al. [2021] analyze the effect of the PPP Lending Facility (PPPLF) on the distribution of PPP loans using measures of prior relationship with the Small Business Administration and familiarity with the posting of loan collateral to the DW as exogenous instruments. Both articles find a strong causal effect of the PPPLF on the quantity of PPP lending, with larger effects for small banks. This paper examines the effect of an alternate source of central bank lending, the discount window, and finds that it primarily supports large banks in PPP lending, especially during Phase 1 of the program before funds from the PPPLF were available. Some banks used the DW to extend more loans and others used it for temporary liquidity before PPPLF funds were available. I find my work to be highly complementary to this literature by exploring how banks acquire liquidity during the early stages of the PPP program and how different types of banks use each funding source.

Another part of the PPP literature examines its role on employment. The articles in this field include Barraza et al. [2020], Chetty et al. [2020], Autor et al. [2022], and Faulkender et al. [2020], all of which find a positive effect of PPP lending on employment outcomes. Specific to my work, Granja et al. [2020] finds that firms that received PPP loans earlier in the program had better employment outcomes than those that received loans later. Li and Strahan [2020] also finds that PPP supply had a strong effect in preserving local employment, especially those received during Phase 1 of the program. I study how DW borrowing during Phase 1 increased the number of PPP loans lent out by large banks, which implies that if banks were more willing to use the DW to relax liquidity constraints, the employment effect of the PPP could have been amplified.

This work also relates to the prior literature that examines DW use for liquidity during financial crises. Armantier et al. [2015] show that banks are willing to pay a premium of 44 basis points across other funding sources (Term Auction Facility (TAF), repos, etc.) to avoid usage of the window due to stigma during 2008. Berger et al. [2014] looks at Federal Reserve lending through the DW and the TAF in 2008 and found that the liquidity injected through these two facilities increased aggregate lending to small and large businesses. Furthermore, they found that small banks that chose to use the DW were weaker than their counterparts, measured by lower capital ratios and higher portfolio risk. This does not hold true for large banks, which could imply that the information channel of stigma faced by small banks could be larger than for big banks. A more recent analysis done by Glancy et al. [2020] shows that deposits were the main source of funding for banks, as aggregate deposit inflows exceeded aggregate growth in commercial and industrial lending. Although this pattern holds in the aggregate, there exists heterogeneity in deposit growth within the banking sector, leading some banks to access external funding. I contribute to this literature by exploring how DW borrowing affected small and large banks heterogeneously during the COVID crisis, and find differences between the two classes of banks in terms of lending behavior.

The rest of the paper is organized as follows. Section 2 describes the institutional details. Section 3 describes the data construction process. Section 4 contains the descriptive statistics from the data. In section 5, I present my empirical methodology and results. Section 6 discusses the policy implications. Section 7 concludes.

## 2 Institutional Background

The Paycheck Protection Program (PPP) began on April 3, 2020, to help small businesses continue to pay their workers through the early phases of COVID. The program was administered by the Small Business Administration (SBA) but was directly distributed to consumers by eligible financial institutions. Banks that qualify to lend included all federally insured depository institutions, credit unions, and Farm Credit System institutions that were pre-qualified to lend through the SBA. Financial Technology (FinTech) companies were approved to offer PPP loans at a later date due to the high demand faced by traditional banks. Although FinTechs were introduced as an alternative source of loans, they did not compete with traditional banking for customers. Erel and Liebersohn [2020] shows that the decision to allow lending through FinTechs expanded overall access to financial services, playing a complementary role to traditional banking.

PPP loans were disbursed in two phases. The program's first phase distributed $349 billion to small businesses and lasted from April 3 to April 16, when government funding quickly depleted due to high demand. Phase 2 began on April 27 when President Trump extended another $320 billion that lasted until August 8, with most of the loans in Phase 2 distributed in April and May. As a borrower, PPP loans had a fixed interest rate of 1%, were deferred for the first six months, and were generally forgiven. The loans had a maturity of two years if originated before June and five years after June. Lenders can obtain 5% of the origination amount as a fee on loans smaller than $350,000, 3% on loans between $350,000 and $2,000,000, and 1% for loans greater than $2,000,000.

The PPP faced many problems during the early stages. First, the SBA was slow at publishing their regulatory forms, causing some banks to devote extra resources to helping customers. Second, SBA computers had limitations on how many PPP loans they can process at a given time during the early stages, causing banks to favor customers with pre-existing relationships. While this may have heterogeneous effects on which businesses succeeded and failed, this preferential treatment should not affect the demand shock on liquidity faced by the banks.

Since PPP loans were insured by the SBA, financial institutions faced no default risk for lending and were only constrained by their liquidity. PPP loans also carried zero weight when calculating the capital ratio for the bank, but are added to the total assets when calculating the leverage ratio unless pledged to the PPPLF as collateral. This zero-weighing made these loans very attractive to banks, as they were riskless and therefore not subject to risk-weighted regulatory capital requirements. PPP loans were generally provided within ten days of a small business applying, so the decision of a bank to approve a loan was likely jointly decided along with the decision to use external funding.

The Fed also established a PPP Lending Facility (PPPLF) to provide long-term funding to the financial sector beginning on April 9, six days after the PPP program began. To apply for funding, banks had to post their PPP loans as collateral, be approved by the Fed, and subsequently receive their funds. This period can take anywhere from one week to three months, with the median time being three weeks. Funds advanced by the PPPLF had an interest rate of 35 basis points and had the same maturity as the PPP loan used as collateral. Loans made under the PPPLF to banks were extended on a non-recourse basis, so banks did not face any liquidity risk from borrower defaults. PPP loans that were pledged to the PPPLF were also not included in the leverage ratio requirements, allowing banks to extend liquidity without regulatory restrictions. Anbil et al. [2021] finds a causal relationship between the choice of banks to access the PPPLF and the amount of PPP loans they originate, with banks that use the PPPLF extended over twice as many PPP loans as their counterparts. The first PPPLF distribution to a bank was made on April 16, the last day of Phase 1 of the PPP program, so lenders who faced liquidity issues during Phase 1 had to use alternative sources for liquidity.

A possible alternative source of funding for banks at this time was the discount window (DW). During times of crisis, the DW is meant to be a lender of last resort to manage liquidity risk and prevent credit rationing from banks. The DW extended overnight loans for up to 90 days at a rate of 25 basis points to all financially sound institutions through their Primary Credit program.[5] DW funds must be collateralized using eligible bank loans and securities before the date of borrowing, including but not limited to PPP loans.[6] Requesting a loan consists of calling the local Reserve Bank and providing verification information. However, before requesting a loan, the bank must file the corresponding Operating Circular No. 10 agreement with the lending Reserve Branch. Banks that have previously used the DW are more likely to use it again in case of an emergency, due to lower information/logistical costs or habit formation. Because the DW can provide instant liquidity with no questions asked, it could have played an integral role during Phase 1 of the PPP program before a long-term funding source was established.

Liquidity issues were most likely during Phase 1 of the program when loan demand outpaced

[5] On March 15, 2020, the Federal Reserve announced changes to primary credit, including changes to the length of DW loans from a period of 30 days to 90 days.

[6] Eligible loans include commercial, industrial, agricultural, consumer, and real estate loans. Eligible assets include corporate bonds, money market instruments, asset-backed securities, collateralized mortgage obligations, and Treasury bills. From the Fed Board: Generally, it is not operationally feasible to pledge collateral (other than book-entry securities issued by the U.S. Treasury, U.S. government agencies, or U.S. government-sponsored enterprises) on the day a loan is requested.

loan supply.[7] After the first two weeks of Phase 2, demand for PPP loans slowed, and the remaining funds were slowly distributed until August 8. Without funding from the PPPLF in Phase 1 of the program, banks flooded to the DW and borrowed $40.8 billion over the two weeks. Although the PPPLF began on April 9, the first disbursement to banks did not occur until April 16, the last day of Phase 1. This meant that for two weeks, banks did not have the necessary long-term funding to extend loans, which could have driven them toward the DW.

## 3 Data

The primary data source for this paper comes from the PPP loan database obtained from the SBA. This data set contains the loan level data for all PPP loans that were distributed throughout the program, the quantity of the PPP loan, select borrower characteristics, ZIP level location, and the name of the originating financial institution. Data linking each financial institution to its unique Federal Reserve ID was compiled and provided by Erel and Liebersohn [2020]. Since one bank can have multiple branches, I aggregate the data to the bank-by-day level and match the resulting data to commercial banks that filed FFIEC Call Reports in Q1 of 2020.

I also used loan-level PPPLF data obtained from the Federal Reserve website. The data contain the borrowing institution, the date of advance, the loan size, and the maturity date. Because the maturity dates of the PPPLF are matched to the maturity dates of the PPP loans, I can calculate the time it takes for the PPPLF to process a request for an advance. Although banks can expect when they will receive PPPLF funds, the exact date is unknown to them. This implies that the date of PPPLF receipt can be taken as an exogenous shock to banks. There also exists a slight negative correlation between the processing time and the date of the PPP program, which suggests that the PPPLF process was more streamlined in the later stages of the PPP program compared to when the PPPLF began operation.

Then I merge information on the daily borrowing of banks from the DW available on the Federal Reserve website. The DW data gives information on the borrowing financial institution, the size and duration of the loan, the collateral posted to the Fed by that institution, and the type of credit (primary credit, secondary credit, and seasonal credit). I include only primary credit in the analysis since seasonal credit is meant for seasonal fluctuations in the credit demand of smaller banks and secondary credit constitutes less than 1% of DW observations in the sample period.

[7] See Li and Strahan [2020] and 'PPP Money Abounded – But Some Got It Faster Than Others', Wall Street Journal. Although the PPP was eventually extended to all eligible businesses, there was a disparity in which businesses received it first.

This data set contains the universe of loans lent by the Federal Reserve from 2010 to 2020. For loans that are borrowed for multiple days, I calculate the overnight-equivalent amount.[8] I count any borrowings from the discount window less than $100,000 as a test loan and drop these values in the analysis.

I gather bank characteristics from quarterly Call Reports published by the FFIEC and filed by all commercial banks with US branches. Banks in this set are split into two groups based on size, with 'small' banks defined as those in the lower 75th percentile of assets measured in the Q1 2020 Call Reports. This cutoff corresponds to a bank with assets equal to $593 million, which was close to the cutoff level of $600 million made in Anbil et al. [2021]. For robustness, I also consider the 90th and 95th percentile cutoff values, corresponding to banks with $1.73 and $4.46 billion in assets, respectively. Since bank-level characteristics are only observed through Call Reports at the quarterly level, I construct the measure of DW borrowing and PPP shock as a share of reserves by dividing the daily size of PPP lending against the last known reserves of that bank.[9] I also consider a normalization based on the assets of banks instead of reserves, but this would over-weigh large banks due to the negative correlation between bank size and the reserve-to-asset ratio.

Finally, I combine information from the 2019 Summary of Deposits, which gives branch-level information about each bank and the amount of reserves held at the branch. I use this deposit share as weights to calculate a bank's COVID exposure at the county level (measured by new cases) and exposure to economic shocks at the week-state level using the time series data from Baumeister et al. [2021]. Although imperfect, these two exposure measures should be sufficient to eliminate most of the differential effects attributed to COVID exposure. Even if COVID exposure cannot be perfectly controlled, Granja et al. [2020] finds little to no evidence that funds flowed to areas more economically affected by COVID.

Since the question of interest is to look at how liquidity demand by banks affects their choice to borrow from the DW, I only include periods where the demand for PPP loans is greater than the supply. From Granja et al. [2020], banks were mostly restricted in liquidity during April and May, when the PPP program had the highest levels of demand from businesses and 97.1% of all PPP loans were issued. After May, demand for PPP loans fell off and the supply was not the constraining factor. Therefore, I include only data from Phase 1 and April and May of Phase 2.

[8] Following Ennis and Klee [2021], a loan of $10 million for three days is equivalent to three overnight loans of $10 million.

[9] In practice, consider a bank with a reserve of $40 million filed in Q1 of 2020 and $42 million filed in Q2 of 2020. A $20 million shock on May 5 would be considered 50% of the bank's reserves, while the same shock on July 3 would be considered 47.6% of the bank's reserves.

| | No Borrowing | Borrowed from DW | Borrowed from PPPLF | Borrowed from both | Total |
|---|---|---|---|---|---|
| Small Community Banks | 2242 | 75 | 239 | 23 | 2579 |
| Large Banks | 757 | 91 | 166 | 34 | 1048 |
| Pooled | 2999 | 166 | 405 | 57 | 3627 |

**Table 1:** Breakdown of banks observed lending PPP loans. The sample contains all banks observed during Phase 1 (April 3 to April 16) and the first two months of Phase 2 (April 27 to May 31).

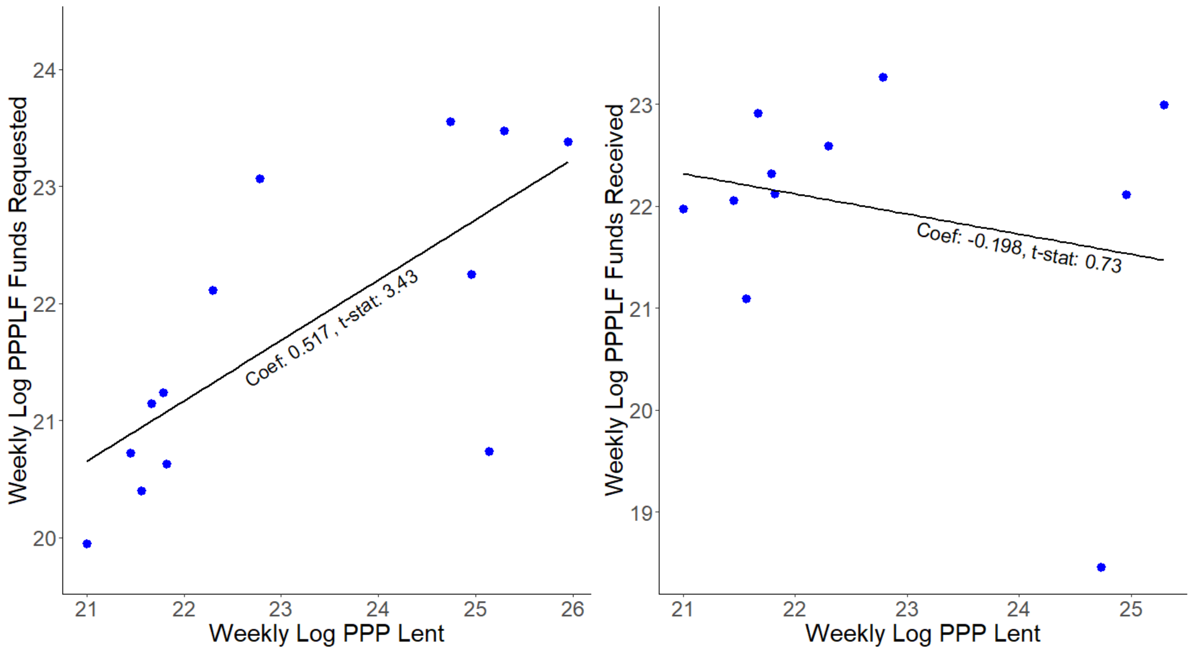
Summary statistics for all variables used in the regressions can be found in Table B.1 for the panel data and Table B.2 for the cross-sectional data. Since the behaviors of the largest banks can drive the majority of the results (Chase, Bank of America, etc.), I winsorize the data to remove the effects of these outliers. All variables, except bank size, are winsorized at the .1 percentile and 99.9 percentile.[10]

# 4 Descriptive Statistics

Table 1 shows the breakdown of small and large banks in the sample. I include only banks that lent out at least one PPP loan during April and May, since banks that choose not to lend out PPP loans may have other financial constraints at play, which would affect their decision to borrow from the window independent of PPP shocks. The table shows that 28% of large banks borrowed from the DW or the PPPLF, while only 13% of small banks did. This could be because 92% of the PPP loans during the first two phases were lent out by these large banks, which contributed to them needing the most liquidity. Large banks also borrowed 89% of the DW funds observed in this period and 83% of the PPPLF funds based on volume. These statistics imply that there is a differential effect of the two lending facilities across the two classes of banks. Larger banks might have the expertise necessary to withdraw funds from the window, whereas smaller banks find it easier to use the PPPLF due to fewer restrictions and greater accessibility. Consistent with the hypothesis, Lopez and Spiegel [2021] also shows evidence that participation in the PPPLF was an important driver for small bank lending during this period.

A possible question that might arise is why do banks not borrow from the PPPLF if they face liquidity constraints. If banks borrow from the DW to fund their PPP loans, they face the issue of maturity mismatch, where the maturity of the liability (DW borrowing) is years shorter than the maturity of the asset (PPP loan). The PPPLF resolves the mismatch issue by extending liquidity advances to banks matching the maturity of the PPP loan posted as collateral, therefore banks

[10] The standard winsorizing method is to use the 1st and 99th percentile as cutoffs, but since only 2% of the observations have DW quantity greater than zero in the time series data, a 99th percentile cutoff would change half of the DW data. I take a more conservative winsorizing approach to keep the majority of the DW borrowing information.




**(a)** Weekly PPPLF funds **requested**. **(b)** Weekly PPPLF funds **received**.

**Figure 2:** X-axis is the log quantity of PPP loans granted in a given week, Panel A plots the total quantity of PPPLF funds requested in the same week, and Panel B plots the total quantity of PPPLF funds received in a given week. The data is aggregated at the country level. Each data point represents one week of the PPP program.

should use the PPPLF instead of the DW to fund PPP loans. One reason why banks cannot do this is that there are logistical issues that banks face when requesting a PPPLF advance. For a bank to receive an advance, they must post the PPP loan as collateral and submit the application materials to the SBA. This application process can take anywhere from one day to up to four months before the SBA approves the PPPLF advance.[11] Therefore, banks cannot receive PPPLF funds before extending PPP loans, forcing them to use either internal funding or alternative funding sources. Figure 2 shows the aggregate amount of PPPLF funds requested in panel **(a)** by banks at the weekly level, and when banks actually received the requested funds in panel **(b)**. There is a strong correlation between PPP lending and PPPLF requests, but no correlation between PPP lending and PPPLF funds received. Therefore, a possible reason why banks used the DW during this period was to fill the liquidity shortage from the PPPLF caused by the processing delay.

Was DW borrowing economically significant? During April and May of the PPP program, the aggregate level of reserves of the financial sector was \$2.4 trillion, \$721 billion in PPP loans disbursed (30% of aggregate reserves), \$42.3 billion in long-term funding through the PPPLF, and \$139 billion lent by the Fed through the DW. Pre-pandemic, quarterly borrowing quantity

[11] Mean: 31.7 days, median: 18 days.

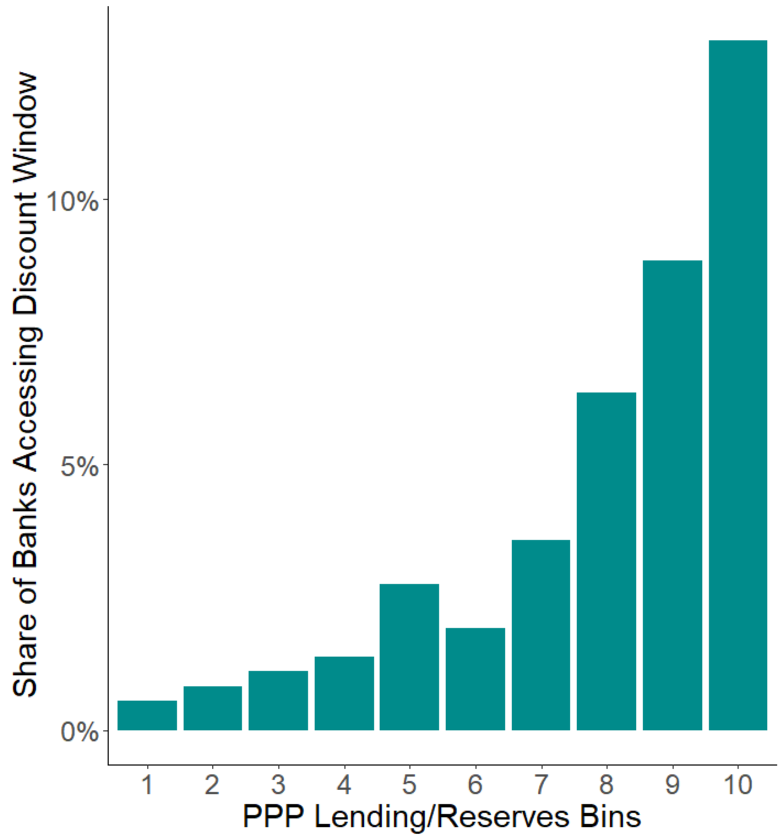
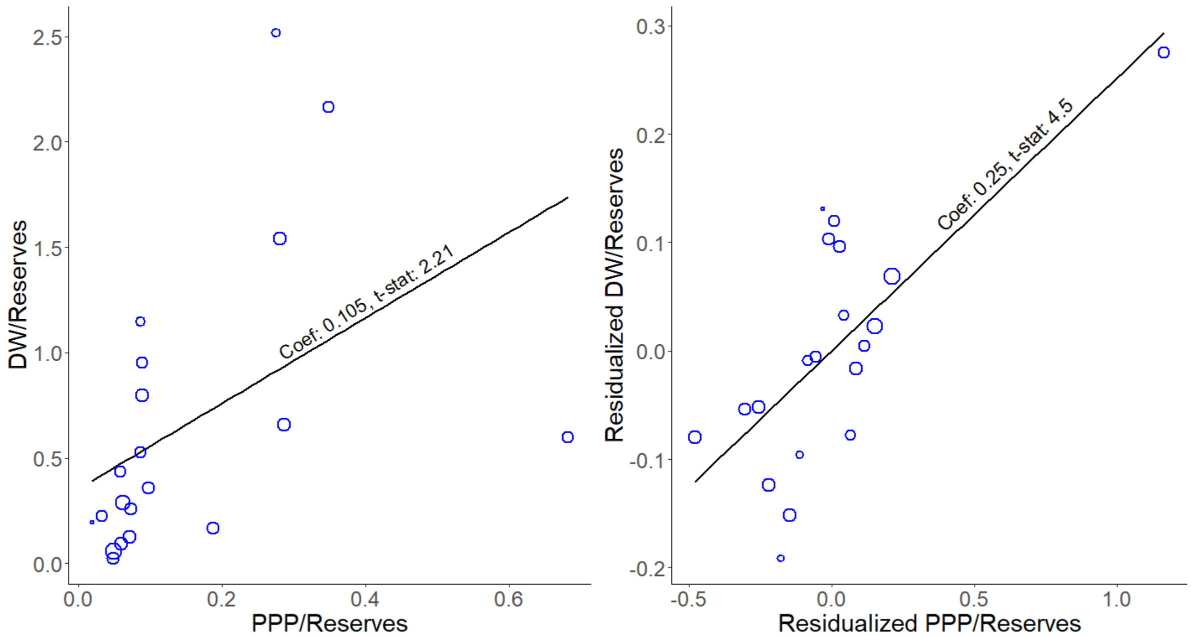



**Figure 3:** Binned bar chart of PPP shock as a share of reserves on the x-axis and the share of banks in that bin that went to the discount window on the y-axis. The bars are an aggregation of each 10% quintile and are aggregated by using means.

from the DW averaged around one to two billion dollars from the financial sector as a whole, with the majority of borrowing coming from small banks using seasonal credit. Not only was there a 100-fold increase in the quantity borrowed, but there also exists a high correlation between banks that lent out PPP loans and DW borrowing. Figure 3 uses the cross-sectional data and divides banks into deciles based on the reserve-adjusted amount of PPP lending. 13% of the highest decile banks used the DW at least once during April and May, while only 0.5% of the lowest decile banks did. This increasing relationship also holds when splitting the banks into groups based on the size cutoff criteria, which shows that bank size is not the main driver of the relationship. When looking at the relationship between the binned reserve-to-asset ratio and the share of banks that access the DW, there is a strong negative relationship between the two series, implying that liquidity constraints are a primary factor that influences banks to borrow from the window.

Given that liquidity-constrained banks might not extend as many loans as their counterparts, would DW borrowing alleviate those restrictions? Figure 4 shows the binned relationship between the reserve-scaled DW borrowing and PPP lending using the time series data. A positive slope




**(a)** **(b)**

**Figure 4:** Binned scatter plot showing the relationship between PPP Lending/Reserves and DW Borrowing/Reserves using the time-series data. Panel **(a)** is the non-residualized data while panel **(b)** uses the residualized data after controlling for bank characteristics. The banks included in this plot are banks that simultaneously borrow from the DW and lend out PPP loans on a given day. Any test loans (defined as DW borrowing < \$100,000) are dropped from the sample. The size of the points represents the average bank asset within the bin.

means that a larger amount of PPP lending is observed jointly with a larger quantity of DW borrowing. The size of the points represents the average bank size in that bin. We can see from the figure that PPP shocks are positively correlated with DW borrowing, and the effect is stronger after controlling for bank characteristics such as small business relationships, liquidity measures, and COVID exposure. One possible explanation from this graph is that when liquidity-constrained banks are faced with the choice to extend loans, they approach the DW to relax these constraints instead of rationing credit. Since the DW and PPP values are normalized by bank reserves, the distribution of bank sizes along the axes are relatively evenly distributed.

# 5 Results

In this section, I first show the correlation between DW usage and PPP shocks using the time-series data for the panel of banks. I then look at the cross-section of banks and answer the question of whether usage of the DW expands the amount of PPP lending.

## 5.1 Relationship between PPP lending and DW borrowing

Using the panel data, I first explore whether banks increase their probability of borrowing from the DW when they lend more PPP loans. I estimate the linear probability model:

$$\mathbb{1}[\mathrm{DW}_{it}] = \beta \mathrm{PPP}_{it} + \gamma \mathbf{X}_{it} + \delta_{F(i)} + \delta_t + e_{it} \quad (1)$$

where $\mathrm{DW}_{it}$ is an indicator that equals one if the bank has borrowed from the DW during that day. PPP is the PPP lending quantity for that day, scaled by the bank's first quarter reserves. $\beta$ estimates the response of DW borrowing probability to a change in the PPP shock. $\mathbf{X}_{it}$ is a vector of time-invariant bank-specific control variables and exposure variables that are time-variant. $\delta$ are both Federal Reserve District and time fixed effects.

This specification allows us to look at the variations between banks within a Fed district within a particular day. I include district fixed effects, since DW policy may differ across Federal Reserve Districts and potentially confound the estimation. I also include time fixed effects to account for changes in the aggregate demand of PPP loans and conditions that affect all banks equally. For example, the first disbursement of PPPLF funds to banks began after phase 1 and before phase 2, therefore the response behavior of banks could change between the phases due to less liquidity need after the first phase. The DW was also closed on weekends, which would affect the borrowing behavior of all banks equally.

In terms of controls, I control for three relationship measures between banks and small businesses: unused CI commitments, small CI loans, and core deposits scaled by bank assets.[12] I include other relevant bank characteristics that could affect a bank's decision to use the DW or lend PPP loans, such as bank size, liquid assets, commercial and industrial (CI) lending, Tier 1 leverage ratio, reserve-to-asset ratio, and deposit-to-asset ratio. I include a proxy for the sophistication of the bank, its branch-weighted bank age, exposure to new cases of COVID at the county level (daily), and exposure to economic conditions at the state level (weekly) using deposits as weights. Most of these controls have been used by Li and Strahan [2020] and Anbil et al. [2021], which explores the relevant characteristics of banks that lent out PPP loans and whether borrowing from the PPPLF affected their lending behavior. Lastly, I include an indicator variable that takes a value of 1 if the bank has borrowed from the DW before COVID, since that could influence their decision to borrow again.

I include specifications with and without controls for the pooled sample in columns (1) and

[12] These controls have been used in Berger and Udell [1995], Berlin and Mester [1999], Norden and Weber [2010].

**Table 2:** LPM of DW borrowing probability. Column (1-2) is the pooled sample with and without controls, column (3) is the pooled sample with the treatment variable interacted with bank size, column (4-5) is for large banks in the upper 25th percentile (assets greater than \$600M), and column (6-7) is for small community banks with assets in the lower 75th percentile. The sample contains observations from Phase 1 (April 3 to 16) and the early stages of Phase 2 (April 27 to May 31).

| Dependent Variable: | DW Indicator | | | | | | |
|---|---|---|---|---|---|---|---|
| | Pooled | | Interacted | Large Banks | | Small Banks | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Variables* | | | | | | | |
| PPP Lending/Reserves | 0.035*** | 0.026** | | 0.038* | 0.036 | 0.023*** | 0.016** |
| | (0.011) | (0.011) | | (0.022) | (0.023) | (0.009) | (0.008) |
| PPP Lending/Reserves × Size=0 | | | 0.013 | | | | |
| | | | (0.008) | | | | |
| PPP Lending/Reserves × Size=1 | | | 0.041* | | | | |
| | | | (0.022) | | | | |
| Previous DW Use Indicator | | 0.022*** | 0.022*** | | 0.010 | | 0.029*** |
| | | (0.006) | (0.006) | | (0.010) | | (0.008) |
| Reserve to Asset | | -0.060*** | -0.061*** | | -0.274*** | | -0.043*** |
| | | (0.013) | (0.013) | | (0.070) | | (0.012) |
| Deposit to Asset | | -0.215*** | -0.216*** | | -0.327*** | | -0.161*** |
| | | (0.041) | (0.041) | | (0.087) | | (0.046) |
| Equity Cap Ratio | | -0.513*** | -0.516*** | | -1.16*** | | -0.307** |
| | | (0.140) | (0.140) | | (0.366) | | (0.128) |
| Tier 1 leverage ratio | | 0.315** | 0.318** | | 1.16** | | 0.138 |
| | | (0.129) | (0.129) | | (0.478) | | (0.098) |
| Economic Exposure | | -0.0005 | -0.0005 | | -0.002 | | 0.0001 |
| | | (0.0007) | (0.0007) | | (0.002) | | (0.0006) |
| Deposit-weighted new COVID rate | | -0.0010* | -0.0010* | | -0.002 | | -0.0007 |
| | | (0.0006) | (0.0006) | | (0.002) | | (0.0006) |
| Bank Controls: | | Yes | Yes | | Yes | | Yes |
| *Fixed-effects* | | | | | | | |
| Fed District | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Date | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | |
| Observations | 250,782 | 242,648 | 242,648 | 62,622 | 58,016 | 188,160 | 184,632 |
| Dependent variable mean | 0.01459 | 0.01475 | 0.01475 | 0.03320 | 0.03449 | 0.00840 | 0.00855 |

*Clustered (Bank) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

(2) of Table 2 and also split the sample into large banks that have assets within the upper 25th percentile (assets $> \$573M$) and small banks. When looking at the pooled sample in columns 1 and 2, the quantity of PPP lending has a strong and positively correlated relationship with whether the bank chooses to borrow from the DW or not irrespective of bank-level controls. The results in column (2) imply that a 10 percentage point increase in the quantity of PPP loaned as a share

of the reserves is associated with an increase of .25 pp in DW borrowing probability. Given that the dependent variable mean is 1.47%, a .25 pp increase can be interpreted as a 18% increase in DW borrowing probability. When looking at the interacted term in column (3), both coefficients for large and small banks are positive, but only large banks have statistical significance. This flips when we look at the subgroups since column (5) shows no significance for large banks after controlling for bank level characteristics, while the coefficient for small banks is still significant.

When looking at the control variables, the reserve-to-asset ratio, the deposit-to-asset ratio, and the equity capital ratio have strong negative relationships with the probability that a bank borrows from the DW since those are the main indicators of liquidity and stability. The coefficients for the tier 1 leverage ratio are strong for large banks but not small banks, implying that leveraged large banks are more likely to use the DW. Previous usage of the DW is a strong indicator of repeat usage for small banks, but not for large banks. Finally, there is no significant correlation when looking at both measures of COVID exposure, suggesting that exposure to COVID was not a strong factor that affected a bank's choice to tap into the DW.

If we believe that banks are very idiosyncratic in their responses to liquidity shocks, then we should look at the within-bank variation over time. For robustness, Table B.3 reports the result of the same regression using bank instead of district fixed effect. Under this specification, we drop all banks that do not access the DW during the period, since those are the least liquidity constrained. Panel 1 shows the linear probability model with the observations dropped and the same column specifications. When looking solely at liquidity-constrained banks, large banks are the ones most likely to increase their chance to borrow from the DW when they lend more PPP loans. This result is similar in both the interacted column (3) and when looking at each subgroup (4-5). Panel 2 runs the same regression without dropping observations of banks that do not borrow. In this specification, banks that do not borrow from the DW still lend out PPP loans, which drives coefficients toward zero. To account for non-linearity, I also estimate the same model under the Poisson (in panel 3) and logistic (in panel 4) specification, which gives similar results to the linear probability model.

## 5.2 DW as a temporary source of liquidity

My final analysis of the panel data uncovers whether banks use the DW when waiting for a PPPLF advance. Since the DW loan has a shorter maturity than PPP loans, banks might substitute away from the DW loans when PPPLF funds become available. It is possible to extract from the data when a bank applies for PPPLF funding and when they received the advance. If banks do in fact use the DW as a stopgap measure of liquidity, we should find an increase in the overall DW borrowing probability after the bank has requested funding from the PPPLF. Furthermore, when banks received funds from the PPPLF, they should stop borrowing from the DW concurrently since their long-term source of funding has been secured.

To estimate whether this behavior holds in the data, I construct an indicator (WAITING) that takes on a value of one if a bank has applied for funds from the PPPLF but has not received the funds yet. Additionally, I create another indicator (POST) that takes on a value of one after the bank has received PPPLF funding. Following intuition, the expected treatment effect for WAITING should be positive, since banks increase their usage of the DW while waiting for long-term liquidity. Inversely, the expected treatment effect of POST should be negative following the same logic. I set up the canonical two-way fixed effects (TWFE) estimation equation:

$$DW_{it} = \beta \mathbf{X}_{it} + \delta_i + \delta_t + e_{it} \tag{2}$$

Where $\mathbf{X}_{it}$ is the WAITING or POST variable, $DW_{it}$ is the indicator of whether the bank was observed to have used the DW, and $\delta$ are individual and time fixed effects. $\beta$ is the difference-in-differences estimator and estimates the average treatment effect of banks that are waiting for PPPLF funds if using the WAITING indicator and after PPPLF funds are received if using the POST indicator.

Table 3 displays the result of the TWFE estimation. The first panel displays results using WAITING as the regressor, and the second panel uses POST as the regressor. Column (1) displays results for the pooled sample, (2) for the interacted sample, and (3) and (4) splits the sample into large and small banks at the 75th percentile cutoff. As expected, when looking at the first column, banks that are in the process of receiving funding from the PPPLF increase their DW usage by 2% compared to the counterfactual bank. Once advances from the PPPLF arrived, those banks drop their DW usage down to baseline levels. This effect holds for both large and small banks, with large banks increasing their DW usage by two to three times the amount of small banks depending on the specification. This could imply that either small banks are more averse to using the DW as compared to large banks, or the relative liquidity needs of small banks are not as large.

I then decompose the average treatment effect of banks to individual time periods to look at the treatment effect over time following an event study approach. To achieve this, I replace $\beta \mathbf{X}_{it}$ in Equation (2) with $\sum_{-t}^{t} \beta_t X_{it}$. Where $t$ represents the relative time period, with the treatment period normalized to zero for each bank. $\beta_t$ would then estimate the pre-treatment trend if $t < 0$ and the post-treatment effect for each period following the treatment when $t \geq 0$. If WAITING is

**Table 3:** Regression of DW borrowing indicator on the waiting indicator is displayed in the first panel. In the second panel, the waiting indicator is replaced with an indicator for whether the bank has received the PPPLF advance. All banks are included. The time period is from April to May 2020. Column (1) is the pooled sample, column (2) is the pooled sample with the treatment interacted with size, and columns (3) and (4) are the sub-sample analysis for large and small banks.

| Dependent Variable: | DW Indicator | | | |
|---|---|---|---|---|
| Model: | Pooled | Interacted | Large | Small |
| ***After PPPLF Requested*** | | | | |
| WAITING | 0.019*** | | 0.026** | 0.013*** |
| | (0.005) | | (0.011) | (0.005) |
| WAITING × Small Banks | | 0.011** | | |
| | | (0.005) | | |
| WAITING × Large Banks | | 0.030*** | | |
| | | (0.010) | | |
| Observations | 296,593 | 296,593 | 73,809 | 222,784 |
| ***After PPPLF Received*** | | | | |
| POST | -0.019*** | | -0.024* | -0.015** |
| | (0.007) | | (0.014) | (0.007) |
| POST × Small Banks | | -0.013* | | |
| | | (0.007) | | |
| POST × Large Banks | | -0.028** | | |
| | | (0.014) | | |
| *Fixed-effects* | | | | |
| Bank | Yes | Yes | Yes | Yes |
| Date | Yes | Yes | Yes | Yes |

*Clustered (Bank) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

the treatment, we should expect to see no pre-treatment trend, since the inclusion of bank fixed effects should net out the variations in liquidity constraints across banks. Any pre-treatment trend would be driven by the differential exposure of banks to PPP lending. If banks that lend out more PPP loans are more financially stable, then they should be more likely to use internal funding to source PPP loans and there would be a negative pre-treatment trend. When using POST as a treatment instead, we should expect to see a positive pre-trend if banks are using the DW before receiving PPPLF funding, with a negative treatment effect due to substitution away from DW funding and into PPPLF funding. The treatment effect should slowly increase in magnitude as banks repay their DW loans.

Since the decision of banks to apply for PPPLF funding is staggered, it is subject to Goodman-Bacon [2018] bias. This bias exists in all staggered treatment designs since units that are treated early are used as a control for units that are later treated. Estimates are more contaminated by this bias if the treatment group is large relative to the control and if treatment effects are heterogenous amongst different treated cohorts. Therefore, we should expect the bias to be larger for large banks since 24% of them accessed the PPPLF during this time as compared to the 11% for small banks. To account for this treatment staggering, I apply the Sun and Abraham [2020] bias correction algorithm, which should give unbiased estimates of the average treatment effect.

Figure 5 displays the result of the event study with the Sun and Abraham [2020] algorithm applied.[13] The series in green shows the estimates using the WAITING variable as treatment, and the series in red uses the POST variable as treatment. It can be seen from the figure that in the pooled sample, banks increase their use of the DW after the PPPLF fund has been requested and decrease their use of the DW after receipt of the funds. This effect is persistent for up to three weeks, close to the median time of PPPLF processing time of 18 days. Because the treatment time is normalized to zero, the effect in $t-1$ and $t-2$ are the two days before a bank apply to the PPPLF. From the pre-treatment trend, we can see that there is a slight anticipation effect, since banks increase their usage of the DW for up to three days before requesting funds from the PPPLF. This effect could be driven by the fact that to request funding from the PPPLF, the bank must post their PPP loan as collateral. Since use of the DW is correlated with PPP borrowing, as seen in Table 2, the negative pre-treatment trend could be driven by banks accessing the DW on days where they also originate a large number of PPP loans. The only large difference between large and small banks is the post-treatment effect after requesting PPPLF funds. For large banks, estimates hover around a 5% increase in DW usage, while for small banks the same estimate is only around 2%.

## 5.3 Did DW borrowing expand PPP lending?

Using the panel data, this paper finds a strong correlation between PPP lending and DW borrowing for large liquidity-constrained banks. Additionally, both large and small banks use the DW as a stopgap measure for funds before advances from the PPPLF was received. To answer whether DW borrowing had any impact on PPP originations, I aggregate the data from April and May to look at the cross-sectional variations across banks. The bank characteristics in this data

[13] The result of the baseline estimates can be found in Figure A.2. There is not a huge difference in the post-treatment estimates, but the pre-treatment trends for large banks are slightly contaminated. This effect also appears for small banks at a smaller magnitude.

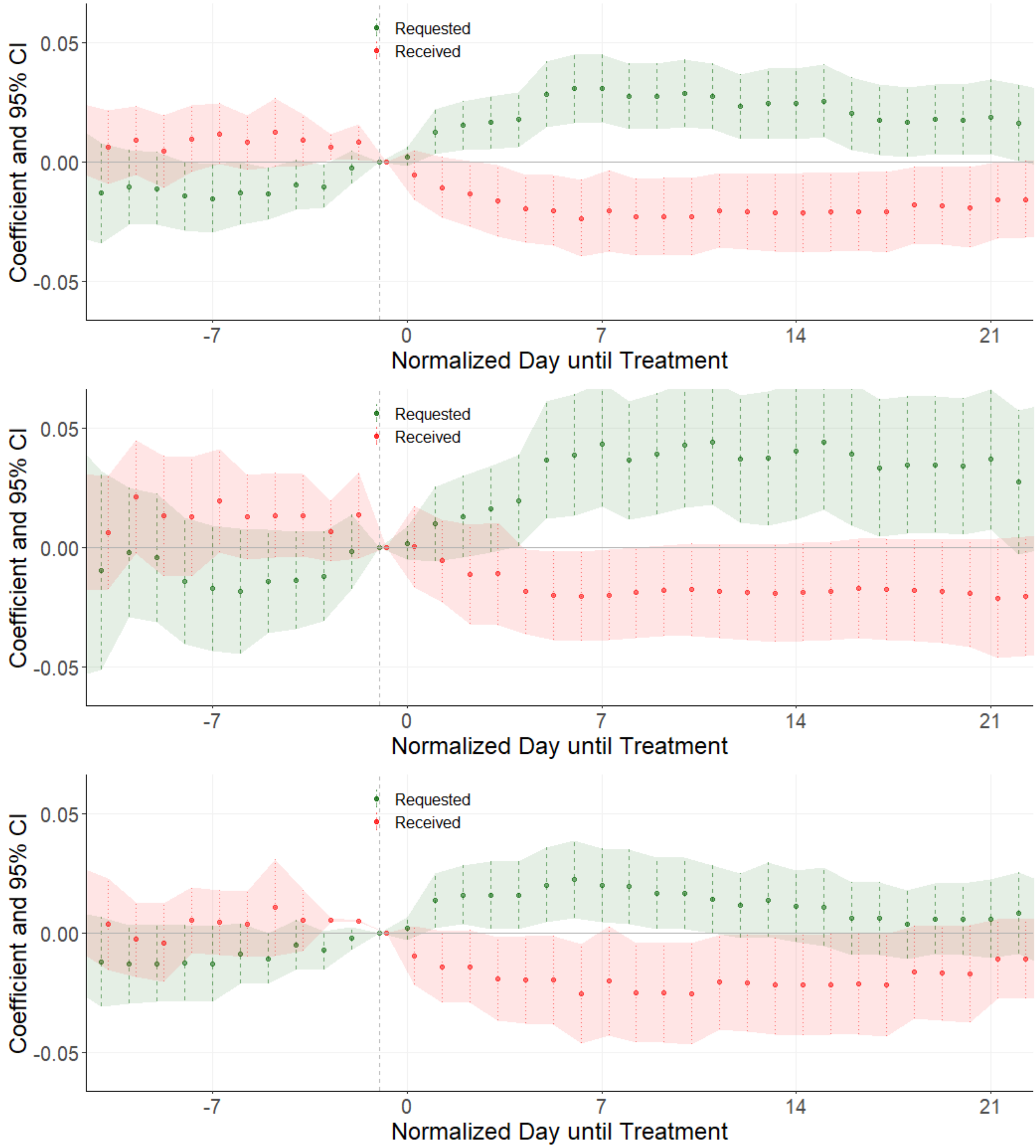



**Figure 5:** Bias-corrected event study results for the pooled sample in the top figure, large banks in the second figure, and small banks in the third figure. The timeline is normalized to when treatment has started for each individual bank. The series in green represents using the date of when banks **requested** the PPPLF money as treatment. The series in red represents using the date of when banks **received** the PPPLF advance as treatment. Displayed is the Sun and Abraham [2020] correction for staggered treatment.

set are taken from Call Reports filed in the first quarter of 2020. All lending facility borrowing and PPP lending are the aggregates from April and May.

I consider two alternative avenues in my empirical analysis. One, on the extensive margin, does borrowing from the DW increase the number of PPP loans that a lender can originate? Two, on the intensive margin, when looking at banks that do access the DW at least once during the period, what is the relationship between the quantity borrowed at the DW and the number of PPP loans lent out? To answer these questions, I set up the following regression equation:

$$\log(\text{Number of PPP loans}) = \beta \mathbb{1}[\text{DW}_i] + \gamma \mathbf{X}_i + \delta_{S(i)} + \delta_{F(i)} + e_i \tag{3}$$

where DW is an indicator variable of whether the bank has been observed to borrow from the DW during the sample. $X$ is a vector of bank-specific control variables from the Q1 2020 Call Report, and $\delta$ are both size decile and Fed District fixed effects. I control for size decile since there might be confounding policies that affect subgroups of banks depending on asset size, and district fixed effects for differential DW policies across districts, such as scrutiny. Furthermore, I include controls that measure a bank's alternate sources of short-term external funding, such as FHLB loans with a maturity of less than one year and total borrowing from the Federal Funds and Reverse Repo markets extracted from the Call Report data. I also control for sources of long-term funding, such as the deposit level and deposit growth from Q1 to Q2 of 2020 as well as money received from the PPPLF.

An issue that might arise in this specification is whether the correlation between DW borrowing and PPP lending still exists. From Figure 1, we see a high correlation in the short horizon, since DW borrowing is correlated with PPP lending at the daily level, but it might not exist in the aggregated cross-section. There are also differences in the correlation between phases 1 and 2 of the PPP program due to institutional changes. Since the first advance from the PPPLF was disbursed on April 16, banks that lent PPP loans during Phase 1 of the program did not have a ready source of long-term liquidity, which could drive them toward the DW. When looking at Phase 2 after PPPLF funds were distributed, banks may not have needed DW funds as much since there was an easier alternative without stigma. Therefore, I split the regression into three parts, looking at the aggregate of only Phase 1 quantity from April 3 to April 16, only Phase 2 from April 27 to May 31, and a pooled sample including all observations during April and May.

Table 4 presents the results of the naive cross-sectional regression. Column 1 regresses the log number of PPP loans on the DW indicator with only fixed effects, column 2 includes all controls for bank characteristics, and column 3 includes alternate sources of short-term funding for the

**Table 4:** This table reports the OLS regression between DW borrowing and the number of PPP loans lent using data aggregated from April and May of the PPP program. Reserves are measured from Call Report data in Q1 of 2020 and are the sum of RCON0071 and RCON0081. The period used for this aggregation was April and May of 2020. Column (1) includes no controls, column (2) includes all bank-level characteristics and relevant covariates, and column (3) includes alternate sources of short-term funding, in this case, funding from FLHB and the Fed Funds/Overnight Repo Repurchase market. Column (4) uses the pooled sample with an interaction term between the bank size and the DW indicator. Column (5) is for large banks in the upper 25th percentile (∼600M Assets), and column (6) is for small banks in the bottom 75th percentile.

| Dependent Variable: | Log Number of PPP Loans | | | | | |
|---|---|---|---|---|---|---|
| | | Pooled | | Interacted | Large Banks | Small Banks |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| DW Borrowing Indicator | 0.261*** | 0.250*** | 0.171** | | 0.177* | 0.218*** |
| | (0.098) | (0.084) | (0.076) | | (0.107) | (0.084) |
| DW Borrowing Indicator × Small Banks | | | | 0.238** | | |
| | | | | (0.093) | | |
| DW Borrowing Indicator × Large Banks | | | | 0.132 | | |
| | | | | (0.107) | | |
| Fed Funds+ONRRP/Reserves | | | 0.0007*** | 0.0007*** | 0.0007* | 0.0005 |
| | | | (0.0002) | (0.0002) | (0.0004) | (0.0003) |
| FLHB/Reserves | | | 0.266*** | 0.262*** | 0.332 | 0.209** |
| | | | (0.082) | (0.082) | (0.605) | (0.083) |
| PPP LF/Reserves | | | 0.264*** | 0.263*** | 0.481*** | 0.184*** |
| | | | (0.034) | (0.034) | (0.059) | (0.030) |
| Deposit Growth | | 0.019*** | 0.017*** | 0.017*** | 0.015*** | 0.015*** |
| | | (0.003) | (0.002) | (0.002) | (0.003) | (0.003) |
| Deposit to Asset | | 1.91*** | 2.30*** | 2.30*** | 3.22*** | 1.87*** |
| | | (0.392) | (0.393) | (0.393) | (0.649) | (0.500) |
| Bank Characteristic Controls: | | Yes | Yes | Yes | Yes | Yes |
| *Fixed-effects* | | | | | | |
| Size Deciles | Yes | Yes | Yes | Yes | Yes | Yes |
| Fed District | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 3,627 | 3,558 | 3,558 | 3,558 | 997 | 2,561 |
| $R^2$ | 0.61964 | 0.70215 | 0.72113 | 0.72117 | 0.55989 | 0.58623 |

*Heteroskedasticity-robust standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

pooled sample. Columns 4 and 5 report the results for large and small banks with the cutoff interval being the 75th percentile of asset size. We see a significant correlation in the pooled sample, as well as when we split the sample between large and small banks. Small banks seem to have a slightly stronger correlation with the DW usage (.217), but not significantly different than the coefficient for large banks (.178). All sources of external funding are significantly correlated in the pooled sample, signifying that external funding was an important factor in the extension of

PPP loans.

## 5.4 Instrumental Variables Analysis

A source of concern in the cross-sectional analysis is that there can exist multiple sources of omitted variables. Balance sheet costs and liquidity constraints for each bank cannot be perfectly extracted from publicly available data, so changes to those factors while the PPP program is ongoing could influence both their decision to access the DW as well as their decision to extend PPP loans. If a bank faced liquidity constraints, they could choose to simultaneously decrease the quantity of PPP lending as well as tap into the DW, biasing the estimates towards zero. Although banks cannot control the quantity of PPP loan applications they receive, they can control the quantity of PPP loans they originate. Therefore, the decision on how many loans to originate is likely positively correlated with the bank's decision to use external funding, resulting in simultaneity bias.

To resolve issues of omitted variable bias, I instrument the DW usage during the PPP program with the bank's previous exposure to the DW. To create this measure, I look at the total borrowing of each bank from the DW from the period of Q1 2010-Q1 2020 normalized by the bank's reserves from their Q1 2020 Call Report as a measure of familiarity of each bank with the Fed's DW program.[14] Since familiarity with the DW was measured before COVID, biases due to simultaneity are effectively eliminated due to the time difference. This approach shares a similarity to Anbil et al. [2021], which uses familiarity with pledging loan collaterals to the DW as an instrument for the bank's probability of using the PPPLF.

The relevancy condition for the instruments comes from the high propensity of banks to use the DW again if they have used it previously. Banks who have previously used the DW have a 9 pp greater chance of using the DW again during Q2 of 2020. This relationship is 10.2% for large banks and 5.7% for small banks. Although current DW usage is driven more by current liquidity shocks than previous usage, the strong correlation between familiarity and current usage makes the instrument strong and relevant.[15] There are two possible channels for why this relationship exists: (1) logistical friction and (2) bank-specific risk preferences. Since the DW requires Operating Circular No. 10 to be filed and collateral to be posted, banks that have previously used the

[14] An alternate version where I only use only DW data since 2018 shows a similar result of a slightly smaller magnitude. This is possibly due to a smaller number of observations and ignoring all bank familiarity with the DW before 2018. If we use data since 2018, then 24.4% of the banks have previously used the DW compared to 32.7% if we use data from 2010.

[15] The F-statistic for all specifications is larger than ten, and in most cases is in the hundreds.

window already paid the fixed cost of setting up operations and are more willing to use it again in the future. For banks that have never used the DW, there is a processing time between filing the required paperwork and borrowing, which makes it difficult for them to acquire DW liquidity quickly. Alternatively, some individual banks can prefer to use institutions rather than borrowing from the interbank market for liquidity. If this was the case, those specific banks would frequently borrow from the DW, in normal periods and during times of crisis.

The primary assumption for this instrument is that prior usage of the DW usage only affects current DW usage and not any other factors that can influence PPP lending. Although previous DW usage might affect a bank's propensity to use other sources of external funding besides the DW, I control for possible sources of short- and long-term funding, including: FHLB loans, Federal Funds (FF), Overnight Reverse Repo Agreements (ON-RRP), and PPP Lending Facility borrowing. Other sources of external funding are second order when compared to those that have been included. Another possible source of endogeneity still exists through unobserved bank-specific risk tolerance. If some banks are inherently willing to take more risks than others, then they could extend more loans and borrow from the DW to fund this extension. This would imply that the estimates we find are driven more by risky banks than usage of the DW itself, since I cannot control for bank fixed effects in the cross-sectional regression. Although this analysis holds for normal loans, PPP loans are a special case, since they carry zero weight when it comes to risk. Due to zero risk weighing on PPP loans, unobserved risk factors should be orthogonal to the amount of PPP loans that a bank chooses to extend.

Table 5 reports the results for the instrumented regression with heteroskedasticity-robust standard errors. The first panel runs the regression only using aggregated data from Phase 1 of the PPP program from April 3 to April 16, where the demand for PPP loans by firms greatly exceeded the supply. The second panel runs the regression on data from Phase 2 of the PPP program, from April 27 to May 31. The third panel runs the regression using the pooled data for Phases 1 and 2, aggregating all borrowing and lending done in April and May of 2020. Column 1 includes only fixed effects for size deciles and districts, column 2 includes controls for bank characteristics, and column 3 includes controls for alternate sources of external funding for the pooled sample of banks. Column 4 shows the interacted term in the pooled sample, column 5 displays the results for large banks in the upper 25th percentile, and column 6 has results for small banks. Since the interacted specification has two endogenous variables, I also interact the instrument with the size class to be just-identified. While this method should still satisfy the exclusion restriction, the preferred specifications are the results from the subgroup analysis.

Looking at the first panel, we can see that the effect of DW borrowing is strong and significant

**Table 5:** This table reports the results of how accessing the DW affects the number of PPP loans originated using a TSLS approach. The columns have the same specification as in Table 4. The instrument used is a measure of familiarity with the DW, measured by the total quantity that the bank has borrowed from the DW since 2010 divided by bank reserves (RCON0071 + RCON0081) from the Q1 2020 Call Report. The first panel uses only data from Phase 1 of the PPP program from April 3 to April 16. The second panel runs the regression on data from Phase 2 of the PPP program, from April 27 to May 31. The third panel runs the regression using the pooled data for Phases 1 and 2, aggregating all the borrowing and lending done in April and May of 2020.

| Dependent Variable: | Log Number of PPP Loans | | | | | |
|---|---|---|---|---|---|---|
| | | Pooled | | Interacted | Large Banks | Small Banks |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Phase 1 Only*** | | | | | | |
| DW Indicator | 0.831*** | 0.934*** | 0.908*** | | 0.928*** | 1.26 |
| | (0.263) | (0.292) | (0.291) | | (0.309) | (0.855) |
| DW Indicator × Small Banks | | | | 1.48* | | |
| | | | | (0.807) | | |
| DW Indicator × Large Banks | | | | 0.734** | | |
| | | | | (0.308) | | |
| Observations | 3,486 | 3,419 | 3,419 | 3,419 | 977 | 2,442 |
| ***Phase 2 Only*** | | | | | | |
| DW Indicator | 0.096 | 0.392 | 0.440* | | 0.691** | 0.069 |
| | (0.267) | (0.267) | (0.261) | | (0.343) | (0.489) |
| DW Indicator × Small Banks | | | | 0.448 | | |
| | | | | (0.466) | | |
| DW Indicator × Large Banks | | | | 0.437 | | |
| | | | | (0.298) | | |
| PPP LF/Reserves | | | 0.297*** | 0.297*** | 0.520*** | 0.221*** |
| | | | (0.036) | (0.036) | (0.061) | (0.032) |
| Observations | 3,621 | 3,552 | 3,552 | 3,552 | 996 | 2,556 |
| ***Phase 1 and 2*** | | | | | | |
| DW Indicator | 0.345 | 0.535** | 0.548** | | 0.688** | 0.380 |
| | (0.240) | (0.255) | (0.249) | | (0.282) | (0.598) |
| DW Indicator × Small Banks | | | | 0.624 | | |
| | | | | (0.556) | | |
| DW Indicator × Large Banks | | | | 0.521** | | |
| | | | | (0.258) | | |
| PPP LF/Reserves | | | 0.258*** | 0.257*** | 0.475*** | 0.181*** |
| | | | (0.034) | (0.035) | (0.059) | (0.032) |
| Observations | 3,627 | 3,558 | 3,558 | 3,558 | 997 | 2,561 |
| Bank Characteristic Controls: | | Yes | Yes | Yes | Yes | Yes |
| *Fixed-effects* | | | | | | |
| Size Deciles | Yes | Yes | Yes | Yes | Yes | Yes |
| Fed District | Yes | Yes | Yes | Yes | Yes | Yes |

*Heteroskedasticity-robust standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

for the pooled sample and large banks, but not for small banks due to large standard errors. Standard errors are better in the pooled interacted sample due to a higher number of observations, in which case the effects for small banks are significant at the 10% level. If we compare differences between columns 2 and 3 in both Table 4 and Table 5, we do not see as significant changes in the coefficients of the pooled sample in the instrumented regression. One explanation for this behavior is that variations in the treatment variable induced by the instrument have very little correlation with other sources of funding, showing that levels of previous DW usage do not significantly affect a bank's choice to tap into other sources of funding. This should be true because previous familiarity with the DW does not imply familiarity with interbank transactions.

Regarding the interpretation of the coefficients, large banks that accessed the DW in Phase 1 of the PPP program extended 92.8% more PPP loans than their counterparts, 69.1% when looking only at the early stages of Phase 2, and 68.8% overall during April and May. This effect is economically significant given that the median number of PPP loans lent out by large banks was $\sim$820 during April and May, so a 69% increase corresponds to 565 loans per bank. The effect is stronger in Phase 1, before a dedicated source of long-term funding from the PPPLF was available, but is still significant during Phase 2. This could have happened because banks substituted away from the DW and borrowed more extensively from the PPPLF. Since the PPPLF provided long-term funding that matches the maturity of the PPP loans, banks would prefer that over overnight loans from the DW. When looking at the interacted column, the results for large banks are weaker than when performing a subgroup analysis and stronger for small banks. One possible reason is that subgroup regression implicitly forces the controls to also interact with bank size, allowing for more fine-tuned controls of bank characteristics. Since the effect of bank liquidity is most likely different amongst bank sizes, the subgroup regression is the preferred specification.

This result is robust to alternate levels of the cutoff criteria for large banks, shown in Table B.4. The regression includes only lending in Phase 1, and columns 1-4 represent the 75th, 80th, 90th, and 95th percentile cutoff criteria for large banks. Although column 4 has only 158 observations, we still see strong and significant effects of DW access on the quantity of PPP lending, giving reliability to the estimation.

I also consider using an alternative instrument: the number of times the bank has borrowed from the DW pre-COVID. Since I measure the information channel of DW familiarity for the instrument, a bank that borrows a large amount once might have less information than another bank that borrows small quantities frequently, even if the total amount is the same. Table B.5 displays results from using the alternative instrument. I find that estimates for large banks are slightly more conservative, and estimates for small banks are twice as large and gain significance at the 10% level. In Panel 3, I include both instruments to perform the Sargan over-identification test, which fails to reject the null hypothesis that both instruments are exogenous.

Finally, I examine the intensive margin between the reserve-adjusted quantity borrowed from the DW and the log quantity of PPP loans. I use Equation 3, substituting the DW indicator variable for a reserve-adjusted quantity. In this sample, I include only banks that have used the DW at least once during the sample period, which drops ~90-95% of the observations since most banks did not access the DW. Table 6 reports the results of the instrumented regression, with the first row of each panel being the most important. The specifications of the columns are the same as in Table 5, and the panels refer to the same phase aggregation method. The results of columns 4 and 5 of the first panel show that the quantity of DW borrowing only affected large banks. An increase in DW borrowing as a share of reserves by 10 percentage points increased the quantity of PPP loans extended by .78%. Although this effect may seem small, the reserve-adjusted DW borrowing series is an aggregation of all borrowing done in Phase 1, with a mean of 3.23 and a standard deviation of 5.58 when looking at banks that have used the DW at least once. Therefore, a one standard deviation increase in DW borrowing increased the quantity of PPP loans lent by 43.6%. This effect is not large or significant for small banks and has no effect at the intensive margin during the early stages of Phase 2. It is important to note that the first panel of column 4 only has 89 observations, but the effect still holds and is significant at the 0.01 level, further giving reliability to the estimation.

# 6 Discussion

What do these results imply when it comes to the implementation of fiscal policy? For one, the implementation of monetary and fiscal policy through the financial sector requires enough liquidity to facilitate a smooth transfer of credit to businesses and households. In that sense, the fiscal authority should have coordinated with the Fed and ensured that the PPPLF was set up before the roll-out of the PPP program, instead of implementing a liquidity facility ex-post. Due to this delay, banks were forced to go to the DW for their liquidity needs, which could have negatively impacted lending for banks that were DW-averse. There could have also existed a source of positive externality, since if more banks were forced to borrow from the DW, the 'stigma' of DW borrowing could be reduced due to observations of borrowing being less informative about the asset quality of the borrower. This asset quality mechanism has been explored in Ennis and Weinberg [2013], where observation of borrowing from the window is observed as a negative signal, therefore agents would pay a higher price in the interbank market to avoid revealing information.

**Table 6:** This table reports the results of how DW borrowing as a share of reserves affects the number of PPP loans originated using a TSLS approach. The columns are the same specifications as in Table 5, but only include the banks that have used the DW at least once. The first panel runs the regression only using aggregated data from Phase 1 of the PPP program. The second panel runs the regression using data from Phase 2 of the program, from April 27 to May 31. The third panel runs the regression using the aggregated data for April and May of 2020.

| Dependent Variable: | Log Number of PPP Loans | | | | | |
|---|---|---|---|---|---|---|
| | | Pooled | | Interacted | Large Banks | Small Banks |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Phase 1 Only*** | | | | | | |
| DW Borr/Res | 0.022 | 0.060** | 0.057** | | 0.078*** | -0.003 |
| | (0.025) | (0.026) | (0.026) | | (0.026) | (0.036) |
| DW Borr/Res × Small Banks | | | | 0.011 | | |
| | | | | (0.033) | | |
| DW Borr/Res × Large Banks | | | | 0.068** | | |
| | | | | (0.030) | | |
| Observations | 149 | 145 | 145 | 145 | 89 | 56 |
| ***Phase 2 Only*** | | | | | | |
| DW Borr/Res | 0.005 | 0.011 | 0.057 | | 0.570 | -0.037 |
| | (0.017) | (0.036) | (0.057) | | (4.63) | (0.056) |
| DW Borr/Res × Small Banks | | | | 0.043 | | |
| | | | | (0.071) | | |
| DW Borr/Res × Large Banks | | | | 0.194 | | |
| | | | | (0.426) | | |
| PPP LF/Reserves | | | 0.402*** | 0.438** | 0.410 | 0.191 |
| | | | (0.094) | (0.208) | (1.45) | (0.155) |
| Observations | 140 | 137 | 137 | 137 | 72 | 65 |
| ***Phase 1 and 2*** | | | | | | |
| DW Borr/Res | 0.005 | 0.014 | 0.021* | | 0.037** | 0.002 |
| | (0.008) | (0.011) | (0.011) | | (0.017) | (0.006) |
| DW Borr/Res × Small Banks | | | | 0.013** | | |
| | | | | (0.006) | | |
| DW Borr/Res × Large Banks | | | | 0.027* | | |
| | | | | (0.016) | | |
| PPP LF/Reserves | | | 0.309*** | 0.313*** | 0.576*** | 0.126** |
| | | | (0.094) | (0.095) | (0.110) | (0.054) |
| Observations | 223 | 218 | 218 | 218 | 121 | 97 |
| Bank Characteristic Controls: | | Yes | Yes | Yes | Yes | Yes |
| *Fixed-effects* | | | | | | |
| Size Deciles | Yes | Yes | Yes | Yes | Yes | Yes |
| Fed District | Yes | Yes | Yes | Yes | Yes | Yes |

*Heteroskedasticity-robust standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Another way the PPP program could have been implemented better is if the processing time of the PPPLF was reduced. On average, the delay between when banks requested an advance from the PPPLF and when they received the funds was around three weeks, which could have negatively impacted the speed of loan distribution. Banks that are inherently averse to borrowing from the DW might have waited for funds from the PPPLF to come in before making any lending decision, subsequently taking longer than necessary to extend credit. From Granja et al. [2020], we know that firms that receive PPP funds earlier have better employment outcomes than firms that receive funds later in the program.[16] A faster processing time from the PPPLF could have improved employment outcomes and reduced the banking sector's dependence on DW lending.

The PPPLF was established to extend funding to banks for a period of two to five years, while loans made through the DW had a maximum maturity of 90 days. The length of funding, as well as the implicit cost of the DW, made these institutions naturally serve different purposes for banks. Since banks prefer to match maturities, the PPPLF seems like the optimal lending facility while the DW remains a stopgap measure of temporary liquidity. The Fed could have folded the functions of the PPPLF into the DW, extending DW credit to longer maturities and allowing PPP collateral to be posted to the window at face value. This would have further reduced the cost of accessing the DW and encouraged banks to further borrow from the window in future crises.

The empirical analysis also points to drastic differences between the behaviors of large and small banks. On both the extensive and intensive margins, DW borrowing did not affect small bank lending, while the PPPLF has been shown to have a greater effect on small banks compared to large banks by Anbil et al. [2021] and Lopez and Spiegel [2021]. One potential reason is that since the PPPLF was an emergency measure, regulations were less strict on the type of banks that could access them. Another possibility could be that small banks face greater stigma when borrowing from the DW and are more reluctant to use it as a source of liquidity. If the Fed wants to encourage usage of the DW amongst small banks, it might be a good idea to make it more accessible for those sets of customers by reducing either the explicit or implicit cost.

Finally, consider the current banking liquidity crisis due to high interest rates. The fall in bond prices count as an unrealized loss in the bank's balance sheet, and deposit withdrawals cannot be sufficiently covered by liquidating bonds. If banks were more willing to access the DW during this time, there would be a decreased probability of bank failures. Therefore, expanding access to the DW either by reducing the associated stigma or targeted outreach could improve the financial stability of the banking sector.

[16] Employment outcomes are measured by the number of hours worked and the number of employees employed. This effect also persisted until August, so it was relatively persistent.

# 7 Conclusion

The discount window is an important tool in the Federal Reserve's arsenal to ensure the continued stability of the financial sector. To that extent, this paper analyzes the relationship between a bank's choice to use the DW and the impact of an exogenous liquidity shock, proxied by the quantity of PPP loans. Primarily, both large and small banks used the DW as a measure of temporary liquidity before a long-term source of funding was available. Using prior familiarity with the DW as an exogenous instrument, I find a causal relationship between DW usage and PPP lending at both the intensive and extensive margins. Large banks were the main users of the DW, and those that used the window during Phase 1 of the PPP program extended 92.8% more PPP loans than their counterparts. This effect decreases to 68.9% after extending the sample to the end of May 2020, when the demand for PPP loans from firms decreased and PPPLF funding was available. At the intensive margin, a one standard deviation increase in reserve-adjusted DW borrowing increased PPP lending by 43.6% during Phase 1 of the program for large banks, but has no significant effect for small banks.

Results from this study suggest that multiple sources of central bank lending might play a complementary role in supporting fiscal policy when implemented through the financial sector. The DW provided medium-term liquidity for banks for up to three months, while the PPPLF provided long-term liquidity for banks from two to five years. The DW and the PPPLF also appeared to serve different subsets of the financial sector, with the DW having a greater effect on larger banks, while the PPPLF has a greater effect on small banks.

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# Appendix A: Figures

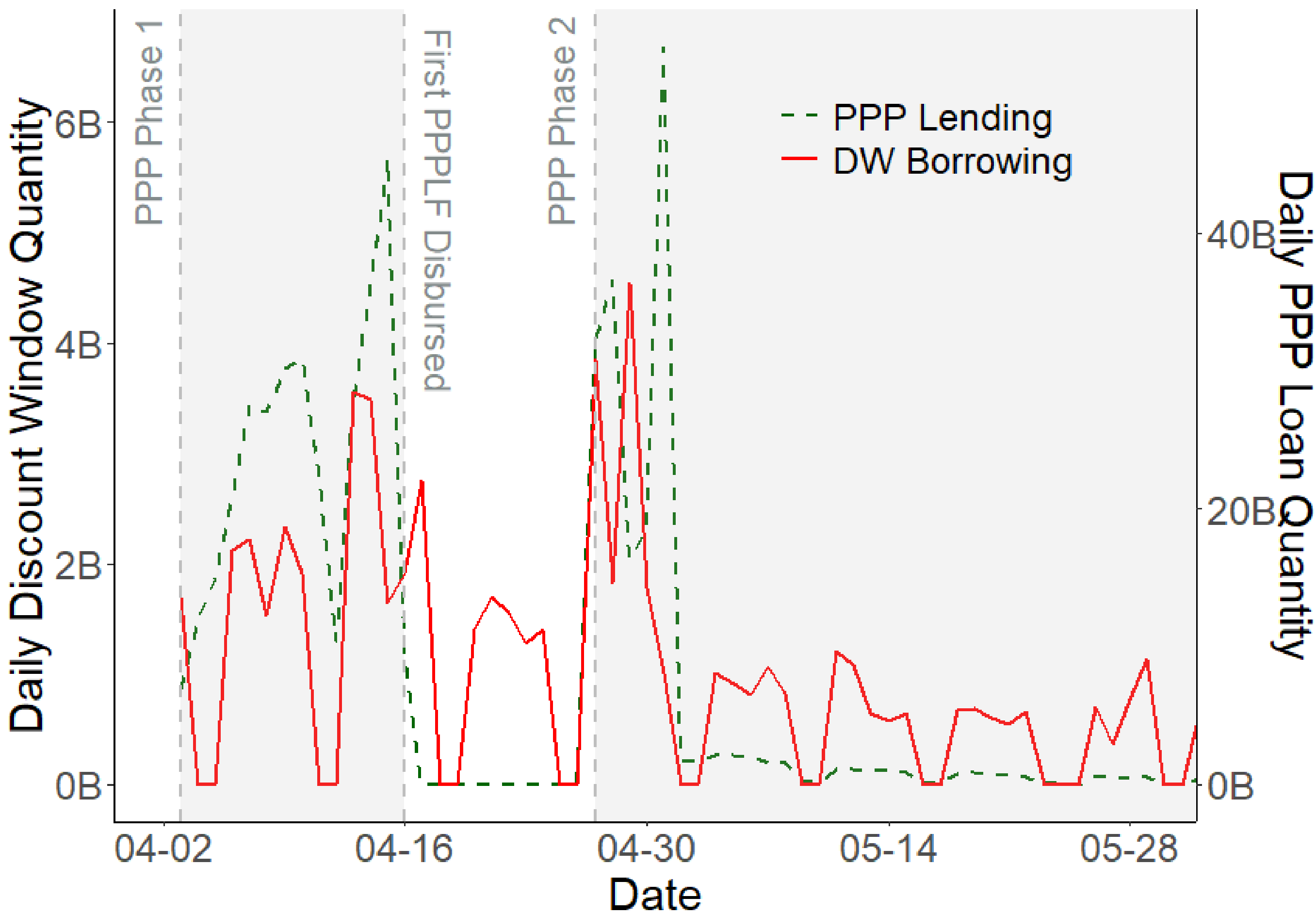
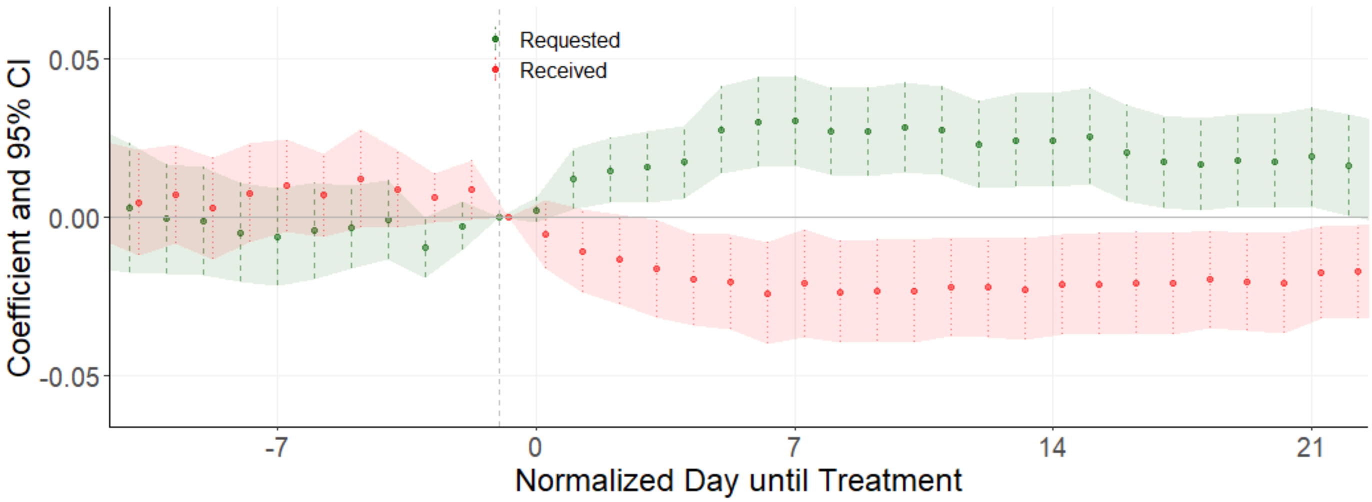
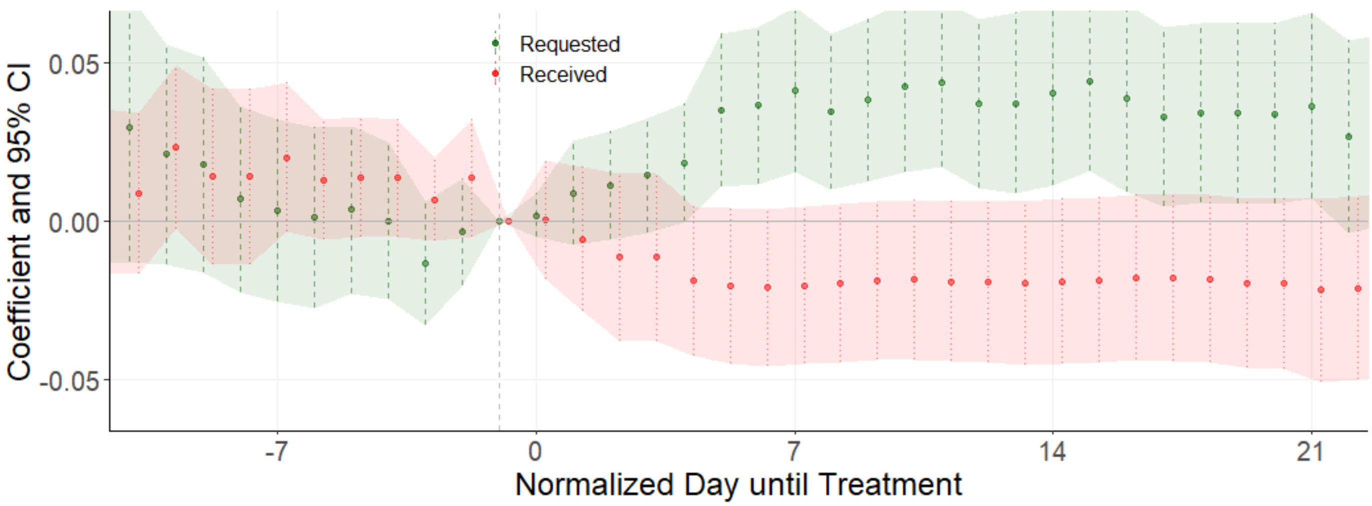



**Figure A.1:** Version of Figure 1 with weekends included.

**(a)** Pooled Sample




**(b)** Large Banks




**(c)** Small Banks

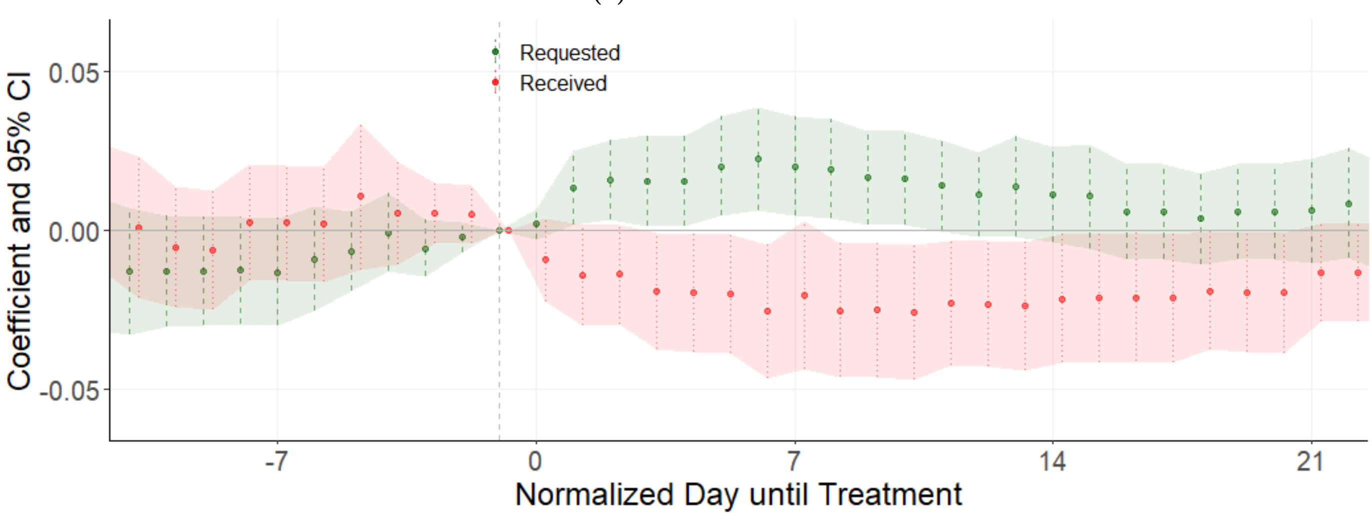



**Figure A.2:** Baseline result for the event studies in Figure 5.

# Appendix B: Tables

**Table B.1:** Summary Statistics Table - Panel Series

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| DW/Reserves | 301,962 | 0.011 | 0.121 | 0 | 0 | 0 | 3 |
| PPP/Reserves | 301,962 | 0.021 | 0.129 | 0 | 0 | 0.000 | 3 |
| Borrowing from LF in last 30 Days/Reserves | 301,962 | 0.072 | 0.487 | 0 | 0 | 0 | 9 |
| DW since 2015 Indicator | 301,962 | 0.121 | 0.326 | 0 | 0 | 0 | 1 |
| Number of Offices | 301,490 | 15.910 | 125 | 1 | 2 | 9 | 4,850 |
| Reserve/Asset | 301,962 | 0.106 | 0.105 | 0.001 | 0.042 | 0.135 | 0.978 |
| Equity Capital Ratio | 301,962 | 0.128 | 0.076 | 0.048 | 0.100 | 0.134 | 0.970 |
| Branch Economic Exposure | 299,720 | −10.779 | 2.877 | −23.874 | −12.612 | −8.879 | −2.869 |
| Unused CI Commitments | 301,962 | 0.031 | 0.035 | 0.000 | 0.007 | 0.042 | 0.255 |
| Small Business share of CI | 301,962 | 0.011 | 0.028 | 0 | 0 | 0 | 0 |
| Core Deposits | 301,962 | 0.432 | 0.248 | 0.000 | 0.216 | 0.596 | 1.531 |
| C&I Loans/Assets | 297,183 | 0.082 | 0.069 | 0.000 | 0.038 | 0.108 | 0.645 |
| Liquid Assets | 301,962 | 0.290 | 0.168 | 0.010 | 0.171 | 0.370 | 0.996 |
| T1 Leverage Ratio | 301,962 | 0.124 | 0.076 | 0.044 | 0.096 | 0.128 | 0.974 |
| Log Assets | 301,962 | 12.573 | 1.457 | 9.513 | 11.611 | 13.294 | 18.110 |
| Branch weighted bank age | 300,546 | 65.603 | 34.514 | 2.475 | 37.125 | 91.962 | 156.351 |
| COVID Exposure | 296,947 | 0.471 | 2.320 | 0.000 | 0.003 | 0.196 | 42.347 |

**Table B.2:** Summary Statistics Table - Cross Section

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Number of PPP Loans | 3,627 | 1,411.938 | 8,061.874 | 1 | 80 | 540 | 134,051 |
| DW/Reserves during PPP | 3,627 | 0.562 | 5.318 | 0 | 0 | 0 | 99 |
| DW/Reserve since 2010 | 3,627 | 0.212 | 1.373 | 0 | 0 | 0.001 | 37 |
| PPPLF/Reserves | 3,627 | 0.156 | 0.852 | 0 | 0 | 0 | 13 |
| Deposit/Asset | 3,627 | 0.832 | 0.065 | 0.065 | 0.805 | 0.875 | 0.936 |
| Deposit Growth | 3,623 | 12.750 | 41.355 | −31.525 | 6.299 | 14.328 | 2,004.353 |
| Number of Offices | 3,624 | 17.346 | 80.882 | 0.109 | 2.000 | 10.000 | 1,298.479 |
| Reserve/Asset | 3,627 | 0.096 | 0.086 | 0.004 | 0.040 | 0.123 | 0.950 |
| Equity Capital Ratio | 3,627 | 0.120 | 0.043 | 0.022 | 0.099 | 0.130 | 0.915 |
| Branch Economic Exposure | 3,627 | −520.065 | 115.379 | −719.985 | −602.696 | −460.184 | 0.000 |
| Unused CI Commitments | 3,627 | 0.034 | 0.036 | 0.000 | 0.010 | 0.046 | 0.254 |
| Small Business share of CI | 3,627 | 0.013 | 0.028 | 0 | 0 | 0.01 | 0 |
| Core Deposits | 3,627 | 0.435 | 0.241 | 0.000 | 0.224 | 0.590 | 1.530 |
| C&I Loans/Assets | 3,579 | 0.088 | 0.068 | 0.000 | 0.043 | 0.114 | 0.643 |
| Liquid Assets | 3,627 | 0.275 | 0.149 | 0.010 | 0.168 | 0.352 | 0.951 |
| T1 Leverage Ratio | 3,627 | 0.116 | 0.044 | 0.045 | 0.096 | 0.125 | 0.964 |
| Log Assets | 3,627 | 12.762 | 1.465 | 9.040 | 11.794 | 13.473 | 21.714 |
| Branch weighted bank age | 3,611 | 63.872 | 34.066 | 1.797 | 36.272 | 88.720 | 188.677 |
| COVID Exposure | 3,627 | 19.161 | 88.036 | 0.000 | 0.537 | 9.882 | 1,783.398 |

**Table B.3:** Robustness results for Table 2. Columns are made under the same specifications as Table 2. Panel A displays the results for the linear probability model, only including banks that have borrowed at least once from the DW during April and May. Panel 2 runs an LPM including all banks. Panel 3 ruins a Poisson regression on the same dataset. Panel 4 runs a binomial logistic regression. The sample includes all observations from April 3 to April 16 and April 27 to May 31. In all the nonlinear regression, banks without variations in the dependent variables are dropped due to perfect collinearity with the bank fixed effects.

| Dependent Variable: | DW Indicator | | | | | | |
|---|---|---|---|---|---|---|---|
| | Pooled | | Interacted | Large Banks | | Small Banks | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *LPM - Dropping Banks* | | | | | | | |
| PPP Lending/Reserves | 0.101* | 0.097* | | 0.188*** | 0.191*** | 0.022 | -0.011 |
| | (0.053) | (0.055) | | (0.065) | (0.063) | (0.039) | (0.041) |
| PPP Lending/Reserves × Small Banks | | | -0.015 | | | | |
| | | | (0.039) | | | | |
| PPP Lending/Reserves × Large Banks | | | 0.216*** | | | | |
| | | | (0.061) | | | | |
| Observations | 8,771 | 8,428 | 8,428 | 5,292 | 4,998 | 3,479 | 3,430 |
| *LPM - Without Dropping* | | | | | | | |
| PPP Lending/Reserves | 0.009 | 0.008 | | 0.021 | 0.023 | -0.002 | -0.004 |
| | (0.007) | (0.007) | | (0.014) | (0.015) | (0.004) | (0.004) |
| PPP Lending/Reserves × Small Banks | | | -0.003 | | | | |
| | | | (0.004) | | | | |
| PPP Lending/Reserves × Large Banks | | | 0.022 | | | | |
| | | | (0.014) | | | | |
| Observations | 250,782 | 242,648 | 242,648 | 62,622 | 58,016 | 188,160 | 184,632 |
| *Poisson* | | | | | | | |
| PPP Lending/Reserves | 0.219* | 0.208* | | 0.333*** | 0.336*** | 0.064 | -0.007 |
| | (0.118) | (0.120) | | (0.127) | (0.125) | (0.130) | (0.130) |
| PPP Lending/Reserves × Small Banks | | | -0.038 | | | | |
| | | | (0.124) | | | | |
| PPP Lending/Reserves × Large Banks | | | 0.376*** | | | | |
| | | | (0.122) | | | | |
| Observations | 8,771 | 8,428 | 8,428 | 5,292 | 4,998 | 3,479 | 3,430 |
| *Logistic* | | | | | | | |
| PPP Lending/Reserves | 1.09*** | 1.10*** | | 1.63*** | 1.67*** | 0.067 | -0.241 |
| | (0.416) | (0.427) | | (0.484) | (0.485) | (0.472) | (0.439) |
| PPP Lending/Reserves × Small Banks | | | -0.215 | | | | |
| | | | (0.453) | | | | |
| PPP Lending/Reserves × Large Banks | | | 1.91*** | | | | |
| | | | (0.525) | | | | |
| Observations | 8,428 | 8,085 | 8,085 | 5,145 | 4,851 | 3,283 | 3,234 |
| Bank Controls: | | Yes | Yes | | Yes | | Yes |
| *Fixed-effects* | | | | | | | |
| Bank | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Date | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Clustered (Bank) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

**Table B.4:** This table reports the results of how DW borrowing as a share of reserves affects the number of PPP loans originated using a TSLS approach with each column denoting a different cutoff size for large banks. The table reports the extensive margin of the effect of DW access on PPP lending for the large bank subset in Phase 1. Column (1) represents the cutoff for large banks at the 75th percentile, corresponding to a bank that has $593 million in assets in Q1 of 2020. Column (2) uses the 80th percentile ($783 million) as a cutoff. Column (3) uses the 90th percentile ($1.73 billion) as a cutoff. Column (4) uses the 95th percentile ($4.46 billion).

| Dependent Variable: | Log Number of PPP Loans | | | |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| DW Indicator | 0.928*** | 0.873*** | 0.877** | 0.906** |
| | (0.309) | (0.318) | (0.352) | (0.380) |
| Deposit Growth | 0.021*** | 0.027*** | 0.023*** | 0.018* |
| | (0.006) | (0.006) | (0.008) | (0.009) |
| Fed Funds+ONRRP/Reserves | 0.001** | 0.0009* | 0.001 | -0.0003 |
| | (0.0004) | (0.0005) | (0.0008) | (0.001) |
| FLHB/Reserves | 0.808 | 1.93 | 3.61 | 16.7* |
| | (0.606) | (1.33) | (2.56) | (8.80) |
| Bank Characteristic Controls: | Yes | Yes | Yes | Yes |
| *Fixed-effects* | | | | |
| Size Deciles | Yes | Yes | Yes | Yes |
| Fed District | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 977 | 777 | 368 | 158 |
| $R^2$ | 0.40955 | 0.37375 | 0.42776 | 0.47337 |
| F-test (1st stage), DW Indicator | 186.49 | 160.43 | 63.194 | 25.632 |

*Heteroskedasticity-robust standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

**Table B.5:** This table reports the results of how DW borrowing as a share of reserves affects the number of PPP loans originated using a TSLS approach. Columns are made under the same specification as 5. The sample is made using the aggregation of only Phase 1 lending. Panel 1 shows the baseline instrument, panel 2 replaces the baseline instrument with the number of times a bank has previously borrowed from the DW. Panel 3 uses both instruments to perform a Sargan test for over-identification. I fail to reject the null hypothesis (both instruments are exogenous) for all specifications.

| Dependent Variable: | Log Number of PPP Loans | | | | | |
|---|---|---|---|---|---|---|
| | | Pooled | | Interacted | Large Banks | Small Banks |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Size of previous borrowing from DW* | | | | | | |
| DW Indicator | 0.831*** | 0.934*** | 0.909*** | | 0.928*** | 1.26 |
| | (0.263) | (0.292) | (0.291) | | (0.309) | (0.855) |
| DW Indicator × Small Banks | | | | 1.48* | | |
| | | | | (0.807) | | |
| DW Indicator × Large Banks | | | | 0.734** | | |
| | | | | (0.308) | | |
| *# of times previously borrowed from DW* | | | | | | |
| DW Indicator | 1.15** | 1.11** | 1.09** | | 0.779* | 2.44* |
| | (0.473) | (0.444) | (0.434) | | (0.457) | (1.37) |
| DW Indicator × Small Banks | | | | 2.70** | | |
| | | | | (1.29) | | |
| DW Indicator × Large Banks | | | | 0.452 | | |
| | | | | (0.419) | | |
| *Both Instruments* | | | | | | |
| DW Indicator | 0.873*** | 0.958*** | 0.934*** | | 0.914*** | 1.57* |
| | (0.259) | (0.284) | (0.282) | | (0.300) | (0.863) |
| DW Indicator × Small Banks | | | | 1.81** | | |
| | | | | (0.821) | | |
| DW Indicator × Large Banks | | | | 0.708** | | |
| | | | | (0.298) | | |
| Bank Characteristic Controls: | | Yes | Yes | Yes | Yes | Yes |
| *Fixed-effects* | | | | | | |
| Size Deciles | Yes | Yes | Yes | Yes | Yes | Yes |
| Fed District | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 3,486 | 3,419 | 3,419 | 3,419 | 977 | 2,442 |
| Sargan Over-Identification Test | 0.45376 | 0.15413 | 0.17737 | 1.8910 | 0.08931 | 1.2939 |

*Heteroskedasticity-robust standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*