Government Loan Guarantees in a Crisis: Bank Protections from Firm Safety Nets

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Abstract

We study bank responses to the Paycheck Protection Program (PPP) and the program's effects on lender balance sheets and profitability. To address the endogeneity between bank decisions and balance sheet effects, we develop a Bayesian joint model that examines the decision to participate, the intensity of participation, and ultimate balance sheet outcomes. Overall, lenders were driven by risk-aversion and funding capacity rather than profitability in their decision to participate and the intensity of their participation. Indeed, with greater participation intensity, banks experienced sizable growth in their loan portfolios but a decline in their interest margins. In counterfactual exercises, we show that the PPP offset a large potential contraction in business lending, and that bank margins would have fallen even more precipitously if lenders had not participated in the program. Although the PPP was intended as a credit support program for small firms, the program indirectly supported the margins of banks that channeled these loans.

Keywords: bank credit, Paycheck Protection Program, COVID-19, loan guarantee, Bayesian inference
JEL Codes: C11, G21, G28, H12

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1 Introduction

The COVID-19 pandemic that swept across the United States impeded economic activity and sharply reduced business revenue and profit expectations. In response, fiscal authorities passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act in an effort to limit the economic damage. A cornerstone of the CARES Act was the Paycheck Protection Program (PPP) which guaranteed certain small business loans through the U.S. Treasury's Small Business Administration (SBA). Importantly, loans could be forgiven if borrowing firms sustained employment levels, making PPP loans essentially small business grants. These guarantee and forgiveness features made the PPP unique in the sense that it relied on an initial private capital investment by financial intermediaries that could later be reimbursed with federal funding if the loans were forgiven or defaulted.

Lender participation in the program was voluntary and the participation decision required lenders to evaluate a number of trade-offs. Therefore, realized lender outcomes resulting from the PPP are influenced not only by the terms of the program, but by ex ante differences across lenders that inform decisions on whether and how much to participate. For instance, banks would have likely opted to participate in the PPP, and participated more intensively, if they expected the program to enhance their profits or minimize their losses. However, the level of participation would have been limited by a bank's access to cheap and plentiful funding given the loans' low interest rate of 1 percent. Similarly, participating banks would need to evaluate whether to extend PPP loans at the cost of reducing other lending or to simultaneously expand both types of loan portfolios. Extending risk-free, but low-yielding PPP loans may have prompted some banks to reexamine the composition of other risky assets with a view toward generating higher revenues.

This complicated decision-making process poses two empirical challenges when estimating the ramifications of the program on banks– selection effects and simultaneity in the determination of PPP intensity and bank outcomes. To address these challenges, we jointly model the decision to participate, the intensity of participation, and bank outcomes using the framework in Vossmeyer [2016]. By doing so, the joint model addresses both the endogeneity of bank selection into the program as well as bank choice regarding participation intensity. Modeling bank decisions and outcomes jointly also allows for covariances across these responses and addresses their simultaneous determination. The model bolsters our evaluation of the PPP by facilitating estimated counterfactual levels of lending growth and profitability margins.

Our joint model requires the use of a variable that affects PPP participation intensity without directly affecting bank outcomes. We use the deposit-weighted share of employment in COVID-affected industries, such as hospitality and retail, as an excluded variable for this purpose. The main exclusion restriction is that the share of employment in contact-sensitive sectors in a bank's operating area does not directly affect its net interest margin and lending growth outside of the PPP. This restriction is met as long as the share of pandemic-affected sectors reflects demand for PPP loans that is isolated from strategic supply considerations by banks. Using data from a survey of PPP applicants, Bartik, Cullen, Glaeser, Luca, Stanton, and Sunderam [2020] found that firms in COVID-affected sectors were over-represented in the pool of PPP applicants, and that approval rates did not vary substantially across sectors. This reveals that these sectors were also over-represented among PPP recipients, without banks displaying distinct preferences for a specific sector. The predominance of COVID-affected sectors in a bank's region of operation is therefore representative of demand for PPP loans, rather than supply.

Our results indicate that selection effects were salient despite wide-spread participation in the program. We find that banks were driven to participate in the program based on their size, ability to finance new loans, and exposure to potential losses from business loans, indicating that participant characteristics were distinct from non-participant characteristics. Moreover, these results show that the risk-sharing design of the program was both important to its success and may have limited participation. Specifically, we find that larger and more profitable lenders, who were consequently better positioned to finance loans, were more likely to participate. Equally, banks with larger C&I loan portfolio concentrations and undrawn commitments, and thus facing greater loan loss risk from the economic downturn, participated in the PPP more actively. Consistent with this risk-aversion explanation of the program's outcomes, we also find that banks with lower leverage capital ratios, and therefore ex-ante riskier banks, were both more likely to participate and originated more PPP loans relative to the size of their total lending portfolio.

Our hypothesis that banks were driven to participate in the PPP by risk-aversion rather than profitability is further confirmed by our results on balance sheet outcomes. The PPP was not immediately profitable for participating banks because the interest rate on the loans was low and many of the fees were deferred over the life of the loan. We estimate that a one percentage point increase in PPP participation intensity resulted in a 4.3 basis point decline in NIM during the quarters when the program was active relative to 2019 levels. For the average participant, this represents a substantial total decline of 37 basis points or about 10 percent from 2019 levels. However, our baseline results do indicate that participating banks allowed their business loan portfolios to expand both due to PPP lending and lending outside the program. Banks grew their overall C&I loan portfolio by 10 percent and their non-PPP C&I portfolio by one percent on a year-over-year basis per one percentage point increase in PPP intensity. However, incremental participation in the PPP did not result in statistically important effects on risk-taking outside the C&I portfolio, as measured by growth in CRE loans.

We further delve into the PPP's effect on risk-taking by evaluating whether the program crowded out private capital or provided an additional boost to business lending. To do so, we recover a counterfactual of what the level of lending and profitability would have been if banks did not participate in the PPP loan program using non-participating banks as a control group. We estimate that absent PPP lending, C&I loan growth would have contracted during the second half of 2020. While the point estimate is large, probability intervals around this estimate indicate that the impact of the pandemic on lending would have been deeply negative. Moreover, the revenue generated by the program helped to offset a much larger profitability drop than would have been realized without the program.

Further, our counterfactual results indicate that the PPP helped to avert a credit crunch primarily by facilitating lending by riskier banks. A decomposition shows a clear pattern of risk aversion driving the loan growth counterfactual and speaks to the success of the PPP program. Namely, larger and less capitalized banks would have contracted lending by the greatest amount. These are precisely the banks we find were more likely to participate in the PPP program. We also find that C&I lending concentration would have offset the credit crunch. While we find a similar result among PPP participants, the PPP's credit protections likely enhanced this effect.

Our counterfactual estimates reconcile with estimated balance sheet effects as follows. Participation in the PPP shifted banks to a distinct profit and loan growth schedule relative to non-participants. Among PPP participants, incremental participation resulted in loan growth and a decline in profitability. But, at zero, or at the point of non-participation, profits and loan growth shift downward and lie fully below the schedule under participation. These findings are intuitive. Participating banks grew their loan books even at the cost of earning lower margins relative to 2019 levels. Non-participants, on the other hand, grew their loan books by a substantially smaller magnitude and underwent an even larger decline in profits relative to participants. It is this difference between the two groups that drive our counterfactual results.

Our paper is most closely related to a literature examining bank behavior in response to the PPP program. Even as this growing body of work studies related and complementary questions, this paper offers two unique areas of contribution to the literature. First, we examine the effects of the program on bank profitability and risk-taking in addition to loan growth. While the literature has focused on the latter question, the former two are as yet unexplored. Second, we derive counterfactual estimates, which are not available in existing literature, to perform a broad-based evaluation of the program.

In line with our findings, Li and Strahan [2020] find that banks utilized existing relationships as measured by prior commitments and geographic distribution to make PPP lending decisions. However, our paper differs in the fact that we document that among community banks, very small banks were *less likely* to make more PPP loans as compared to community banks as a whole who were *more likely* to make PPP loans as compared to their large bank counterparts. In a similar vein, Chodorow-

Reich, Darmouni, Luck, and Plosser [2020] document that small firms have less capital access available than larger firms and demonstrate that the COVID shock represented a supply contraction for small firms that was alleviated by PPP lending. This aligns with the result from our counterfactual analysis that the PPP offset a potential credit crunch. However, their analysis examines only large bank responses whereas we examine only smaller community banks. Finally, our paper is also closely related to works by Anbil, Carlson, and Styczynski [2021] and Lopez and Spiegel [2021], both of which find that better positioned banks made more PPP loans and that the PPPLF helped to bolster participation, particularly among smaller banks. While these papers emphasize the role of liquidity support in increasing PPP lending, we uncover the risk aversion channel to participate in the PPP.

Finally, we contribute to the literature on public credit guarantees. Previous literature in this area has focused on Japanese credit guarantee programs that were instituted following the crises in the late 1990's and 2008. Ono, Uesugi, and Yasuda [2013] found that relationship lenders used the latter guarantees to transfer credit risk to the government. Wilcox and Yasuda [2019] found that loan guarantees in the late 1990's served as complements to private non-guaranteed lending and increased bank risk-taking. Our findings align more closely to the former rather than the latter study. The PPP offset a potential decline in private lending among risk-averse banks without substantially increasing risk-taking or lending outside the program. In a study of the ECB's enhanced provision of liquidity to banks during the Global Financial Crisis, Boeckx, de Sola Perea, and Peersman [2020] found that smaller, liquidity-constrained banks that depended on unsecured wholesale funding expanded lending in response to the credit support policies. These effects were muted for banks with low levels of capital. These results broadly align with our findings of bank responses to the PPP, with one key exception. Banks with lower capital ratios participated more intensively in the PPP, presumably because loans under the program were capital-preserving for lenders.

The rest of the paper proceeds as follows: Section 2 describes the PPP program parameters as well as the associated liquidity facility that the Federal Reserve established. Section 3 describes the Bayesian model setup and assumptions in the model. Section 4 discusses the datasets used in the analysis and the construction of various needed to estimate the model. Section 5 examines the question of which bank characteristics predicted PPP participation. Section 6 examines the effect of PPP lending on bank balance sheets and income. Section 7 estimates lending counterfactuals absent the PPP program to assess whether PPP lending crowded out other borrowing. Section 8 provides estimates of our key results using alternative instruments. Finally, section 9 concludes.

2 The Paycheck Protection Program

The Paycheck Protection Program was initiated to help small businesses offset the effects of precautionary measures taken to prevent the spread of COVID-19. As COVID cases began to appear and then rise steadily in the United States in early 2020, many local governments imposed restrictive social distancing measures to curtail the spread of the virus. Many people and businesses also began to exercise caution in their own daily behaviors to limit their potential for exposure to themselves, others, or their employees. As as a result, economic activity dropped sharply and the economic outlook for the future looked dim with the potential for large declines in revenues, sharply lower employment, and the potential for widespread business failures and permanent closures.

To offset these negative economic developments and provide resources to combat the health effects of COVID-19, the U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act on March 27, 2020. The Paycheck Protection Program (PPP) was created as part of this legislation. The aim of the PPP was to provide low cost, government guaranteed loans via the Small Business Administration (SBA) to small and mid-sized businesses that would enable them to offset the revenue shocks experienced as a result of the COVID-19 pandemic. By doing so, businesses would be able to retain employees that would otherwise be furloughed or suffer permanent job loss at a time when seeking new employment would be challenging. Thus, cash received through the PPP would both keep businesses open for their owners and workers during a transitory shock but also possibly help to offset declines in spending at a time when consumers were increasingly risk averse due to the prospect of job loss. In some cases, PPP loans were forgiven for businesses that were able to retain specified, pre-pandemic employment levels.

Demand for the PPP program following the CARES Act was high as it appeared that business revenues would suffer substantially due to government-imposed and voluntary social distancing measures. It also increasingly became clear that the COVID-19 pandemic would be a longer-term event than initially thought. As a result, Congress subsequently approved additional PPP funding rounds. In total, Congress has appropriated a total of $954 billion in funds for PPP programs on three separate occasions since March of 2020, inclusive of the CARES Act funding.[1]

The terms of the loans guaranteed by the program were set to correspond to the program's small and mid-sized business target.[2] In general, PPP loans were available to U.S. firms that employed 500 or fewer employees whose principal residence was in the United States. Eligible firms also had to meet the SBA's definition of a small business concern, including meeting certain industry size parameters, and had to be in operation before February 15, 2020. Firm-level borrowing limits depended on average monthly payroll costs and the amount of currently outstanding SBA loans. During most of the program, loans had 5 year maturities and charged a 1 percent interest rate.[3] No fees were paid by the borrower. All payments on the loans were deferred for 6 months but interest accrued during this period.

In line with the program's objective of supporting private employment, most of the eligible costs that could be covered by the loan's principal were related to employee expenses or payroll. These costs included employee compensation in the form of wages, salaries, tips, and commissions, as well as costs for employee leave or to fund health and retirement accounts. Funds received through PPP loans could also cover state and local taxes assessed on employee compensation. In addition to these payroll costs, PPP funds could also cover mortgage interest and rent on existing

[1] These funding round appropriations, their respective enactment dates, and the program funding round dates are summarized in Table A1 of Appendix A.

[2] PPP loan terms are described in detail in Appendix B.

[3] Initially, the interest rate on PPP loans was set at 50 basis points but was increased to encourage greater bank participation. See Hayashi [2020] for details.

loans and leases as well as utility payments. However, forgiveness rules required that a substantial portion of the funds were used toward associated payroll costs.

Loan funds were disbursed by financial institutions including commercial banks, thrifts, credit unions, and fintechs. This mode of distribution mirrored the standard SBA loan programs that support small businesses and utilized the SBA's existing lender networks. That said, the loan terms, eligibility, and forgiveness conditions differed substantially from existing SBA loan programs.

In practice, PPP loans were originated and held by banks but guaranteed by the SBA, thus requiring financial institutions to potentially raise capital and funding. Loan funding was probably not an issue because many financial institutions were flush with cheap funding or it was readily available. Liquidity supply was high due to Federal Reserve actions that increased available reserves and deposit availability increased as federal support programs came on line. Commercial banks were potentially constrained by the leverage ratio as PPP loans increased however. The leverage ratio is essentially a simple ratio of tier 1 capital to assets that declines as assets increase without regard to the risk of the underlying assets. As opposed to a risk-based capital standard which is dependent upon the riskiness of the underlying asset growth, banks can be constrained by the leverage ratio simply as the balance sheet grows.[4]

To address these capital and liquidity concerns, the Federal Reserve established the Paycheck Protection Program Liquidity Facility (PPPLF).[5] Under the PPPLF, the Federal Reserve agreed to lend funds to institutions participating in the PPP by taking whole loans as collateral. Both the principal and the maturity of the PPPLF loans matched the remaining balance and maturity of the underlying PPP collateral. The Federal Reserve charged no fees to institutions borrowing from the PPPLF but did charge 35 basis points of interest. Perhaps most importantly, PPP loans used as collateral in the PPPLF were excluded from the lending institution's leverage ratio. Therefore, a participating institution could neutralize the effect of PPP lending on their balance sheet capacity by borrowing through the PPPLF. Doing so would also

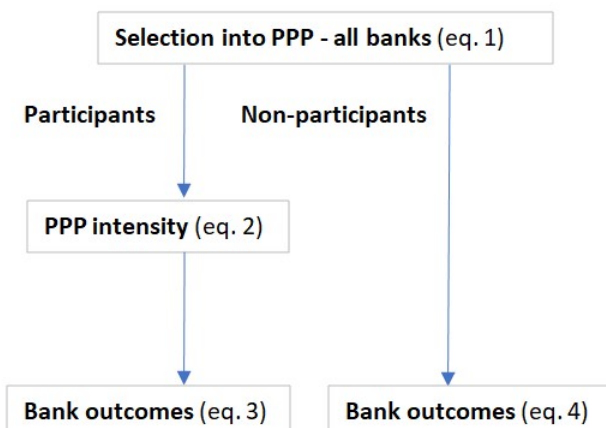
[4]PPP loans were assigned a zero percent risk weight under the CARES Act for regulated banks.
[5]Terms on loans extended by the PPPLF are described in Appendix C.

guarantee a reasonable profit on the PPP loan due to the 65 basis point spread between the PPP loan interest rate and the PPPLF's borrowing cost.

3 Bayesian Joint Model Setup

We develop a Bayesian estimation procedure to address the multiple steps involved in a bank's participation in the PPP. Namely, each bank must decide whether to participate in the PPP and select their intensity of participation in the program. Conditional upon both of these decisions, our model allows us to evaluate the effect of participation intensity on bank outcomes. Figure 1 illustrates the steps involved in the decision to participate in the PPP and their position preceding the ultimate measurement of bank performance. We specify a separate equation for the outcome from each step to construct the joint model. We define Y_1 to be the decision to participate in the PPP, Y_2 to be the level of intensity of participation, Y_3 to be the financial outcomes of participants, and Y_4 to be the outcomes of non-participants.

Figure 1: Joint model of PPP participation, intensity, and bank outcomes



This model structure follows the multivariate specification for sample selection and treatment in Vossmeyer [2016]. This model differs from the previous setup in the nature of treatment variable – the former study applies the method on a censored treatment whereas our treatment is continuous. An alternative modeling structure consists of collapsing equations 1 and 2 into a single equation and specifying PPP lending as a censored outcome. In the alternative approach, PPP intensity would take values of zero among non-participants and observed intensities among participants. Our approach, however, is to model participation and intensity decisions as separate outcomes in order to allow for distinct determinants of the two decisions. As a consequence, our main treatment is the intensity of PPP lending among participants, which is continuous.

The full model is shown in equations 1 - 4. The exogenous variables $\mathbf{x_i'}$ are common to all four equations and consist of bank characteristics that control for size, share of business loans, capital and liquid asset ratios, and profitability, all of which are measured as of 2019. We assume a multivariate normal distribution, $\mathcal{N}_4(0, \mathbf{\Omega})$, for the errors $\epsilon_i = (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}, \epsilon_{i4})$. We discuss the components of each equation and the covariance matrix, $\mathbf{\Omega}$, below.

$$\begin{aligned}
\text{Selection into PPP - all banks:} \quad y_{i1}^* &= \mathbf{x_i'}\beta_{\mathbf{1}} + z_{i1}\gamma_1 + \epsilon_{i1}, && (1)\\
\text{PPP intensity - participants:} \quad y_{i2} &= \mathbf{x_i'}\beta_{\mathbf{2}} + z_{i2}\gamma_2 + \epsilon_{i2}, && (2)\\
\text{Bank outcomes - participants:} \quad y_{i3} &= \mathbf{x_i'}\beta_{\mathbf{3}} + y_{i2}\delta + \epsilon_{i3}, && (3)\\
\text{Bank outcomes - non-participants:} \quad y_{i4} &= \mathbf{x_i'}\beta_{\mathbf{4}} + \epsilon_{i4}. && (4)
\end{aligned}$$

We estimate the probability of each bank selecting to participate in the PPP in equation 1. The outcome y_{i1}^* is a continuous latent variable that determines the underlying utility to bank i from participation in the program. Accordingly, a bank chooses to participate in the program if the resultant utility is positive and forgoes participation otherwise. The observed outcome y_{i1} can therefore be expressed as a function of the latent variable through the indicator operator, $y_{i1} = \mathbf{1}(y_{i1}^* > 0)$. This equation consists of independent variables $\mathbf{x_{i1}'}$ and a covariate z_{i1} that is excluded from subsequent equations. The exclusion restriction allows the model to achieve identification beyond what is offered by the functional form of the normal distribution.

Equation 2 specifies the relationship between the intensity of participation in the PPP and bank-level characteristics. The assumptions on the instrument z_{i2} are that it is independent of the errors, but related to the treatment y_{i2}, as specified in Li and Tobias [2014] and Greenberg [2012].

Equation 3 is the main treatment equation that measures the effect of incremental participation in PPP on bank outcomes of participants, y_{i3}. The share of PPP to total assets, y_{i2}, enters this equation as an endogenous variable and its coefficient is the main treatment effect of interest, δ. Finally, equation 4 measures outcomes for non-participating banks.

We can partition the full set of outcomes into those that pertain to participants and non-participants, $\boldsymbol{y}_{i,p}$, and $\boldsymbol{y}_{i,np}$, respectively, where,

$$\boldsymbol{y}_{i,p} = \begin{pmatrix} y_{i1}^* \\ y_{i2} \\ y_{i3} \end{pmatrix}, \quad \boldsymbol{y}_{i,np} = \begin{pmatrix} y_{i1}^* \\ y_{i4} \end{pmatrix}. \tag{5}$$

The marginal mean of each set of outcomes based on equations 1 - 4 is obtained from the following expressions.

$$\mu_{i,p} = \begin{pmatrix} \mathbf{x_i'}\beta_\mathbf{1} + z_{i1}\gamma_1 \\ \mathbf{x_i'}\beta_\mathbf{2} + z_{i2}\gamma_2 \\ \mathbf{x_i'}\beta_\mathbf{3} + y_{i2}\delta \end{pmatrix}, \quad \mu_{i,np} = \begin{pmatrix} \mathbf{x_i'}\beta_\mathbf{1} + z_{i1}\gamma_1 \\ \mathbf{x_i'}\beta_\mathbf{4} \end{pmatrix}. \tag{6}$$

We consider the elements of the covariance matrix pertaining to participants and non-participants separately and label them Ω_p and Ω_{np}, respectively. Accordingly, the two covariance matrices are defined as,

$$\Omega_p = \begin{pmatrix} 1 & \Omega_{12} & \Omega_{13} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} \end{pmatrix}, \quad \Omega_{np} = \begin{pmatrix} 1 & \Omega_{14} \\ \Omega_{41} & \Omega_{44} \end{pmatrix}.$$

The term Ω_{12} measures the effects of unobservables that underlie both the decision to participate and the intensity of participation. The covariance terms Ω_{13} and Ω_{14} record the joint effects of unobservables across the decision to participate and bank outcomes for participants, and non-participants respectively. The covariance term Ω_{23} records the effect of unobservables across the intensity of participation in the PPP and bank-level outcomes.

The overall covariance matrix combines the terms from both sub-matrices.

$$\boldsymbol{\Omega} = \begin{pmatrix} 1 & \Omega_{12} & \Omega_{13} & \Omega_{14} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} & \cdot \\ \Omega_{31} & \Omega_{32} & \Omega_{33} & \cdot \\ \Omega_{41} & \cdot & \cdot & \Omega_{44} \end{pmatrix}$$

The elements Ω_{24} and Ω_{34} are not identified as they correspond to covariances across outcomes for participants and non-participants, which are mutually exclusive.

We denote N_p and N_{np} as the set of participant and non-participant banks in the sample. We obtain the complete-data likelihood function for the full sample of observations by combining the elements pertaining to each group of banks,

$$f(y, y_1^*|\mathbf{x_i}, \theta, \Omega_p, \Omega_{np}) = \prod_{i \in N_p} [f_{\mathcal{N}}(\boldsymbol{y}_{i,p}|\mu_{i,p}, \Omega_p)] \prod_{i \in N_{np}} [f_{\mathcal{N}}(\boldsymbol{y}_{i,np}|\mu_{i,np}, \Omega_{np})] \tag{7}$$

We assign independent multivariate normal priors to the coefficients $f(\theta) = f_{\mathcal{N}}(\theta|\Theta_0, T_0)$, where $\theta = [\gamma_1, \gamma_2, \delta, \boldsymbol{\beta}]$, and $\boldsymbol{\beta} = \{\beta_1, \beta_2, \beta_3, \beta_4\}$. The covariance matrices Ω_p and Ω_{np} are assigned Inverse Wishart priors, $f(\Omega_p) = f_{\mathcal{IW}}(\Omega_p|\nu_p, Q_p)$, and $f(\Omega_{np}) = f_{\mathcal{IW}}(\Omega_{np}|\nu_{np}, Q_{np})$, which are independent of priors assigned to the coefficients. On combining the complete-data likelihood, and priors, we obtain the augmented posterior as follows.

$$f(\theta, \Omega_p, \Omega_{np}, y_1^*|y) \propto f(y, y_1^*|\mathbf{x_i}, \theta, \Omega_p, \Omega_{np}) f(\theta) f(\Omega_p) f(\Omega_{np}) \tag{8}$$

The Markov Chain Monte Carlo (MCMC) algorithm used to estimate this model and the results from simulation exercises are provided in Appendix D. We recover the true values of parameters within a 95% posterior credibility interval, both when we specify an instrument in the selection equation and when the instrument is excluded.

4 Data and Variables

We require data on bank balance sheets, lending program activity, and various local measures of both the pandemic's impact as well as the economic well-being of the local area. We collect these data from various public data sources.

4.1 Data sources

Data on bank balance sheets comes from the FFIEC call reports. These data are collected by federal banking regulators on all supervised institutions at the end of each calendar quarter. The Call Reports contain a wide variety of items on bank balance sheets, income, and regulatory capital. As of the second quarter of 2020, these forms also collect quarter-end balances on PPP loans outstanding as well as PPP loans pledged to the PPPLF. An item reporting the quarterly average balance of PPP loans pledged to the PPPLF allows adjustments to the leverage ratio in each quarter the PPPLF was active.

From the Call Report data, we consider only community banks, defined as banks with less than $10 billion in total assets. The consideration of community banks gives us the widest possible source of variation considering that the majority of the nearly 5,000 banks operating in the United States are below this asset level. In addition, the focus on community banks provides us with a set of more uniform business models of banks that are focused on business lending as a core activity. Larger banks often have more complex or specialized business models that may complicate the analysis.

We also drop non-deposit trusts from our sample. Non-deposit trusts do not operate as typical deposit banks and instead primarily conduct fiduciary business and hold only limited deposit types.[6] Given their unique business model and the fact that none of these entities participated in the program, we exclude these entity

[6]See U.S. DOL's SIC code description for more information: https://www.osha.gov/sic-manual/6091

types from our bank sample.

Overall program participation was otherwise broad within the community bank space. On average, about 85 percent of community banks reported at least one PPP loan outstanding at quarter end on the Call Report between 2020:Q2 and 2020:Q4. Participation across all quarters among community banks was slightly higher, with about 87 percent of community banks reporting a PPP loan at the end of *any* quarter in 2020.

We determine a bank's local market using the Summary of Deposits (SOD) data. The SOD data are collected annually by the FDIC and report the location and holdings of bank branches and their booked deposits. These data are geocoded to facilitate linking the branches to geographic borders such as counties, MSAs, or other census designations. We use the SOD data to both determine a bank's footprint but to also determine its relative activity in different geographic areas.

4.2 Key Variable Construction

The main instrument used throughout the analysis is the share of employment in COVID-affected industries at the county-level. Equation 9 depicts the instrument $Z_{emp,i}$ which provides a bank-specific measure of COVID-affected employment in bank i's local market.

$$Z_{emp,i} = \frac{\sum_{j=1}^{J} Emp_j d_{i,j}}{\sum_{j=1}^{J} d_{i,j}}, \tag{9}$$

In equation 9, Emp_j is the employment in COVID-affected industries in county j, and $d_{i,j}$ is the total amount of bank i's deposits in county j as reported in the SOD data. COVID-affected industries are identified as the quartile of 3-digit NAICS industries that underwent the largest decline in employment within the first quarter of the pandemic using the method in Boyarchenko, Kovner, and Shachar [2020]. Contact-intensive industries within retail, hospitality, and entertainment constituted the preponderance of COVID-affected sectors.[7] National employment statistics are

[7]The change in industry level employment between January and April 2020 are shown in Table

drawn from the Current Employment Statistics from the Bureau of Labor and Statistics (BLS). Local employment shares are drawn from the BLS's Quarterly Census of Employment and Wages (QCEW) as of 2019, prior to the pandemic.

We use an analogous methodology to estimate the local share of firms eligible for PPP loans. To do so, we use the Quarterly Workforce Indicators (QWI) from the Longitudinal Employer-Household Dynamics (LEHD). Because the QWI provides only a few rough size buckets of firm employment, we calculate the share of firms with fewer than 500 full-time equivalent employees by county. This definition ignores any industry specific firm-size thresholds used in the PPP. Bank specific eligibility criteria are determined by weighting county firm counts with fewer than 500 full-time equivalents by local deposit holdings.

Finally, we use the same weighting procedure to develop a bank's market exposure to COVID. Data on local COVID case counts are collected from John Hopkins University's COVID database. These data are reported daily at the county level. We average over these daily counts by county to determine quarterly exposure rates that can be linked to the quarterly bank data. Bank specific COVID exposure rates are determined by weighting county-level COVID cases per capita by county deposit totals as of 2019.

4.3 Summary Stats

Table 1 shows the summary statistics for our core Call Report sample. The table is divided into participants with PPP to loan shares above the median and those below the median share. Non-participants, defined as those that do not report any PPP loans outstanding on their Call Reports, are shown in the far right columns. Overall, banks with larger PPP loan shares have larger C&I loan concentrations, more unused C&I loan commitments, more core deposit funding and liquid assets, and are slightly larger than banks with lower PPP loan shares. High share banks also have slightly lower capital ratios but are somewhat more profitable prior to the pandemic. Post pandemic, we see that high participating banks had slightly lower

F1 of Appendix F.

Table 1: Summary Stats By PPP Lending Intensity

	High PPP		Low PPP		Non-Participants	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Pre-pandemic Averages						
C&I to Assets	10.85	(6.92)	7.59	(5.42)	8.13	(9.47)
C&I Commitments to Assets	15.41	(9.77)	9.85	(6.76)	9.84	(10.62)
Unused C&I Commitments to Assets	4.57	(3.87)	2.26	(2.35)	1.71	(2.77)
Small C&I to Assets	6.22	(3.99)	5.36	(3.97)	6.23	(8.00)
Core Deposits to Assets	71.56	(10.31)	68.15	(10.48)	67.78	(13.21)
Liquid Assets to Total Assets	20.70	(11.95)	19.29	(11.58)	25.65	(15.30)
Total Assets ($ Millions)	0.68	(1.02)	0.42	(0.86)	0.22	(0.62)
ln(Total Assets)	12.77	(1.10)	12.17	(1.10)	11.52	(1.10)
Leverage Ratio	10.98	(2.71)	11.87	(3.20)	12.88	(4.49)
Tier 1 Ratio	15.71	(6.16)	17.67	(7.11)	21.82	(10.56)
$NIM^{2019\ Avg}$	3.96	(0.64)	3.89	(0.63)	3.85	(0.80)
Post-Pandemic Outcomes						
NIM	3.46	(0.59)	3.49	(0.62)	3.37	(0.78)
ΔNIM	-49.99	(49.55)	-39.79	(38.13)	-47.18	(47.24)
CI Gwth	131.11	(119.76)	51.00	(62.31)	9.11	(34.75)
CI Gwth Less PPP	-3.28	(23.44)	-2.13	(26.03)	9.11	(34.75)
Total Banks	1,837		1,736		390	

Notes: Pre-pandemic outcomes are averaged over all of 2019. High PPP banks are those with exposures greater than the median PPP loans to total loans share. Banks with low exposures are those with PPP loans to total loans shares less than the median. Non-participants are banks that did not report holding any PPP loans over 2020:Q2 or 2020:Q3.

net interest margins (NIMs) and had a larger drop in NIMs from their pre-pandemic averages. C&I growth overall was higher, which includes the impact of the PPP loans, but was lower for non-PPP loans. Non-participating banks were less profitable than both participating groups, but made significantly more C&I loans compared to the C&I growth rate of participating banks less PPP loans.

5 Who Participated in the PPP?

PPP participation was voluntary and several factors likely constrained bank participation. First, low capital buffers may have limited bank participation decisions because banks could breach their regulatory capital minimums due to PPP loans.[8]

[8]The leverage ratio is typically the binding regulatory capital ratio for community banks. Moreover, PPP loans were assigned a zero percent regulatory risk weight, negating the loan's impact on

Second, banks with limited ability to fund loans, or those more reliant on costlier funding types such as brokered deposits or short-term debt, may have found participation too risky or unprofitable. Third, banks that had limited relationships with eligible businesses at the onset of the crisis may have had trouble participating in the program due to the time and cost constraints required to build new relationships with eligible borrowers. Finally, banks could have forgone the program if they had alternative and more profitable opportunities to lend outside the program.

Table 2 summarizes the results of Equations 1 and 2 of the Bayesian joint model that represent banks' participation and intensity of participation in the PPP.[9] We obtain separate estimates for these equations for every outcome specified in Equations 3 and 4 as a consequence of jointly estimating all four equations. The top row of the table indicates the bank outcome that was considered in the latter two equations. We find that the results for bank participation and intensity are qualitatively similar irrespective of the measure of bank performance that is ultimately evaluated.

Columns (1), (3), (5), (7), and (9) represent the results for banks' decision to participate in the PPP. We evaluate the statistical importance of posterior means by determining whether the 95 percent credibility interval reported in brackets cross the real line at zero. Participation is only weakly associated with the share of small C&I loans, defined as loans with original amounts less than $1 million, to assets. Across all five specifications, larger, more profitable banks were more likely to participate in the PPP. Banks with more concentrated shares of total C&I loans, and thereby, more exposed to risks in business loans were more likely to participate in the PPP according to most specifications. We also find that banks with lower levels of capital were also more likely to participate in the program. Participation was higher for banks with higher ratios of liquid assets to assets. The share of total loans reserved for loss allowance is not statistically important under any specification unlike the

risk-based capital measures. For these reasons, we only consider the Tier 1 leverage ratio in our analysis.

[9] To ensure robustness of our results, we estimate our key results from the Bayesian joint model using classical frequentist procedures including estimating the participation decision as a logit selection model and using a two-stage least squares instrumental variable regression specification to disentangle the effect of PPP intensity and balance sheet impacts. These results are presented in Appendix K.

Table 2: Results for participation and intensity from the Bayesian joint model

	NIM		ΔNIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity
Small CI to assets	0.007		0.005		-0.001		-0.001		0.001	
	[0, 0.01]		[0, 0.01]		[-0.01, 0.01]		[-0.01, 0.01]		[0, 0.01]	
COVID-affected employment share		-0.006		0.04		0.085		0.104		0.035
		[-0.01, 0]		[0.03, 0.05]		[0.07, 0.1]		[0.09, 0.12]		[0.02, 0.05]
ln Assets	0.175	1.243	0.169	1.149	0.135	0.833	0.192	0.593	0.182	1.263
	[0.15, 0.2]	[1.1, 1.38]	[0.14, 0.2]	[1.01, 1.29]	[0.11, 0.16]	[0.7, 0.97]	[0.17, 0.22]	[0.45, 0.73]	[0.16, 0.21]	[1.13, 1.39]
CI to assets	0.032	0.296	0.034	0.3	-0.022	0.375	-0.006	0.356	0.036	0.294
	[0.03, 0.04]	[0.27, 0.32]	[0.03, 0.04]	[0.28, 0.33]	[-0.03, -0.02]	[0.35, 0.4]	[-0.01, 0]	[0.33, 0.38]	[0.03, 0.04]	[0.27, 0.32]
Leverage Ratio	-0.049	-0.332	-0.047	-0.325	-0.024	-0.268	-0.037	-0.209	-0.045	-0.304
	[-0.06, -0.04]	[-0.39, -0.28]	[-0.06, -0.04]	[-0.38, -0.27]	[-0.03, -0.01]	[-0.32, -0.21]	[-0.05, -0.03]	[-0.27, -0.15]	[-0.05, -0.04]	[-0.36, -0.25]
Liquid Assets to Assets	0.008	0.075	0.008	0.072	-0.001	0.089	-0.007	0.099	0.008	0.071
	[0.01, 0.01]	[0.06, 0.09]	[0.01, 0.01]	[0.06, 0.09]	[0, 0]	[0.07, 0.1]	[-0.01, 0]	[0.08, 0.11]	[0.01, 0.01]	[0.06, 0.09]
ALLL to Total Loans	-0.02	0.07	-0.028	0.081	0.005	0.442	-0.011	0.41	-0.017	0.118
	[-0.06, 0.02]	[-0.18, 0.32]	[-0.07, 0.02]	[-0.17, 0.33]	[-0.03, 0.04]	[0.2, 0.69]	[-0.05, 0.03]	[0.16, 0.66]	[-0.06, 0.02]	[-0.13, 0.36]
ROA	0.06	0.26	0.078	0.333	0.075	0.112	0.134	-0.168	0.068	0.267
	[0.01, 0.11]	[-0.01, 0.54]	[0.03, 0.13]	[0.05, 0.61]	[0.03, 0.12]	[-0.15, 0.38]	[0.08, 0.19]	[-0.43, 0.09]	[0.02, 0.12]	[-0.01, 0.54]
Cases Per 100k	0.022	0.101	0.032	0.132	0.04	0.116	0.025	0.133	0.023	0.109
	[-0.01, 0.05]	[-0.07, 0.28]	[0, 0.06]	[-0.04, 0.31]	[0.01, 0.07]	[-0.05, 0.28]	[-0.01, 0.07]	[-0.03, 0.3]	[-0.01, 0.05]	[-0.07, 0.29]
Constant	-1.076	-8.807	-1.017	-8.663	-0.375	-6.888	-0.589	-4.08	-1.195	-10.131
	[-1.44, -0.71]	[-10.75, -6.81]	[-1.42, -0.62]	[-10.65, -6.73]	[-0.7, -0.07]	[-8.74, -5.04]	[-0.91, -0.27]	[-6.02, -2.2]	[-1.51, -0.88]	[-11.9, -8.37]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

earlier findings. Finally, participation increased with the deposit-weighted share of COVID cases in the bank's operating region under the setting where ΔNIM was the main outcome of interest. The effect of the pandemic on participation decisions is not statistically important in the remaining settings.

Columns (2), (4), (6), (8), and (10) represent the results from Equation 2, which corresponds to equation 2. Accordingly, these results quantify the association between PPP participation intensity– PPP loans outstanding as a share of total loans, the instrument– deposit-weighted share of employment in COVID-affected sectors, and other bank-level controls. Overall, the relationship between COVID-affected employment in banks' region of operation and the intensity with which they participated in the PPP is statistically important. This relationship is positive and statistically different from zero in specifications for all outcomes except for NIMs, where we find a small but statistically important negative relationship. This difference in the direction of the effect arises from the covariances estimated across participation, intensity, and bank outcomes. The relationship between COVID-affected employment and intensity of participation becomes negative after accounting for the covariance between unobservable factors that affect both the intensity of participation and NIMs of participating banks. In the remaining specifications, a percent increase in the share of COVID-affected employment is associated with an increase in the intensity of PPP participation between 4 to 10 basis points.

The estimated coefficients for the controls support the hypothesis that risk-aversion and availability of funds determined the intensity with which a bank participated in the PPP. Larger and more liquid banks were more likely to participate more intensively in the PPP. Banks with larger concentrations of C&I loans, and consequently, greater exposure to risk from business loans lent larger shares of total loans under the PPP. In line with the results for the participation equation, banks that were more leveraged participated more intensively in the PPP. We find no systematic relationship between allowances for losses and the intensity of participation. We estimate positive, statistically important relationships between the two measures under the specification where we measure growth in total C&I loans and the portion of C&I loans that were booked outside the PPP. In line with the risk aversion motive, this result suggests that banks that expected large loan losses participated more intensively in the PPP. More profitable banks participated more intensively under the setting in which the final outcome of interest is the change in NIM relative to 2019. This relationship was not statistically important in the remaining settings. Finally, exposure to COVID cases did not result in a statistically important effect on participation intensity.

Overall, our results on participation and intensity of participation are consistent with the design and intentions of the program. The program offered low cost, government guaranteed loans to borrowers that were facing hardship. Moreover, the loans were legislatively required to have a zero percent risk weight so that banks did not have to post capital against these loans under the risk-based capital rules and loans could also be pledged to the Federal Reserve's PPPLF to negate any impact on the bank's leverage ratio. Overall, we find that larger and more profitable banks were more likely to participate. However, we also find compelling evidence of a risk neutralizing channel for participating banks. Specifically, banks with lower capital ratios and those facing greater exposure to C&I lending were more likely to participate but also to participate more intensively. PPP loans likely diffused potentially problematic situations for these riskier banks. For example, the PPP provided a guaranteed loan to a riskier borrower that allowed banks to earn a modest amount of income but not risk their own capital. Similarly, a PPP loan may help meet borrower demand so that same borrower does not draw on her existing line of credit. Given this scenario, a riskier bank would prefer to make a PPP loan as it protects against loan losses and demand driven draws on outstanding commitments at a time when borrower uncertainty was climbing.

6 What Was the Balance Sheet Impact on Participating Banks?

Table 3 reports the estimates for equations 3 and 4, which correspond to bank outcomes for participants and non-participants in the PPP respectively. Columns (1), (3), (5), (7), and (9) report the results for participants. The first row in all of these columns report the main treatment effect of interest. These estimates show that incremental participation in the PPP diluted bank profitability. A one percent increase in PPP participation intensity resulted in a 42 basis point decline in NIM, and a 4.3 basis point change in NIM relative to 2019 levels. At the mean level of PPP participation of 8.5 percent of total loans, the latter estimate entails a decline in NIM of 37 basis points, which is close to the full decline in NIM since 2019 experienced by participants in the PPP of 33 bps. Banks that participated more intensively in the PPP expanded their overall C&I loan portfolio as well as loans within this category outside of the PPP. A one percent increase in PPP lending resulted in a 10.2 percent growth in C&I loans and a 1 percent growth in C&I loans outside of the program on a year-over-year basis. These findings suggest that participating banks allowed their business loan portfolios to expand rather than offset the growth with a contraction in non-PPP lending.[10] Finally, incremental participation in the PPP did not result in statistically important effects on risk-taking, as revealed by the coefficient on CRE loan growth of 35 basis points and credibility intervals that cross the real line at zero.

The estimated coefficients for bank-level controls for participants show that bank size explained substantial variation in profitability and loan growth. Larger banks underwent relative increases in NIM and change in NIM relative to 2019, as well as a statistically important growth in total C&I lending. When combined with previous results that showed that larger banks were more likely to participate and to participate with greater intensity in the PPP, these findings suggest that gains in profitability during the operation of the PPP primarily accrued to large banks that were able to participate materially in the program. Banks with a larger concentration in C&I loans experienced a statistically important but economically modest rise in NIM of 13 basis points per percent increase in loans in this category. Elevated concentration in C&I loan shares was also associated with a 7 percentage point decline in the growth rate of C&I loans. Base effects are likely to have contributed

[10]In Appendix L we show that C&I and CRE outcomes were much more favorable for banks that experienced rapid C&I loan growth and more C&I loan draws during the acute financial panic during the first quarter of 2020. It is likely the case that these active C&I lenders drive the overall result.

Table 3: Results for profitability and loan growth of participating and non-participating banks

	NIM(ppt.)		ΔNIM(bps)		CI Gwth(%)		Non-PPP CI Gwth(%)		CRE Gwth(%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)
PPP Loans to Total Loans	-0.423		-4.29		10.234		1.029		0.35	
	[-0.56, -0.31]		[-6.22, -2.87]		[9.13, 11.2]		[0.37, 1.65]		[-0.26, 1.07]	
ln Assets	0.371	-0.316	4.051	-2.614	6.22	-7.303	-0.158	-10.191	0.244	-3.576
	[0.22, 0.56]	[-0.37, -0.26]	[2.83, 5.52]	[-5.51, 0.87]	[5.32, 7.16]	[-8.29, -6.37]	[-0.7, 0.39]	[-11.33, -9.1]	[-0.54, 0.95]	[-4.29, -2.9]
CI to assets	0.129	-0.021	0.413	-0.484	-6.967	1.353	-0.245	0.543	0.062	-1.185
	[0.09, 0.17]	[-0.03, -0.01]	[-0.05, 1.02]	[-1.29, 0.45]	[-7.43, -6.49]	[0.98, 1.73]	[-0.49, 0.01]	[0.17, 0.91]	[-0.16, 0.25]	[-1.4, -0.97]
Leverage Ratio	-0.163	0.012	-2.484	0.103	-0.299	0.814	-0.123	1.731	0.325	1.037
	[-0.22, -0.12]	[0, 0.02]	[-3.4, -1.72]	[-0.94, 1.07]	[-0.98, 0.39]	[0.21, 1.41]	[-0.39, 0.14]	[1.06, 2.42]	[0.05, 0.62]	[0.66, 1.43]
Liquid Assets to Assets	0.01	-0.029	-0.075	-0.394	-0.741	-0.065	-0.134	0.304	-0.044	-0.265
	[0, 0.02]	[-0.03, -0.03]	[-0.21, 0.08]	[-0.65, -0.13]	[-0.92, -0.56]	[-0.24, 0.11]	[-0.22, -0.05]	[0.1, 0.51]	[-0.1, 0.01]	[-0.38, -0.15]
ALLL to Total Loans	0.037	-0.003	-3.475	-9.545	-3.634	-2.225	-3.337	-1.287	-0.548	-0.833
	[-0.07, 0.15]	[-0.05, 0.04]	[-5.46, -1.52]	[-12.11, -7.03]	[-6.19, -1.13]	[-4.71, 0.22]	[-4.34, -2.34]	[-4.02, 1.46]	[-1.27, 0.16]	[-2.42, 0.76]
ROA	0.346	0.226	-10.418	-1.499	1.067	-0.471	-0.484	-3.769	-1.887	0.72
	[0.23, 0.48]	[0.15, 0.3]	[-12.55, -8.18]	[-5.24, 2.25]	[-1.52, 3.75]	[-3.61, 2.65]	[-1.57, 0.59]	[-7.25, -0.33]	[-2.64, -1.13]	[-1.4, 2.84]
Cases Per 100k	-0.033	-0.011	-8.363	-4.016	3.095	-2.976	-0.127	-2.476	-0.011	-0.628
	[-0.11, 0.05]	[-0.06, 0.04]	[-9.69, -7]	[-7.04, -1.05]	[1.29, 4.91]	[-5.29, -0.65]	[-0.82, 0.57]	[-5.23, 0.18]	[-0.49, 0.45]	[-2.21, 0.94]
Constant	2.171	6.346	-0.191	-0.565	-0.241	-1.173	-1.908	-0.238	0.654	-2.287
	[0.54, 3.47]	[5.75, 6.95]	[-6.23, 5.87]	[-6.73, 5.54]	[-6.06, 5.74]	[-7.06, 4.72]	[-6.79, 3.09]	[-6.26, 5.81]	[-4.83, 6.31]	[-8.16, 3.74]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

to this result, as banks with larger shares of the loans likely grew their books by a lower percent. Notably, banks that were better capitalized underwent a larger decline in profitability. NIM declined by 16 basis points and change in NIM by 2.5 basis points for a one percent increase in the leverage ratio. Banks that were constrained by the leverage ratio likely made use of the PPPLF to a greater extent, which also proved to be a source of low-interest funds and thereby supported net interest margins.[11] Banks with larger leverage ratios were more likely to grow their CRE portfolio as their capital position likely permitted them to expand risky lending.

Banks with a larger share of liquid assets experienced a statistically important but economically insignificant decline in NIM of 0.07 basis points. Growth in overall C&I loans and non-PPP C&I loans declined by 0.7 and 0.1 percentage points for a 1 percent increase in liquid assets. These results are consistent with findings that showed that less liquid banks were more likely to participate in the PPP. Banks that had reserved larger shares of their loan portfolios for loan loss allowances underwent larger declines in NIM relative to 2019, and decline in overall as well as non-PPP C&I growth. When banks set aside larger reserves to meet expected losses, they have a diminished pool of funds to expand lending, which likely led to lower margins. Banks with larger ALLL shares also face greater risk in their loan portfolios, possibly leading them to pull back lending more than peers facing less risk. As table shows, much of this effect is due to a decline in non-PPP lending. More profitable banks prior the pandemic, as denoted by institutions with larger ROA from 2019, underwent a relative increase of 34 basis points in NIM, but a decline of 10 basis points in NIM relative to 2019 for every percent increase in ROA. Growth in CRE loans declined by 1.8 percentage points for a one percent increase in ROA, suggesting that banks that were profitable prior to the pandemic were more conservative in expanding risky lending. Exposure to the pandemic, as measured by the deposit-weighted share of COVID cases per 100,000 population, was associated with a statistically important decline in NIM relative to 2019, and an increase in C&I growth. Participants in

[11]The results on PPPLF participation and intensity of use are shown in Appendix H which confirm that banks with lower leverage ratios and less core deposit funding were more likely to use the PPPLF facility.

the PPP likely responded to the firm needs resulting from disruptions due to the pandemic, which exerted downward pressure on their profit margins.

Columns (2), (4), (6), (8), and (10) report the coefficient estimates for non-participants. Notably, the direction of coefficients associated with bank-level controls are opposite to those of participants. This difference is largest for bank size. Banks that did not participate in the PPP underwent statistically important declines in profitability, loan growth, and risk-taking. Non-participants with larger concentration of C&I loans underwent a statistically important decline in NIM, an increase in C&I growth, as well as a decline in CRE loan growth. This runs counter to the effect of C&I concentrations on participants, and suggests that banks that did not participate in the PPP, but were specialized in C&I lending, continued to expand lending in this category by making use of their own capital. This finding is also consistent with the estimates associated with the leverage ratio. Banks with larger capital buffers underwent an increase in NIM and saw higher growth in C&I and CRE loan portfolios. This is likely due to their ability to extend more credit using their resources without running into regulatory capital constraints.

Banks with larger shares of liquid assets underwent larger declines in NIM, change in NIM, and growth of CRE loans. Since lending opportunities outside of the PPP were limited over the course of the pandemic, banks that did not participate in the PPP were likely constrained in their ability to generate interest revenue from their liquid assets. The decline in outcomes is not economically significant–NIM and change in NIM declined by 3 and 0.3 basis points respectively, and CRE loan growth by 26 basis points in response to a 1 percent increase in the share of liquid assets. Change in NIM relative to 2019 declined with increased loan loss allowances, likely due to the constraints imposed by the reserves on banks' ability to use their resources for lending. Banks that were more profitable in 2019, as measured by their ROA underwent a modest increase in their NIM in 2020, as well as a decline in C&I loan growth. Non-participants in the PPP that were relatively more profitable were likely conservative in their lending decisions and grew their loan portfolio to a lesser extent than banks that were less profitable. Finally, exposure to the pandemic resulted in similar effects on participants and non-participants. The latter group of banks experienced a larger decline in NIM and growth in C&I loans. This suggests that non-participants responded to firm demand resulting from pandemic-related disruptions by lending C&I loans using their own capital, and that such lending diluted their profitability.

Table 4 characterizes the direction and magnitude of covariances. Positive and negative relationships that are statistically important are depicted in blue and red symbols respectively. Estimates that are not statistically different from zero are represented in grey.[12] The joint model addresses endogeneity of PPP intensity and the sample selection effects by allowing for covariances across outcomes. Left unaddressed, covariances across unobserved factors bias the estimates of coefficients. The first row shows that overall, participation into the PPP was positively associated with the intensity of participation. Banks that were likely to participate in the PPP were also more likely to participate more intensively in the program. This relationship is only weakly positive when the growth in non-PPP loans is the final outcome. The second row shows that unobserved factors underlying bank participation were positively related to the unobserved component of bank profitability and loan growth. The relationship was weakly negative between unobserved factors in participation and CRE loan growth. These covariances represent the sample selection effects of bank participation on final outcomes. The third row depicts a positive relationship between the intensity of bank participation in the PPP and final outcomes, except with growth in C&I loans outside the PPP, and CRE loans. These results support our hypothesis on the source of endogeneity in the intensity of bank participation – banks that were more likely to experience higher interest margins participated more intensively in the program. Finally, the relationships in the bottom row pertaining to non-participants move in an approximately opposite direction to those in the second row that represents results for participants. This shows that for non-participants, bank outcomes were negatively related to factors that made participation more likely. This is further confirmation that the selection effects of the PPP were salient and that banks that were better positioned to expand their loan portfolios and maximize their interest margins strategically opted in to the program.

[12] The underlying numerical estimates are presented in Table E5 in Appendix E.

Table 4: Covariance estimates from the Bayesian joint model

	NIM	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	+	+	+	+	+
COV(participation, bank outcome)	+	+	+	+	−
COV(intensity, bank outcome)	+	+	+	−	−
COV(non-participation, bank outcome)	−	−	−	−	−

This table characterizes the direction and magnitude of covariances estimated from the Bayesian joint model. Positive and negative relationships that are statistically important are depicted in blue and red symbols respectively. Estimates that are not statistically different from zero are represented in grey. The numerical estimates underlying this table are in Table E5 in the Appendix.

7 Did the PPP Crowd Out Lending or Offset A Loan Supply Contraction?

A critical component in evaluating the effect of the PPP is understanding how banks would have performed absent the program. In addressing this question, we generate counterfactual margins and loan growth rates that participating banks would have realized, had they not participated in the PPP. This counterfactual is different from the potential outcome of banks in the event that the PPP itself had not been introduced. The latter is not estimable as the PPP was an unprecedentedly large support program that was available to a broad range of financial institutions including banks, thrifts, credit unions, and fintechs. The counterfactual in the PPP's absence could have been estimated if any of the sub-category of institutions had been ineligible to participate in the program. In light of the broad-based nature of the PPP, we instead estimate counterfactuals for participants by studying the outcome for non-participants.

Specifically, we utilize the estimates from Equation 4 that corresponds to outcomes for non-participants and substitute for the independent variables $\mathbf{x_i}$ pertaining to participants. Subsequently, we obtain the mean value of each balance sheet outcome across all participants for every MCMC iteration.

Figure 2 shows the distribution of the counterfactual change in NIM relative to 2019 levels. In line with the findings for NIM, this chart shows that banks' net interest margins for participants would have fallen by 62 basis points on average relative to 2019 levels. This decline is larger than the realized fall of 33 basis points for participating banks as well as the 44 basis point decline experienced by non-participants. This result is economically significant. Even though bank margins declined with incremental participation in the PPP, margins would have been more strained if banks did not have the option to participate in the program.

Figure 3 summarizes the counterfactual values of C&I loan growth for PPP participants. The posterior density of counterfactual values suggests that in the absence of the PPP, participating banks would have substantially reduced lending and allowed portfolio runoffs to reduce the size of their balance sheets. The average counterfactual

Figure 2: Counterfactual values of Δ NIM

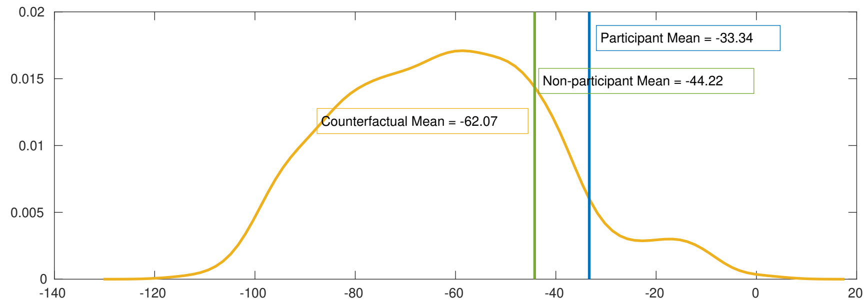


Chart shows the kernel density of mean change in NIM relative to 2019 for participating banks in the event of non-participation. The blue and green lines represent the realized average change in NIM for participants and non-participants respectively over Q2 and Q3 2020 relative to 2019 levels. Source: Authors' calculations.

growth in C&I loans is -77.94 percent, which contrasts with the 91.28 percent realized growth in loans for PPP participants. These findings are in line with the results from Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) that provided evidence of a tightening of lending standards.[13] These predictions also align with the actions of banks with respect to other loan categories that were not supported by government credit programs such as consumer loans. Banks substantially reduced consumer lending during 2020 to the extent that households, particularly those in the subprime category reported lack of access to credit during this period [Horvath, Kay, and Wix, 2021].

Appendix G reports the posterior densities for the counterfactual levels of NIM, the growth in C&I loans outside the PPP, and growth in CRE loans. The findings are in line with the results for change in NIM and growth in C&I loans reported in this section. Banks would have experienced a decline in NIM and curtailed CRE and other C&I lending if they had not participated in the PPP.

The counterfactuals from the Bayesian joint model reveal the full effects of the PPP by considering the balance sheet outcomes of non-participants. These findings

[13] See SLOOS results for April 2020 https://www.federalreserve.gov/data/sloos/sloos-202004.htm and July https://www.federalreserve.gov/data/sloos/sloos-202007.htm

Figure 3: Counterfactual values of C&I Loan Growth

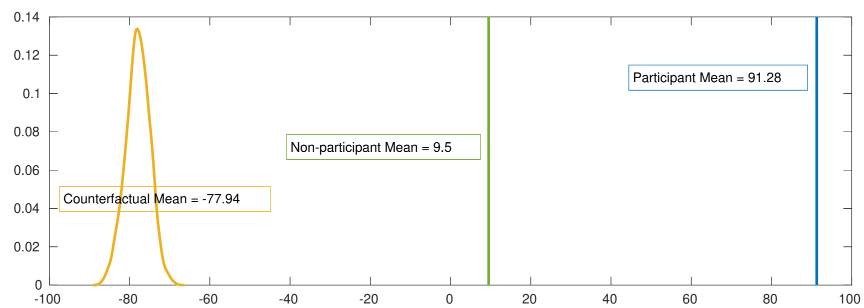


Chart shows the kernel density of YoY growth in C&I loans for participating banks in the event of non-participation. The blue and green lines represent the realized average C&I growth for participants and non-participants respectively over year ending in Q2 and Q3 2020.
Source: Authors' calculations.

are not apparent from the estimated effects on the program participants alone. Participants underwent a decline in margins with incremental participation in the PPP. If these institutions had withheld participation altogether, they would have undergone an even larger decline in margins. Thereby, the program supported bank margins during a period of substantial economic uncertainty. We previously showed that banks were motivated by risk-aversion in participating in the PPP. The counterfactual values for bank lending are consistent with this finding. Banks that participated in the PPP would not have expanded lending to address business needs for credit had they not participated in the program. The PPP, crucially, did not crowd out private lending. Instead, it offset what would have been a sharp decline in bank lending.

We examine the drivers of the predicted counterfactuals for participants and in Table 5. To this end, we evaluate $\bar{\mathbf{x}}_{p,j}\beta_{4j}^{(g)}$, $g = 1, 2, ..., 10,000$, which is the product of the mean value of each covariate j across participants and the posterior draws of the associated coefficient from equation 4 for non-participants. The table reports the mean and standard deviation of this product across the 10,000 posterior draws.

Bank size is the primary determinant of the lower counterfactual NIM, change in NIM, growth in C&I loans both, overall as well as outside of the PPP, and growth in CRE loans for participants. Participants with asset size at the mean of the group

Table 5: Decomposition of predicted outcomes for participants and non-participants

	NIM	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
	(1)	(2)	(3)	(4)	(5)
ln Assets	-3.95	-32.69	-91.32	-127.43	-44.71
	[-4.59, -3.3]	[-68.92, 10.89]	[-103.66, -79.68]	[-141.69, -113.81]	[-53.63, -36.27]
CI to assets	-0.19	-4.48	12.52	5.02	-10.96
	[-0.26, -0.12]	[-11.98, 4.2]	[9.03, 16.04]	[1.58, 8.45]	[-12.95, -9.01]
Leverage Ratio	0.14	1.17	9.24	19.65	11.77
	[0, 0.28]	[-10.69, 12.12]	[2.41, 16.05]	[12, 27.42]	[7.45, 16.24]
Liquid Assets to Assets	-0.57	-7.82	-1.29	6.05	-5.26
	[-0.64, -0.5]	[-12.91, -2.59]	[-4.75, 2.14]	[2.01, 10.22]	[-7.52, -3.02]
ALLL to Total Loans	0	-12.66	-2.95	-1.71	-1.1
	[-0.07, 0.06]	[-16.05, -9.32]	[-6.25, 0.29]	[-5.33, 1.94]	[-3.21, 1.01]
ROA	0.27	-1.78	-0.56	-4.48	0.86
	[0.18, 0.35]	[-6.23, 2.67]	[-4.29, 3.15]	[-8.62, -0.4]	[-1.67, 3.37]
Cases Per 100k	-0.01	-3.24	-2.4	-2	-0.51
	[-0.05, 0.03]	[-5.68, -0.85]	[-4.27, -0.52]	[-4.22, 0.14]	[-1.78, 0.76]
Constant	6.35	-0.57	-1.17	-0.24	-2.29
	[5.75, 6.95]	[-6.73, 5.54]	[-7.06, 4.72]	[-6.26, 5.81]	[-8.16, 3.74]

Note: The reported values are posterior means of the product of covariates and parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

would have undergone a decline in NIM of 32 basis points relative to 2019, and a reduction of the C&I loan portfolio by 91 percent had they not participated in the PPP. These findings are driven by the differences in the outcomes of small and large non-participants. Small, non-participant banks continued to lend C&I and CRE loans over the course of the pandemic where large non-participants curtailed such lending as depicted in Table 3. Smaller non-participants underwent lesser declines in NIM relative to large non-participants. Since participants were, on average, larger than non-participants, our results predict magnified effects of bank size for the former set of institutions.

The second most important factor driving the predicted decline in counterfactual profitability and loan growth is the ratio of ALLL to total loans. Participating banks with average levels of this ratio were likely to undergo a 12.66 basis point decline change in NIM and declines of 2.95, 1.71, and 1.1 percentage points in overall and non-PPP C&I loans, and CRE loans respectively. This finding is consistent with loan loss allowances serving as a constraint from lending more, and earning larger margins.

Unlike bank size and the ratio of ALLL to total loans, other covariates do not predict as large a decline in margins and lending. Participants with a mean level of shares of liquid assets were likely to experience a decline of 7.82 basis points in the change in NIM relative to 2019, and a decline of 5.26 percentage points in CRE growth. Participant banks that were already driven by risk-aversion to engage in PPP lending, would have been further unwilling to engage in risk-taking to support their interest margins if the program was inaccessible to them. Exposure to the pandemic would have likely placed downward pressure on interest margins and loan growth. Participating banks with a mean level of exposure to COVID cases in their region of operation would have likely undergone a decline of 3.24 basis points in their change in NIM, and a 2.4 percentage point decline in C&I loan growth. This finding suggests that in the absence of the PPP, banks would have been unlikely to fill the need for credit arising from an increased incidence of the pandemic in their region of operation. Finally, banks with a mean level of C&I loans to assets would have undergone a 19 basis point decline in NIM, and a 10.96 percentage point decline in

CRE loan growth. Banks with a concentration in business lending would not have shifted their portfolios in favor of CRE loans upon the onset of the pandemic.

Even though the leverage ratio was positively associated with growth in margins and lending, these effects did not sufficiently offset the negative effects on counterfactual values predicted by the remaining covariates. Previous mean levels of profitability denoted by ROA did not result in statistically important effects on counterfactual outcomes.

Overall, the estimated counterfactuals from the Bayesian joint model predict that banks that participated in the PPP would have experienced additional declines in NIM and reduced lending if they had not participated in the program. This result is primarily driven by relatively larger institutions and those anticipating larger loan losses potentially reducing the size of their lending portfolios more substantially.

8 Robustness: Bayesian Results with Alternative Instrument

As a robustness check on our main results, we construct a set of alternative instruments for equation 2 and re-estimate the Bayesian joint model. Specifically, we consider three alternative instruments. First, we construct the share of small-firm employment using county-level shares of firms with less than 500 employees. This proxies for the share of eligible firms in a county. We weight these county-level shares by the bank deposit shares to generate a bank specific measure of eligible PPP borrowers. Second, we consider the share of unused C&I loan commitments relative to the bank's total assets. This measure is similar to C&I lending concentration but also reflects the immediate risk a bank faces of loan draws which were a particular concern during the early days of the pandemic for banks. Third, we consider the share of core deposits relative to total deposits. Core deposits provide a cheap funding source for banks and their use to fund PPP loans would generate a more profitable lending arrangement as opposed to funding the loans with borrowings or more high priced deposits. Therefore, we expect that banks with larger shares of core deposits would participate with more intensity because the loans were marginally more profitable compared to banks with more expensive funding arrangements.

We consider a wide number of additional instruments as a robustness check because each alternative has potentially significant drawbacks. The instrument measuring the share of potentially eligible firms suffers from measurement error because we cannot implement industry specific employee cutoffs used in the PPP. Therefore, we might severely underestimate eligible firm shares for counties that are concentrated in industries with higher employee cutoffs. Alternatively, unused commitments reflect both loan demand and supply. Ideally, the instrument should control for loan demand which, in turn, isolates the loan supply effects which we seek to measure. Unused commitments are an equilibrium outcome though, dependent on both credit standards (supply) and loan demand. Finally, core deposits prior to the pandemic may not accurately represent a bank's funding stance at the time the PPP began. The massive amount of fiscal and monetary support increased liquidity at banks significantly through both additional reserves holdings and increased core deposit funding. Therefore, most banks were likely not facing funding shortages at that time. Nonetheless, we do find a significant impact of pre-pandemic funding composition on PPPLF activity as shown in Appendix H suggesting that funding concerns may have affected some banks. COVID affected employment, then, remains our preferred instrument over these alternatives because it should be a cleaner measure of potential loan demand at the onset of the crisis.

All that said, we find these to be compelling instruments because they represent conditions that the bank faced prior to the pandemic but are reflective of the bank's propensity to engage with the PPP program. Given the historic changes in the banking landscape since March 2020, pre-pandemic measures may reflect a bank's underlying potential to engage in PPP lending but may not influence bank balance sheet outcomes during that time. For example, a bank with large average shares of core deposits prior to the pandemic may be willing to participate more heavily in PPP lending because they are not concerned about pandemic-era deposits running off and have a proven ability to raise cheap funding should PPP loans remain outstanding longer than anticipated. However, fiscal and monetary policy shifts have greatly altered bank balance sheet composition since March 2020 to the extent that current net interest margins are not reflective of prior-pandemic characteristics.

Table 6 shows the standardized coefficients for each of these alternative instruments, along with our preferred instrument of COVID-affected employment. The standardized coefficient represents the impact of a one standard deviation shock to the level of the instrument on the intensity of the average bank to participate in the PPP. For the level NIM regression, the sign is either incorrect or the coefficients are mostly statistically unimportant. The one exception is the unused commitment share which is both positively signed and statistically important, indicating that banks with greater unused shares were more likely to originate a greater share of PPP loans relative to their loan book size. The other coefficients in this specification are all negative including the demand focused instruments such as COVID employment share and small firm shares.

Table 6: Standardized coefficients of instruments in predicting PPP intensity

Instrument	NIM(ppt.)	ΔNIM(bps)	CI Gwth(%)	Non-PPP CI Gwth(%)	CRE Gwth(%)
COVID-affected employment share	-0.007	0.045	0.096	0.119	0.04
	[-0.01, 0]	[0.03, 0.06]	[0.08, 0.12]	[0.1, 0.14]	[0.03, 0.05]
Unused CI Commitments to Assets	0.123	0.139	0.259	0.264	0.164
	[0.1, 0.15]	[0.12, 0.16]	[0.23, 0.28]	[0.24, 0.29]	[0.11, 0.28]
Core Deposits to Assets	-0.008	0.087	0.108	0.106	0.104
	[-0.01, 0]	[0.07, 0.1]	[0.09, 0.13]	[0.08, 0.13]	[0.08, 0.13]
Small firm employment share	-0.084	-0.091	-0.135	-0.171	-0.09
	[-0.11, -0.05]	[-0.11, -0.07]	[-0.16, -0.11]	[-0.19, -0.15]	[-0.11, -0.07]

In the other specifications, we see that nearly all the instruments are correctly signed. Banks with more core deposit funding, more unused commitments, and operating in markets with more COVID-impacted employment all had larger PPP lending shares. However, in all specifications, banks in markets with more eligible firms had lower PPP lending. This may reflect either an inability of the program to reach the most eligible borrowers, a breakdown in relationship lending, or mismeasurement of our instrument.

Finally, comparing the size of the coefficients across the instruments and specifications tells us which had the larger impact on lending intensity. Given a one standard deviation shock to the COVID-affected employment share, we find that PPP lending intensity increased between 0.04 and 0.11 standard deviations across specifications. A one standard deviation shock to core deposits similarly increased PPP lending intensity about 0.08 to 0.10 standard deviations across specifications. In all cases, the small firm share *decreases* lending participation as already discussed. A one standard deviation shock to unused commitments however increases PPP lending intensity by between 0.13 and 0.26 standard deviations. This result provides further evidence to our hypothesis that C&I loan risk, and in particular, near-term risks, arising from C&I lending, were important drivers of PPP participation for smaller banks. While outstanding C&I lending represents a loan loss risk, unused commitments represent both a liquidity risk and a capital risk. Draws on existing loans require banks to essentially fund new lending but also generate larger exposures that can increase losses in the event of default. Banks therefore have a strong incentive to offset demand for loan draws by originating PPP loans which transfer much of the loss risk to the government and reduce demand for new funding.

Table 7 reports the full results from each dependent variable specification using the unused share of commitments as an instrument. These results are roughly unchanged from our earlier results. Larger, more profitable banks and those with more ex-ante C&I loan exposure were more likely to participate and originate larger shares of PPP loans. Notably, the coefficients on unused commitments from these specifications are qualitatively somewhat larger than those on the C&I loan outstanding share, but this difference is small in most cases.

Table 8 reports the results for the outcomes among participants and non-participants. Again our results are mostly unchanged. Banks that originated larger PPP loan shares had lower core profitability as measured by both the level and change in net interest margins. They also had higher C&I lending growth, due almost entirely to PPP lending. Importantly, there was no statistically important increase in CRE lending, reflecting a lack of increase in risk-taking due to government guarantees.

Table 7: Results for participation and intensity from the Bayesian joint model

	NIM		ΔNIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity
Small CI to assets	-0.008		-0.014		-0.001		0		-0.005	
	[-0.02, 0]		[-0.02, -0.01]		[-0.01, 0.01]		[-0.01, 0.01]		[-0.01, 0]	
Unused CI Commitments to Assets		0.246		0.277		0.517		0.527		0.328
		[0.21, 0.29]		[0.24, 0.32]		[0.47, 0.57]		[0.47, 0.58]		[0.21, 0.56]
ln Assets	0.147	1.027	0.126	0.976	0.125	0.462	0.191	0.272	0.209	0.871
	[0.11, 0.18]	[0.88, 1.17]	[0.09, 0.16]	[0.83, 1.12]	[0.1, 0.15]	[0.33, 0.6]	[0.16, 0.22]	[0.13, 0.41]	[0.15, 0.33]	[0.18, 1.23]
CI to assets	0.038	0.236	0.04	0.226	-0.024	0.227	-0.005	0.201	0.026	0.222
	[0.03, 0.04]	[0.21, 0.26]	[0.03, 0.05]	[0.2, 0.25]	[-0.03, -0.02]	[0.2, 0.25]	[-0.01, 0]	[0.17, 0.23]	[0, 0.04]	[0.18, 0.25]
Leverage Ratio	-0.048	-0.326	-0.048	-0.327	-0.026	-0.278	-0.037	-0.213	-0.044	-0.275
	[-0.06, -0.04]	[-0.38, -0.27]	[-0.06, -0.04]	[-0.38, -0.27]	[-0.04, -0.02]	[-0.33, -0.22]	[-0.05, -0.03]	[-0.27, -0.16]	[-0.06, -0.03]	[-0.35, -0.16]
Liquid Assets to Assets	0.007	0.074	0.006	0.074	-0.001	0.088	-0.007	0.101	0.003	0.082
	[0, 0.01]	[0.06, 0.09]	[0, 0.01]	[0.06, 0.09]	[0, 0]	[0.07, 0.1]	[-0.01, 0]	[0.09, 0.11]	[-0.01, 0.01]	[0.06, 0.11]
ALLL to Total Loans	-0.014	0.111	-0.001	0.185	0.002	0.379	-0.013	0.331	-0.014	0.182
	[-0.06, 0.03]	[-0.14, 0.36]	[-0.04, 0.04]	[-0.06, 0.43]	[-0.03, 0.04]	[0.14, 0.63]	[-0.06, 0.03]	[0.08, 0.58]	[-0.06, 0.03]	[-0.1, 0.51]
ROA	0.072	0.245	0.093	0.27	0.075	0.067	0.133	-0.247	0.109	0.104
	[0.02, 0.13]	[-0.03, 0.53]	[0.04, 0.15]	[-0.01, 0.54]	[0.03, 0.12]	[-0.19, 0.32]	[0.08, 0.19]	[-0.51, 0.01]	[0.02, 0.25]	[-0.44, 0.49]
Cases Per 100k	0.019	0.128	0.027	0.132	0.037	0.128	0.024	0.146	0.011	0.133
	[-0.01, 0.05]	[-0.05, 0.3]	[-0.01, 0.06]	[-0.04, 0.31]	[0.01, 0.07]	[-0.04, 0.29]	[-0.01, 0.06]	[-0.01, 0.31]	[-0.03, 0.05]	[-0.04, 0.3]
Constant	-0.673	-6.622	-0.443	-6.089	-0.177	-0.885	-0.572	1.673	-1.247	-5.185
	[-1.1, -0.25]	[-8.59, -4.65]	[-0.86, -0.02]	[-8.06, -4.11]	[-0.44, 0.09]	[-2.69, 0.87]	[-0.9, -0.25]	[-0.29, 3.63]	[-2.11, -0.7]	[-9.49, 2.84]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table 8: Results for profitability and loan growth of participating and non-participating banks

	NIM(ppt.)		ΔNIM(bps)		CI Gwth(%)		Non-PPP CI Gwth(%)		CRE Gwth(%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)
PPP Loans to Total Loans	-0.056		-1.775		5.801		-0.85		0.354	
	[-0.07, -0.04]		[-2.99, -0.58]		[4.74, 6.83]		[-1.34, -0.43]		[-0.09, 0.78]	
ln Assets	-0.079	-0.153	2.167	4.638	8.585	-7.418	0.958	-10.226	0.248	-4.552
	[-0.11, -0.05]	[-0.21, -0.1]	[1.11, 3.23]	[2.75, 6.43]	[7.66, 9.52]	[-8.43, -6.44]	[0.51, 1.42]	[-11.38, -9.1]	[-0.31, 0.77]	[-7.07, -3.16]
CI to assets	0.021	0.018	-0.32	1.223	-5.297	1.431	0.41	0.506	0.058	-0.716
	[0.02, 0.03]	[0.01, 0.03]	[-0.72, 0.1]	[0.69, 1.78]	[-5.77, -4.81]	[1.05, 1.8]	[0.23, 0.6]	[0.13, 0.88]	[-0.08, 0.21]	[-1.21, 0.19]
Leverage Ratio	-0.041	-0.026	-1.41	-1.619	-1.764	0.905	-0.574	1.741	0.323	1.081
	[-0.05, -0.03]	[-0.04, -0.01]	[-2.06, -0.8]	[-2.42, -0.85]	[-2.48, -1.08]	[0.31, 1.5]	[-0.81, -0.34]	[1.07, 2.43]	[0.11, 0.54]	[0.64, 1.61]
Liquid Assets to Assets	-0.018	-0.022	-0.221	-0.1	-0.379	-0.071	0.053	0.308	-0.046	-0.079
	[-0.02, -0.02]	[-0.03, -0.02]	[-0.34, -0.09]	[-0.33, 0.13]	[-0.57, -0.19]	[-0.25, 0.11]	[-0.02, 0.13]	[0.1, 0.52]	[-0.09, 0]	[-0.33, 0.38]
ALLL to Total Loans	0.013	-0.029	-3.201	-10.27	-2.426	-2.169	-2.746	-1.155	-0.558	-0.953
	[-0.01, 0.04]	[-0.07, 0.01]	[-5.04, -1.38]	[-13.11, -7.5]	[-5.09, 0.27]	[-4.73, 0.28]	[-3.74, -1.8]	[-3.83, 1.6]	[-1.28, 0.16]	[-2.63, 0.68]
ROA	0.249	0.296	-11.446	0.443	1.57	-0.432	-0.887	-3.731	-1.878	-0.411
	[0.22, 0.28]	[0.23, 0.37]	[-13.38, -9.52]	[-3.38, 4.16]	[-1.25, 4.42]	[-3.44, 2.62]	[-1.92, 0.13]	[-7.22, -0.24]	[-2.62, -1.13]	[-5.05, 2.79]
Cases Per 100k	-0.071	0.025	-8.696	-2.343	3.512	-2.74	0.085	-2.436	-0.014	-0.404
	[-0.09, -0.05]	[-0.03, 0.08]	[-9.93, -7.46]	[-5.46, 0.8]	[1.52, 5.5]	[-5.08, -0.49]	[-0.59, 0.75]	[-5.28, 0.25]	[-0.48, 0.46]	[-2.09, 1.27]
Constant	5.364	6.288	3.133	-0.204	-2.485	-2.028	-4.783	-0.377	0.623	-1.206
	[5.08, 5.63]	[5.7, 6.89]	[-2.96, 9.11]	[-6.35, 5.9]	[-8.46, 3.42]	[-7.92, 3.93]	[-9.51, 0.07]	[-6.39, 5.74]	[-4.15, 5.56]	[-7.73, 5.83]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

9 Discussion and Policy Implications

Under the Paycheck Protection Program (PPP), banks issued business loans that could later be fully forgiven and reimbursed with federal funding. Banks—especially small community banks—participated extensively, with PPP loans representing nearly all new lending in 2020. However, the program's effects on the balance sheets of community banks have not been fully understood.

Our results show that the PPP provided support to community banks as well as businesses. Although the PPP carried a low interest rate, the program ensured a modest revenue stream for participating banks when safe and profitable lending opportunities were scarce. At the same time, by guaranteeing credit extensions, the program was able to avoid a credit crunch to small and midsized businesses while revenues were falling quickly. Overall, the PPP indirectly provided crucial support to community banks in the form of income and credit growth and likely protected banks from business-related credit losses during the height of the pandemic. In addition, we find that community banks with ample funding—namely, larger and more profitable banks—were more likely to participate in the PPP; however, participating community banks with weak capital originated more PPP loans relative to their size. This suggests that the PPP helped mitigate risk for weaker banks at a time of high economic and financial uncertainty.

The PPP highlights a few important lessons for structuring government lending programs in the future. First, government guarantees serve as an antidote to a credit crunch in times of severe economic uncertainty. We generate counterfactual analyses that show that small businesses would have likely faced steep constraints in accessing credit during the pandemic in the absence of the PPP.

Second, the benefits of large-scale credit guarantee programs likely outweigh their costs in the event of large, exogenous shocks like the COVID-19 pandemic but may be less effective in a financial crisis. The PPP elicited more intensive participation among banks that were relatively weakly capitalized. If such a program were to be offered following a financial shock such as the Global Financial Crisis, weakly managed banks potentially at the risk of failure may have used the program to gamble for resurrection and transfer substantial risks to the federal government.

Third, the parameters of the guarantee program must balance incentives for participation with those for underwriting. Our findings show that bank interest margins declined with the intensity of participation in the PPP. Low interest rates and deferral of fees until forgiveness likely diluted margins, but also curtailed incentives for originating poor-quality loans that may have later been deemed ineligible for forgiveness. Similarly, requiring banks to initially use their own capital to lend these loans also likely served to check moral hazard incentives.

Overall, the PPP serves as a new tool that may be used in times of a large, exogenous shock to the economy. Future uses of this program may require adjusting loan terms to ensure credit support while disincentivizing moral hazard.

A Key Paycheck Protection Program Dates

Table A1 summarizes the key funding developments in the PPP program through 2020 and 2021. Round one funding appropriated by the CARES Act was $349 billion. The program was scheduled to run from the earliest possible date following passage of the act until June 30, 2020. The SBA began making loans just a few days after CARES Act passage and the funding was quickly exhausted. By April 15, less than three weeks after the CARES Act was signed, the SBA announced that the initial funds were exhausted. In response, Congress approved an additional $321 billion in appropriations to continue making loans though the program end date remained June 15. During this time, government provided support via fiscal and monetary agents began to stabilize the economic situation and financial markets. Consumers and businesses also began to adapt to social distancing restrictions that allowed economic activity to increase substantially from their early pandemic levels. Due to this rise in economic activity and the stabilization of financial markets, demand for PPP loans likely waned during the later part of the program. Thus, fund use slowed and funds remained available as the original expiration date of the program approached, spurring Congress to extend the program by several weeks in July 2020.

Finally, in late 2020, COVID cases again began to rise in the United States, prompting concerns that economic activity would again decline. In response, Congress appropriated an additional $284 billion in funding for a renewed PPP program for the first quarter of 2021. The legislation also rescinded the remaining $146.5 billion in unused funds from the program's second round.

Table A1: Key Paycheck Protection Program Dates

	Enactment Date	Appropriations	End Date
CARES Act	03/27/2020	$349 billion	06/30/2020
PPP and Health Care Enhancement Act	04/24/2020	$321 billion	06/30/2020
S.4116	07/04/2020	–	08/08/2020
Consolidated Appropriations Act	12/21/2020	$284 billion	03/31/2021

Notes: Funds originally appropriated by the CARES Act were authorized for use until June 30, 2020. However, funds were exhausted on April 15, 2020. Second round funds appropriated by the Paycheck Protection Program and Health Care Enhancement Act were also to be used by June 30, 2020. This deadline was later extended by S. 4116 to August 8, 2020. Third round funding was appropriated under the Consolidated Appropriations Act for use through March 31, 2021. While allocating new funds, the act also recinded $146.5 billion in unsed funds from round 2 and placed them into the Treasury General Account.

B Paycheck Protection Program Loan Terms

Table B2 describes the PPP loan terms.

Table B2: Paycheck Protection Program Loan Details

Category	Details
Program Dates:	Rounds 1-2: 2/15/20 - 8/8/20 Round 3: 01/11/20 - 3/15/20
Eligibility:	Less than 500 U.S. employees meets SBA's small business concern definition or, tax-exempt nonprofit org operating before 2/15/20
Loan Amount:	lesser of, - 2.5 times avg monthly payroll costs up to $100k per employee plus any oustanding EIDL loans - $10 million
Maturity:	2 years if originated before 06/05/20 5 years otherwise
Covered expenses	payroll costs: - employee compensation - employee leave payments - health and retirement benefits costs - state and local taxes assessed on compensation mortgage interest and rent utility payments previously incurred interest on debt
Rate and Fees:	1 percent No borrower paid fees
Payment:	Deferral up to 10 months (originally 6 months) Interest accrues
Forgiveness:	Generally requires that 75% of fund use is attributed to payroll costs

Notes: Third round PPP appropriations made a number of changes to the original PPP program terms including additional eligible expenses including property damage and certain worker protection costs. The third round also allowed modifications of exisitng loan amounts as well as second draw loans. Second draw loans were limited to firms with less than 300 employees that had same quarter, year-over-year income reductions of 25 percent or more in 2019 and 2020.
Sources: SBA, Federal Register.

C PPP Liquidity Facility Loan Terms

Table C3 describes the terms of the PPP Liquidity Facility (PPPLF) program as well as the capital treatment on PPP loans and PPP loans pledged to the PPPLF.

Table C3: Paycheck Protection Program Liquidity Facility Terms

Eligibility	All DIs originating PPP Loans
Collateral	Whole PPP loans
Maturity	Equals maturity of the pledged PPP loan
Principal	Equals principal amount of the pledged PPP loan
Rate	35 bps
Fees	No Fees
Regulatory Capital Treatment	Risk weights on PPP loans equal 0% Loans pledged to PPPLF excluded from leverage ratio assets

Sources: Federal Reserve Board.

D Estimation of the Bayesian Joint Model

This appendix presents the Markov Chain Monte Carlo (MCMC) algorithm used to estimate the Bayesian Joint Model and the results from a simulation study. To implement this algorithm, we rearrange the data in a Seemingly Unrelated Regressions setup [Zellner, 1962]. The rearranged covariate matrices are,

$$\mathbf{X}_{i,p} = \begin{pmatrix} \mathbf{x_i'} & z_{i1} & \mathbf{0} & 0 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 0 & \mathbf{x_i'} & z_{i2} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 0 & \mathbf{0} & 0 & \mathbf{x_i'} & \mathbf{0} \\ \mathbf{0} & 0 & \mathbf{0} & 0 & \mathbf{0} & \mathbf{0} \end{pmatrix}, \quad \mathbf{X}_{i,np} = \begin{pmatrix} \mathbf{x_i'} & z_{i1} & \mathbf{0} & 0 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 0 & \mathbf{0} & 0 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 0 & \mathbf{0} & 0 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 0 & \mathbf{0} & 0 & \mathbf{0} & \mathbf{x_i'} \end{pmatrix}.$$

The outcomes are stacked into vectors $\boldsymbol{Y}_{i,p}$ and $\boldsymbol{Y}_{i,np}$,

$$\boldsymbol{Y}_{i,p} = \begin{pmatrix} y_{i1}^* \\ y_{i2} \\ y_{i3} \\ 0 \end{pmatrix}, \quad \boldsymbol{Y}_{i,np} = \begin{pmatrix} y_{i1}^* \\ 0 \\ 0 \\ y_{i4} \end{pmatrix}.$$

D.1 Markov Chain Monte Carlo Algorithm

[14] The likelihood and priors we have specified generate conditional conjugacy. We thereby develop the following Gibbs sampler to estimate the model.

1. Sample Ω from $\Omega|\theta, y, y_1^*$ in one block by partitioning into sub-matrices, where $\theta = [\beta, \gamma_1, \gamma_2, \delta]'$.

2. Sample θ from the distribution $\theta|\Omega, y, y_1^*$.

3. Sample y_{i1}^* from $y_{i1}^*|\theta, y, \Omega$ for $i = 1, 2, ..., n$.

The details underlying each step of the algorithm are discussed in the following subsections.

[14] The trace plots for the results in Section 5 and the simulation study are available upon request.

D.1.1 Sampling Ω

We sample the elements in Ω_p and Ω_{np} separately using the algorithm in Chib, Greenberg, and Jeliazkov [2009], as applied in Vossmeyer [2016] and Sharma [2019]. The conditional distributions consist of inverse Wishart and matrix-variate normal distributions.

To specify the sampling steps, define η_p, η_p, R_p, and R_{np} as,

$$
\begin{aligned}
\eta_p &= \left(y^*_{1,p} - \left(\mathbf{x'_p}\beta_\mathbf{1} + z_{1,p}\gamma_1\right) \quad y_2 - \left(\mathbf{x'_p}\beta_\mathbf{2} + z_2\gamma_2\right) \quad y_3 - \left(\mathbf{x'_p}\beta_\mathbf{3} + y_2\delta\right)\right), \\
\eta_{np} &= \left(y^*_{1,np} - \left(\mathbf{x'_{np}}\beta_\mathbf{1} + z_{1,p}\gamma_1\right) \quad y_4 - \left(\mathbf{x'_{np}}\beta_\mathbf{4}\right)\right), \\
R_p &= \begin{pmatrix} Q_{11} & Q_{12} & Q_{13} \\ Q_{21} & Q_{22} & Q_{23} \\ Q_{31} & Q_{32} & Q_{33} \end{pmatrix} + \eta'_p\eta_p, \\
R_{np} &= \begin{pmatrix} Q_{11} & Q_{14} \\ Q_{41} & Q_{44} \end{pmatrix} + \eta'_{np}\eta_{np}.
\end{aligned}
$$

Finally, define,

$$
\begin{aligned}
\Omega_{tt.l} &= \Omega_{tt} - \Omega_{tl}\Omega_{ll}^{-1}\Omega_{lt}, \\
B_{lt} &= \Omega_{ll}^{-1}\Omega_{lt}.
\end{aligned}
$$

Expressions for $R_{tt.l}$ are analogous to the expression for $\Omega_{tt.l}$. Using these elements, we sample each term of Ω as follows.

1. $\Omega_{22.1}|\theta, y, y_1^* \sim \mathcal{IW}\left(\nu + n_p, R_{p,22.1}\right)$
2. $B_{12}|\theta, y, y_1^*, \Omega_{22.1} \sim \mathcal{N}\left(R_{p,11}^{-1}R_{p,21}, R_{p,11}^{-1}\Omega_{22.1}\right)$
3. Define $\Omega_u = \begin{pmatrix} 1 & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{pmatrix}$
4. $\Omega_{33.u}|\theta, y, y_1^*, \Omega_{33.u} \sim \mathcal{IW}\left(\nu + n_p, R_{p,33.u}\right)$

5. $B_{u3}|\theta, y, y_1^* \sim \mathcal{MN}\left(R_u^{-1} R_{u3}, \Omega_{33.u} \otimes R_u\right)$

6. $\Omega_{44.1}|\theta, y, y_1^* \sim \mathcal{IW}\left(\nu + n_{np}, R_{np,22.1}\right)$

7. $B_{14}|\theta, y, y_1^*, \Omega_{44.1} \sim \mathcal{N}\left(R_{np,11}^{-1} R_{np,21}, R_{np,11}^{-1}\Omega_{44.1}\right)$

D.1.2 Sampling θ

We sample the elements of θ in one step by stacking the outcomes and covariates in Equations 1-4 in a SUR setup as described above. The conditional distribution of *theta* is multivariate normal, $\mathcal{N}(\hat{\theta}, \hat{T})$, where

$$
\begin{aligned}
\hat{\theta} &= \hat{T}\left(T_0^{-1}\theta_0 + \mathbf{X'}_{i,p}\left(\mathbf{I}_{n_p} \otimes \Omega_p^{-1}\right)\mathbf{Y}_{i,p} + \mathbf{X'}_{i,np}\left(\mathbf{I}_{n_{np}} \otimes \Omega_{np}^{-1}\right)\mathbf{Y}_{i,np}\right) \\
\hat{T} &= \left(T_0^{-1} + \mathbf{X'}_{i,p}\left(\mathbf{I}_{n_p} \otimes \Omega_p^{-1}\right)\mathbf{X}_{i,p} + \mathbf{X'}_{i,np}\left(\mathbf{I}_{n_{np}} \otimes \Omega_{np}^{-1}\right)\mathbf{X}_{i,np}\right),
\end{aligned}
$$

D.1.3 Sampling y_1^*

We sample the latent variables y_{i1}^* for $i = 1, 2, ..., n$ from a truncated normal distribution whose bounds are $(-\infty, 0)$ for non-participants and $(0, \infty)$ for participants. Accordingly, $y_{i1}^*|\theta, y, \Omega \sim \mathcal{TN}_{(-\infty,0)}\left(\mu_{i,np|\backslash 1}, \Omega_{np|\backslash 1}\right)$ for $i \in N_{np}$ and $y_{i1}^*|\theta, y, \Omega \sim \mathcal{TN}_{(0,\infty)}\left(\mu_{i,p|\backslash 1}, \Omega_{p|\backslash 1}\right)$ for $i \in N_p$. The parameters in the conditional distributions of $y_{i1}^*|\theta, y, \Omega$ are the standard conditional moments from a Normal distribution where the conditioning is on all except for the first element in the vectors $\boldsymbol{y}_{i,p}$ and $\boldsymbol{y}_{i,np}$.

D.2 Simulation Study

Table D4: Simulation Results

	No exclusion		Exclusion	
	True values	95% credibility interval	True values	95% credibility interval
β_{11}	-0.1	[-0.23, 0.08]	-0.1	[-0.16, -0.06]
β_{12}	-0.2	[-0.37, -0.14]	-0.2	[-0.21, -0.1]
β_{13}	0.1	[-0.07, 0.15]	0.1	[0.08, 0.13]
β_{14}	0.2	[0.06, 0.27]	0.2	[0.16, 0.22]
β_{21}	1	[0.8, 1.95]	1	[0.88, 1.12]
β_{22}	0.5	[0.43, 0.72]	0.5	[0.47, 0.51]
β_{23}	-0.6	[-0.67, -0.43]	-0.6	[-0.62, -0.57]
β_{24}	-1	[-1.13, -0.88]	-1	[-1.03, -0.96]
β_{31}	2	[1.37, 2.58]	2	[1.89, 2.12]
β_{32}	-3	[-3.21, -2.66]	-3	[-3.05, -2.99]
β_{33}	2.5	[2.31, 2.69]	2.5	[2.46, 2.52]
β_{34}	4	[3.77, 4.29]	4	[3.94, 4.03]
β_{41}	-2	[-2.58, -1.67]	-2	[-2.37, -1.66]
β_{42}	1.5	[1.42, 1.65]	2	[1.94, 2.02]
β_{43}	-3	[-3.09, -2.85]	-3	[-3.08, -2.95]
Ω_{12}	0.5	[-0.69, 0.6]	0.5	[0.33, 0.57]
Ω_{22}	0.8	[0.57, 1.06]	0.8	[0.69, 0.86]
Ω_{13}	0.5	[-0.34, 1.08]	0.5	[0.45, 0.67]
Ω_{23}	-0.1	[-0.82, -0.12]	-0.1	[-0.14, -0.04]
Ω_{33}	0.75	[0.7, 1.53]	0.75	[0.69, 0.87]
Ω_{14}	-0.2	[-0.82, 0.5]	-0.2	[-0.72, 0.3]
Ω_{44}	0.8	[0.74, 1.28]	0.8	[0.77, 1.11]

Note: The 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000. The specification of "Exclusion" consists of an instrument in the selection equation. The specification of "No exclusion" consists of no instruments in the selection equation.

We set the following priors under the two specifications: $\theta \sim \mathcal{N}(0, 10 \times \mathbf{I})$, $\Omega_p \sim \mathcal{IW}(7, 3 \times \mathbf{I}_4)$, and $\Omega_{np} \sim \mathcal{IW}(7, 3 \times \mathbf{I}_3)$ where $\theta = [\gamma_1, \gamma_2, \delta, \boldsymbol{\beta}]$, and $\boldsymbol{\beta} = \{\beta_1, \beta_2, \beta_3, \beta_4\}$.

E Covariances from the Bayesian Joint Model

Table E5: Covariance estimates from the Bayesian joint model

	NIM	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	6.939	6.88	3.683	0.031	6.898
	[6.83, 7.06]	[6.76, 7]	[3.34, 4.07]	[-0.51, 0.63]	[6.78, 7.02]
COV(participation, bank outcome)	2.949	18.08	65.94	21.768	-1.013
	[2.14, 3.9]	[7.86, 31.83]	[62, 69.88]	[20.58, 22.88]	[-6.08, 3.23]
COV(intensity, bank outcome)	20.801	145.598	71.661	-46.498	-8.044
	[15.06, 27.64]	[76.42, 240.11]	[28.19, 117.67]	[-71.71, -20.14]	[-43.14, 21.6]
COV(non-participation, bank outcome)	-0.862	-12.599	-60.535	-63.844	-35.861
	[-1, -0.72]	[-35.02, 16.27]	[-64.73, -56.66]	[-67.77, -59.7]	[-38.91, -32.71]

F Categorization of COVID-sensitive industries

This appendix presents the sorted declines in employment by NAICS sector bet ween January and April 2020. These sectors are used to determine pre-pandemic county level exposures to COVID as-of 2019:Q4. Bank-market specific COVID exposures are assembled by weighting county exposures by bank deposits. The methodology is taken from Boyarchenko et al. [2020].

Figure F1: Change in employment

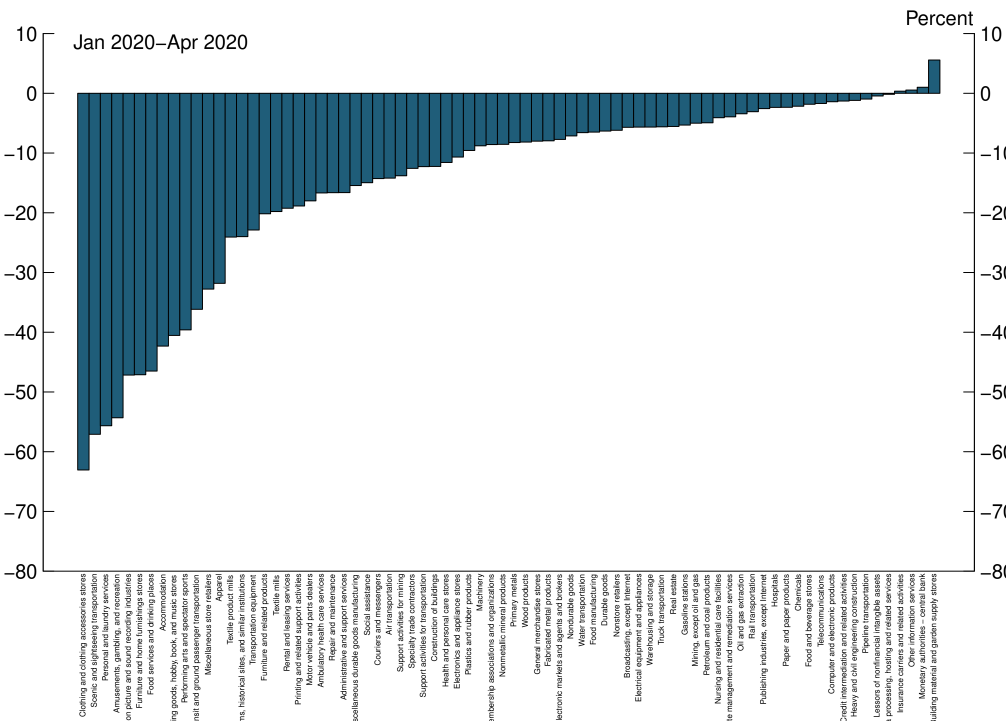


Chart shows percent change in employment over Jan - Apr 2020 across industries.
Source: CES data from the Bureau of Labor Statistics.

G Additional Counterfactual Densities

Figure G2: Counterfactual values of NIM

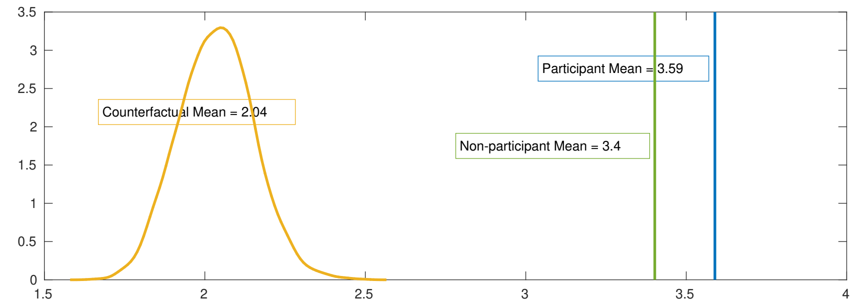


Chart shows the posterior density of counterfactual average NIM for participating banks in the event of non-participation. The blue and green lines represent the realized average NIM for participants and non-participants in Q2 and Q3 2020.
Source: Authors' calculations.

Figure G3: Counterfactual values of Non-PPP C&I Loan Growth

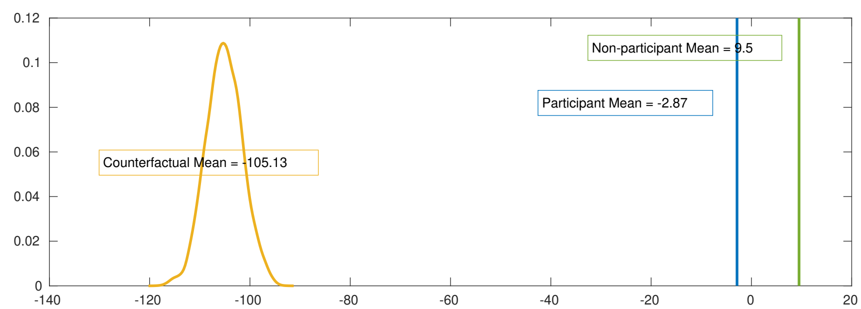


Chart shows the posterior density of counterfactual average YoY growth in C&I loans outside of the PPP for participating banks in the event of non-participation. The blue and green lines represent the realized average non-PPP C&I growth for participants and non-participants respectively over year ending in Q2 and Q3 2020.
Source: Authors' calculations.

Figure G4: Counterfactual values of CRE Loan Growth

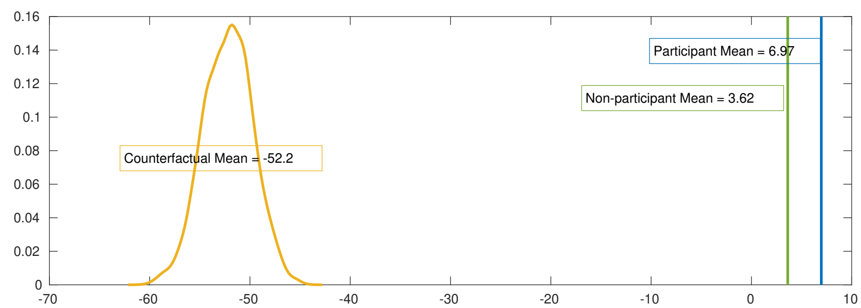


Chart shows the posterior density of counterfactual average YoY growth in CRE loans outside of the PPP for participating banks in the event of non-participation. The blue and green lines represent the realized average non-PPP CRE growth for participants and non-participants respectively over year ending in Q2 and Q3 2020.
Source: Authors' calculations.

H Who Participated In The PPPLF?

Participation in the Federal Reserve's PPP Liquidity Facility (PPPLF) has two main advantages. First, it provides a source of low cost funding to banks that originate PPP loans because the secured advances from the PPPLF carry an interest rate of just 35 basis points. Second, it provides a source of capital relief to banks that might be bound by the leverage capital ratio. Pandemic rules provided that loans pledged to the PPPLF would not count toward leverage capital assets. Thus, the effect of PPP lending was neutralized for banks that fully pledged their PPP loans to the PPPLF.

We hypothesize that these two channels – funding and capital – were the main drivers of participation in the PPPLF among community banks. Regarding funding, community banks typically receive the bulk of their funding from low cost deposits and Federal Home Loan Bank (FHLB) advances. Core deposit funding– consisting of transactional, savings, small time deposits – is a cheap, stable source of funding for all banks, although rates at community banks tend to be higher than those paid by larger banks due to implicit guarantees or the availability of alternative funding sources for large institutions [Jacewitz and Pogach, 2018]. Outside of core deposits, small community banks derive the rest of their funding primarily from other deposit types, such as large time deposits, and FHLB advances.[15] These funding types are a relatively more expensive funding source for community banks than core deposits. Regarding capital, the tier 1 leverage ratio is typically the more binding ratio for community banks. Recent regulatory changes allow community banks to opt into a provision that requires them to have a leverage capital ratio of nine percent but provides an exemption to risk-based capital guidelines. Alternatively, CBOs that do not opt in to this provision are required to have a five percent leverage ratio as well as meeting all PCA risk-based capital requirements.

[15] As of 2019:Q4, 79 percent of total liabilities at CBOs were core deposits. Core deposit shares at regional and large banks were 80 percent and 70 percent, respectively. Other deposit types made up 15 percent of total liabilities at CBOs while FHLB advances were about 4 percent. At RBOs, other deposits were less than 10 percent and FHLB advances were just over 5 percent. At large institutions, other deposits were about 16 percent and FHLB advances were only about 2 percent of total liabilities.

Figure H5 shows that CBOs with higher quarterly interest expenses relative to average interest bearing liabilities prior to the pandemic were more likely to participate in the PPPLF. On average, participants in the PPPLF paid about 15 basis points more for funding compared to non-participants during 2019. At the onset of the pandemic, a lower Federal Reserve policy rate combined with a sharp increase in deposits pushed funding costs lower for both participants and non-participants. Moreover, this funding gap declined significantly between the two groups, with the average difference only about 2 to 3 basis points during 2020. Nonetheless, interest rates on secured loans from the PPPLF were still competitively priced because the 35 basis point rate was still lower than the average costs of interest bearing liabilities throughout the year.

The PPPLF also provided a non-trivial, regulatory capital benefits to participants. Figure H6 shows median leverage ratio buffers for PPPLF participants and non-participants. The leverage ratio buffer is determined based on the CBO's status as an opt-in community bank leverage ratio reporter or not. Non-participants had a median leverage ratio buffer of about 400 basis points during the quarters that the PPP was operational. In contrast, PPPLF participants would have had buffers 30 to 50 basis points lower had the PPP loans pledged to the liquidity facility been counted toward their leverage ratios. By neutralizing these loans, PPPLF participants enjoyed leverage ratio buffers nearly identical to those of non-participants.

We formally assess the characteristics of CBOs that participated in the PPPLF by estimating a logit model where the outcome is an indicator for whether the CBO was a PPPLF participant or not. The sample is restricted to banks that reported at least one PPP loan outstanding on their balance sheets during the sample quarters of 2020:Q2 and 2020:Q3. All explanatory variables are average levels over 2019 from the Call Reports. We consider a wide range of participant characteristics including size, regulatory capitalization levels, loan allowance holdings, share of business lending, and core deposit funding shares.

Table H6 shows the regression estimation for several samples and specifications including all CBOs and CBOs with less than $1 billion in average asset holdings in 2019. Across all specifications and samples, larger, more poorly capitalized, and

Figure H5: Interest Expenses by PPP Liquidity Facility Participant Type

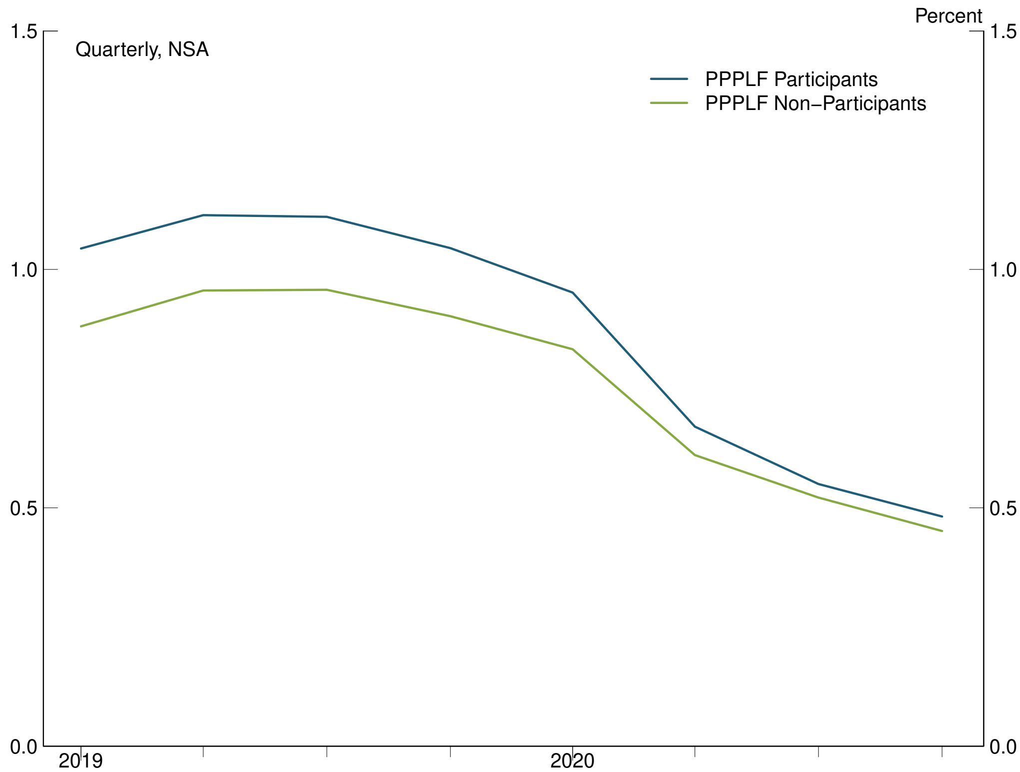


Chart shows quarterly interest expenses as a share of average interest bearing liabilities of PPP participants for PPPLF pledged loans.
Source: Call Reports.

highly concentrated banks were more likely to participate in the PPPLF program. We find that for every percentage point increase in the leverage ratio, the log odds of participation declines 0.115 indicating better capitalized banks were less likely to participate and take advantage of the leverage ratio adjustments. The results are similar for banks with less than $1 billion in total assets shown in column (6) with smaller banks' odds ratio declining 0.123 points for each percent increase in the leverage ratio. Across all specifications and samples, we find that banks that had more allowance for loan and lease losses (ALLL) relative to total loans were also less likely to participate. Specifically, for every one percentage point increase in the ratio of ALLL to total loans, the PPPLF participation log odds ratios declines about 0.3

Figure H6: PPP Liquidity Facility Adjusted Leverage Ratio Buffers

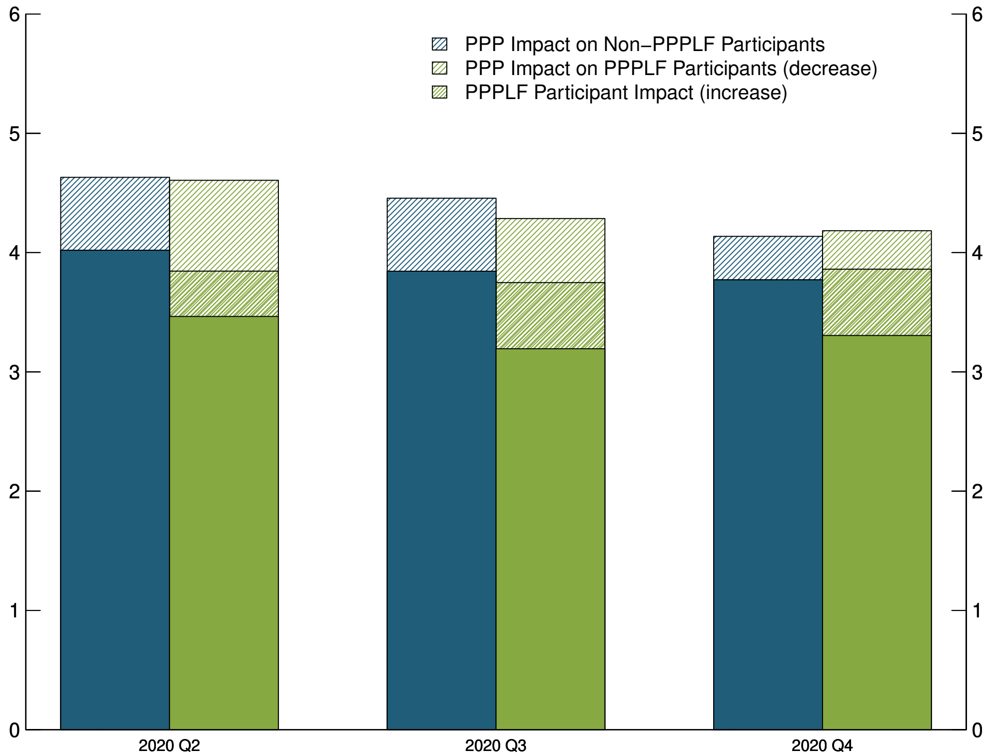


Chart shows adjusted leverage capital ratio buffers by PPPLF participant status.
Source: Call Reports.

points. This effect is similar to the capital effect in that banks that with greater protections against loan losses were more likely to forego program participation. However, unlike with the leverage ratio, there is no direct benefit to this ratio by participating in the PPPLF.

Turning to asset concentration, we find that banks that had high concentrations of C&I loans were more likely to participate in the PPPLF program, indicating some desire by banks to diversify their portfolios away from business lending using the PPPLF. This would be done by raising cash using the PPP loans that could then be used to acquire non-C&I loan assets. We find that the log odd ratio of participation increases 0.057 points for every 1 percentage point increase in the C&I concentration

Table H6: PPPLF Participation Determinants

	All Banks					Banks < \$1 billion				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage Ratio	-0.115***				-0.114***	-0.123***				-0.118***
	(0.020)				(0.020)	(0.022)				(0.022)
CI to assets		0.057***			0.035***		0.074***			0.057***
		(0.005)			(0.009)		(0.006)			(0.012)
Small CI to assets			0.072***		0.010			0.093***		0.002
			(0.009)		(0.013)			(0.010)		(0.015)
Unused CI Commitments to Assets				0.102***	0.059***				0.111***	0.050***
				(0.009)	(0.013)				(0.011)	(0.015)
ln *Assets*	0.376***	0.343***	0.482***	0.284***	0.274***	0.607***	0.599***	0.779***	0.517***	0.506***
	(0.030)	(0.030)	(0.031)	(0.032)	(0.037)	(0.052)	(0.052)	(0.054)	(0.053)	(0.060)
ROA	-0.380***	-0.434***	-0.465***	-0.444***	-0.372***	-0.423***	-0.463***	-0.498***	-0.475***	-0.404***
	(0.095)	(0.086)	(0.088)	(0.088)	(0.092)	(0.105)	(0.095)	(0.098)	(0.098)	(0.100)
Core Deposits To Assets	-0.031***	-0.023***	-0.025***	-0.030***	-0.030***	-0.033***	-0.023***	-0.026***	-0.032***	-0.030***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ALLL to Total Loans	-0.266***	-0.384***	-0.373***	-0.401***	-0.283***	-0.300***	-0.431***	-0.409***	-0.436***	-0.327***
	(0.082)	(0.083)	(0.082)	(0.083)	(0.087)	(0.094)	(0.097)	(0.096)	(0.095)	(0.101)
Cases Per 100k	-0.026	-0.040	-0.031	-0.032	-0.033	0.003	-0.004	0.004	0.002	0.002
	(0.039)	(0.041)	(0.040)	(0.040)	(0.041)	(0.041)	(0.043)	(0.042)	(0.043)	(0.044)
Constant	-2.432***	-4.168***	-5.641***	-2.724***	-1.819***	-4.951***	-7.396***	-9.286***	-5.466***	-4.735***
	(0.548)	(0.464)	(0.507)	(0.483)	(0.625)	(0.777)	(0.712)	(0.774)	(0.721)	(0.890)
Observations	7,048	7,048	7,048	7,048	7,048	6,131	6,131	6,131	6,131	6,131
Loglik	-2,630.31	-2,585.90	-2,615.41	-2,597.57	-2,554.01	-2,134.57	-2,077.41	-2,109.55	-2,107.39	-2,052.92
Psuedo R^2	0.07	0.08	0.07	0.08	0.09	0.08	0.11	0.09	0.09	0.12

Notes: Dependent variable is an indicator for PPP loans pledged to the PPP Liquidity Facility at the end of the quarter. Sample is 2020:Q2 and 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019.
t statistic in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ratio. This effect is similar if we use only the share of small C&I loans– defined as those with origination amounts less than \$1 million– as shown in column (3). The effect is slightly larger if we use the share of unused C&I commitments shown in column (4). We find similar effects in the sample of smaller C& banks.

Finally, we find that banks with more cheap deposit funding are less likely to participate. For every 1 percentage point increase in the share of core deposits to assets, the log odds ratio of PPPLF participation decreases by about 0.3 points across specifications and samples. This suggests that banks that had access to cheaper funding sources were less likely to participate, all else equal. Thus, it seems that banks with more expensive funding costs were more likely to take advantage of the PPPLF's low interest rates in order to increase liquidity after participating in the PPP.

We next turn to the determinants of how much banks decided to rely on the PPPLF. To do so, we estimate an OLS model of the share of PPP loans pledged to the PPPLF against a set of bank characteristics as described previously. Rather than looking solely at the participation decision, this exercise tells us how intensively CBOs chose to participate in the PPPLF given their PPP lending level. The results of this exercise are shown in Table H7.

Table H7: PPPLF Participation Intensity Determinants

	All Banks					Banks < \$1 billion				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage Ratio	-0.610***				-0.542***	-0.632***				-0.516***
	(0.098)				(0.097)	(0.099)				(0.098)
CI to assets		0.519***			0.599***		0.657***			0.781***
		(0.059)			(0.114)		(0.067)			(0.132)
Small CI to assets			0.581***		-0.199			0.728***		-0.253
			(0.090)		(0.144)			(0.095)		(0.162)
Unused CI Commitments to Assets				0.604***	-0.019				0.688***	-0.073
				(0.103)	(0.136)				(0.114)	(0.145)
ln *Assets*	1.878***	1.594***	2.648***	1.420***	1.115***	2.442***	2.325***	3.532***	2.043***	1.753***
	(0.262)	(0.262)	(0.263)	(0.288)	(0.314)	(0.342)	(0.338)	(0.345)	(0.367)	(0.393)
ROA	-2.892***	-3.422***	-3.583***	-3.420***	-2.872***	-2.923***	-3.451***	-3.636***	-3.451***	-2.925***
	(0.739)	(0.702)	(0.715)	(0.721)	(0.720)	(0.769)	(0.725)	(0.742)	(0.750)	(0.741)
Core Deposits To Assets	-0.324***	-0.259***	-0.276***	-0.305***	-0.288***	-0.338***	-0.256***	-0.280***	-0.313***	-0.283***
	(0.035)	(0.032)	(0.033)	(0.033)	(0.034)	(0.036)	(0.034)	(0.035)	(0.035)	(0.035)
ALLL to Total Loans	-1.090***	-1.564***	-1.540***	-1.727***	-1.025***	-1.001***	-1.434***	-1.381***	-1.633***	-0.947**
	(0.381)	(0.384)	(0.389)	(0.391)	(0.380)	(0.381)	(0.381)	(0.385)	(0.393)	(0.377)
Cases Per 100k	0.140	0.062	0.106	0.122	0.070	0.274	0.215	0.244	0.265	0.220
	(0.294)	(0.290)	(0.292)	(0.293)	(0.290)	(0.303)	(0.299)	(0.301)	(0.301)	(0.299)
Constant	18.394***	7.041*	-3.390	15.292***	20.341***	12.729**	-3.381	-14.868***	7.988	10.765*
	(4.730)	(4.054)	(4.348)	(4.419)	(5.251)	(5.477)	(4.795)	(5.141)	(5.199)	(6.044)
Observations	6,935	6,935	6,935	6,935	6,935	6,020	6,020	6,020	6,020	6,020
Adjusted R2	0.041	0.056	0.046	0.044	0.059	0.047	0.070	0.056	0.050	0.074

Notes: Dependent variable is the share of PPP loans pledged to the PPP Liquidity Facility in 2020:Q2 and 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019. COVID cases are county level case counts averaged over counties where the bank operates a branch according to the Summary of Deposit data. Daily county-level COVID case counts are drawn from John Hopkins.
t statistic in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our findings on PPPLF intensity mirror those on the PPPLF participation decision. Better capitalized banks with more ALLL holdings and core deposit funding pledged a smaller share of their loans to the PPPLF. In addition, those with greater concentrations of C&I loans or shares of unused commitments pledged more loans. Thus we find a similar effect that banks that were likely to benefit were more likely to participate in the program at a greater level. The effects are similar for banks with total assets below \$1 billion as shown in columns (6) - (10).

In total, we find evidence that banks that were most likely to benefit from the two advantages presented by the PPPLF were more likely to participate. In particular, banks that relied on more expensive or less stable funding sources and those that were more capital constrained were more likely to use the facility. This suggests that the facility achieved its directives and likely helped to facilitate PPP lending by attracting a wider range of CBOs to participate. Absent the PPPLF, it is likely that many banks may have found PPP lending unprofitable given the low interest rate. Additionally, PPP lending may have taken up too much balance sheet space for many CBOs, putting them too close to their regulatory capital ratio minimums. By alleviating these concerns, the PPPLF likely made the PPP program more successful than it otherwise would have been.

I Quarterly Results from the Bayesian Model

Tables I8 and I9 provide results for the specifications presented in Table 2 for the quarters 2020:Q2 and 2020:Q3, respectively. Columns (1), (3), (5), (7), and (9) report the results for participation in the program. The results for each quarter are qualitatively similar to the combined results. In particular, larger banks were more likely to participate while more capitalized banks were less likely to participate across both quarters. In Q2 2020, when the first round of the PPP was in operation, more profitable banks were more likely to participate. This result continued to hold in Q3 2020, but the estimated effects were statistically weaker relatively to the previous quarter.

Columns (2), (4), (6), (8), and (10) report the results for PPP lending intensity. The results remain qualitatively similar with banks facing more C&I exposure typically making more PPP loans. Large and riskier banks– as measured by leverage capital ratios–also participated more intensively across quarters. In Q2 2020, more profitable banks participated more intensively in the PPP, but this relationship was weaker in Q3 2020. The share of COVID-affected employment was weakly associated with the intensity of participation in the estimations pertaining to NIM levels, but was statistically important and positive in all other specifications.

Tables I10 and I11 report results for Q2 and Q3 2020 respectively, under the specifications presented in Table 3. Columns (1), (3), (5), (7), and (9) report the results for participants. The results remain qualitatively similar with the results combined across quarters. The estimates in the first row show that incremental participation in the PPP diluted bank profitability. These results are weaker for the level of NIM in Q3, but retain the negative sign of the overall effect of PPP intensity on profitability. Banks that participated more intensively in the PPP experienced growth in their overall C&I loan portfolio as well as non-PPP C&I loans, with weaker growth in the latter category in Q3 2020. Finally, incremental participation in the PPP did not result in statistically important effects on risk-taking in either quarter. The results across the remaining control variables are consistent with the combined results across quarters, with one exception. Banks that were concentrated to a greater extent in C&I loans experienced a statistically important increases in NIM relative to 2019 in Q2 2020. This relationship reversed in Q3 2020, when banks with larger concentrations in C&I loans underwent statistically important declines in the change in NIM. This finding suggests that banks with a focus on C&I lending experienced a larger decline in NIM relative to 2019 during the second round of the PPP, at a time when lending was likely more targeted to firms that were affected by the pandemic than during the first round.

Columns (2), (4), (6), (8), and (10) report the coefficient estimates for non-participants. The results continue to be consistent with overall results in Table 3. Larger non-participants underwent declines in profitability as well as a decline in C&I and CRE loan growth. The effects of other controls are also consistent with overall results for both quarters. Tables I12 and I13 report the estimated covariances in Q2 and Q3 2020 respectively. These results are qualitatively similar to the overall results across the two quarters reported in Table E5. The decision to participate, and the intensity of participation are positively correlated across both quarters. Even though participation, and intensity of participation are positively related to profitability as measured by the change in NIM in the overall sample, these relationships become weakly negative in Q3 2020. This finding likely points to PPP lending that was less opportunistic, and more conservative in Q3 than in Q2 2020. The relationship between participation intensity and C&I loan growth continue to be positive and statistically important. PPP participation intensity was weakly negatively associated with growth in non-PPP C&I growth in Q2 2020. This relationship became statistically important in Q3 2020, suggesting that banks that participated more intensively in the second round cut back lending outside of the program. The decision to not participate in the PPP is negatively related to bank profitability and loan growth, or is only weakly positive across the two quarters.

Table I8: Results for participation and intensity from the Bayesian joint model in Q2 2020

	NIM		ΔNIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity
Small CI to assets	0.006		0		-0.002		0.002		0.001	
	[0, 0.01]		[-0.01, 0.01]		[-0.01, 0.01]		[0, 0.01]		[-0.01, 0.01]	
COVID-affected employment share		0.018		0.041		0.088		0.041		0.04
		[-0.01, 0.06]		[0.03, 0.06]		[0.06, 0.11]		[0.02, 0.06]		[0.02, 0.06]
ln Assets	0.164	1.173	0.165	1.204	0.121	0.804	0.141	1.055	0.186	1.229
	[0.12, 0.21]	[0.96, 1.38]	[0.12, 0.21]	[1.04, 1.37]	[0.09, 0.16]	[0.62, 0.98]	[0.11, 0.17]	[0.87, 1.23]	[0.15, 0.22]	[1.05, 1.4]
CI to assets	0.031	0.287	0.035	0.289	-0.023	0.359	0.034	0.293	0.034	0.285
	[0.02, 0.04]	[0.25, 0.32]	[0.03, 0.05]	[0.26, 0.32]	[-0.03, -0.01]	[0.33, 0.39]	[0.03, 0.04]	[0.26, 0.33]	[0.03, 0.04]	[0.25, 0.32]
Leverage Ratio	-0.051	-0.35	-0.048	-0.334	-0.026	-0.297	-0.044	-0.329	-0.046	-0.324
	[-0.06, -0.04]	[-0.43, -0.27]	[-0.06, -0.03]	[-0.41, -0.26]	[-0.04, -0.01]	[-0.38, -0.22]	[-0.06, -0.03]	[-0.4, -0.25]	[-0.06, -0.03]	[-0.4, -0.25]
Liquid Assets to Assets	0.008	0.072	0.007	0.073	-0.001	0.088	0.007	0.069	0.008	0.07
	[0, 0.01]	[0.05, 0.09]	[0, 0.01]	[0.05, 0.09]	[0, 0]	[0.07, 0.11]	[0, 0.01]	[0.05, 0.09]	[0, 0.01]	[0.05, 0.09]
ALLL to Total Loans	-0.029	0.018	-0.013	0.156	0.007	0.377	-0.039	0.029	-0.03	0.022
	[-0.09, 0.03]	[-0.32, 0.37]	[-0.08, 0.05]	[-0.19, 0.51]	[-0.04, 0.06]	[0.03, 0.72]	[-0.09, 0.01]	[-0.31, 0.38]	[-0.09, 0.03]	[-0.32, 0.37]
ROA	0.088	0.471	0.11	0.599	0.092	0.288	0.086	0.48	0.095	0.5
	[0.01, 0.16]	[0.08, 0.86]	[0.03, 0.19]	[0.23, 0.97]	[0.03, 0.16]	[-0.09, 0.66]	[0.02, 0.15]	[0.11, 0.84]	[0.03, 0.17]	[0.12, 0.88]
Cases Per 100k	0.027	-0.1	0.059	0.09	0.055	-0.102	0.006	-0.126	-0.005	-0.133
	[-0.08, 0.13]	[-0.65, 0.44]	[-0.04, 0.17]	[-0.42, 0.58]	[-0.02, 0.13]	[-0.61, 0.39]	[-0.08, 0.09]	[-0.63, 0.37]	[-0.09, 0.09]	[-0.64, 0.38]
Constant	-0.887	-8.166	-0.976	-9.576	-0.161	-6.128	-0.645	-7.366	-1.187	-9.545
	[-1.44, -0.32]	[-10.72, -5.58]	[-1.55, -0.41]	[-11.87, -7.38]	[-0.57, 0.29]	[-8.62, -3.67]	[-1.07, -0.19]	[-9.77, -4.97]	[-1.65, -0.69]	[-11.89, -7.14]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table I9: Results for participation and intensity from the Bayesian joint model in Q3 2020

	NIM		ΔNIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity
Small CI to assets	0.005		0.004		-0.003		-0.004		-0.001	
	[0, 0.01]		[-0.01, 0.01]		[-0.01, 0.01]		[-0.01, 0.01]		[-0.01, 0.01]	
COVID-affected employment share		-0.006		0.038		0.083		0.104		0.037
		[-0.01, 0]		[0.02, 0.06]		[0.06, 0.11]		[0.08, 0.13]		[0.02, 0.06]
ln Assets	0.159	1.165	0.162	1.108	0.142	0.773	0.198	0.509	0.171	1.173
	[0.12, 0.2]	[0.97, 1.35]	[0.12, 0.21]	[0.91, 1.3]	[0.11, 0.18]	[0.58, 0.96]	[0.16, 0.24]	[0.31, 0.7]	[0.13, 0.21]	[0.99, 1.36]
CI to assets	0.033	0.31	0.034	0.314	-0.018	0.389	-0.003	0.37	0.037	0.308
	[0.03, 0.04]	[0.28, 0.35]	[0.03, 0.04]	[0.28, 0.35]	[-0.03, -0.01]	[0.35, 0.42]	[-0.01, 0.01]	[0.34, 0.4]	[0.03, 0.04]	[0.27, 0.34]
Leverage Ratio	-0.047	-0.333	-0.044	-0.314	-0.02	-0.252	-0.033	-0.186	-0.043	-0.306
	[-0.06, -0.03]	[-0.42, -0.25]	[-0.06, -0.03]	[-0.4, -0.23]	[-0.03, -0.01]	[-0.33, -0.17]	[-0.05, -0.02]	[-0.27, -0.11]	[-0.06, -0.03]	[-0.39, -0.23]
Liquid Assets to Assets	0.007	0.074	0.007	0.072	-0.001	0.088	-0.006	0.098	0.007	0.071
	[0, 0.01]	[0.05, 0.09]	[0, 0.01]	[0.05, 0.09]	[0, 0]	[0.07, 0.11]	[-0.01, 0]	[0.08, 0.12]	[0, 0.01]	[0.05, 0.09]
ALLL to Total Loans	-0.026	0.142	-0.031	0.135	-0.001	0.464	-0.014	0.434	-0.017	0.206
	[-0.08, 0.03]	[-0.22, 0.5]	[-0.09, 0.03]	[-0.23, 0.5]	[-0.05, 0.05]	[0.11, 0.82]	[-0.07, 0.05]	[0.07, 0.79]	[-0.07, 0.04]	[-0.15, 0.56]
ROA	0.048	0.074	0.06	0.031	0.063	-0.038	0.113	-0.358	0.05	0.057
	[-0.02, 0.12]	[-0.32, 0.47]	[-0.02, 0.14]	[-0.38, 0.43]	[0.01, 0.12]	[-0.41, 0.33]	[0.04, 0.18]	[-0.74, 0.02]	[-0.02, 0.12]	[-0.32, 0.43]
Cases Per 100k	0.028	0.135	0.031	0.142	0.037	0.144	0.024	0.172	0.025	0.136
	[-0.02, 0.07]	[-0.11, 0.38]	[-0.01, 0.08]	[-0.09, 0.38]	[0, 0.08]	[-0.08, 0.37]	[-0.02, 0.07]	[-0.06, 0.4]	[-0.02, 0.07]	[-0.11, 0.38]
Constant	-0.873	-7.858	-0.943	-8.112	-0.508	-6.301	-0.722	-3.194	-1.041	-9.028
	[-1.42, -0.33]	[-10.44, -5.24]	[-1.51, -0.38]	[-10.76, -5.45]	[-0.92, -0.11]	[-8.83, -3.77]	[-1.21, -0.23]	[-5.76, -0.57]	[-1.49, -0.59]	[-11.44, -6.63]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table I10: Results for profitability and loan growth of participating and non-participating banks in Q2 2020

	NIM(ppt.)		ΔNIM(bps)		CI Gwth(%)		Non-PPP CI Gwth(%)		CRE Gwth(%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)
PPP Loans to Total Loans	-0.074		-6.653		10.623		0.36		0.271	
	[-0.3, 0.15]		[-8.63, -4.8]		[8.49, 12.69]		[-0.89, 1.75]		[-0.64, 1.29]	
ln Assets	-0.089	-0.302	5.19	0.618	5.787	-6.706	-0.409	-6.013	0.383	-3.626
	[-0.36, 0.19]	[-0.37, -0.23]	[3.76, 6.75]	[-4.66, 4.36]	[4.41, 7.3]	[-7.92, -5.49]	[-1.55, 0.61]	[-7.32, -4.86]	[-0.59, 1.28]	[-4.47, -2.77]
CI to assets	0.027	-0.02	1.33	0.267	-7.049	1.284	0.012	-1.736	0.057	-1.137
	[-0.04, 0.09]	[-0.03, -0.01]	[0.72, 1.99]	[-1.12, 1.36]	[-7.86, -6.2]	[0.79, 1.79]	[-0.41, 0.39]	[-2.19, -1.28]	[-0.24, 0.33]	[-1.44, -0.86]
Leverage Ratio	-0.054	0.007	-3.667	-0.3	-0.097	0.674	0.235	1.732	0.379	0.934
	[-0.14, 0.03]	[-0.01, 0.02]	[-4.78, -2.64]	[-1.59, 1.11]	[-1.2, 0.96]	[-0.11, 1.45]	[-0.32, 0.86]	[0.92, 2.52]	[-0.03, 0.83]	[0.41, 1.46]
Liquid Assets to Assets	-0.016	-0.028	0.218	-0.29	-0.715	-0.119	0.025	-0.498	-0.057	-0.217
	[-0.03, 0]	[-0.03, -0.02]	[0.01, 0.44]	[-0.64, 0.04]	[-0.98, -0.43]	[-0.35, 0.11]	[-0.09, 0.13]	[-0.74, -0.23]	[-0.14, 0.02]	[-0.37, -0.07]
ALLL to Total Loans	-0.002	0.014	-2.998	-9.145	-3.819	-2.022	-2.652	0.252	-0.269	-0.567
	[-0.07, 0.07]	[-0.05, 0.08]	[-6.04, 0.04]	[-12.4, -5.78]	[-7.12, -0.55]	[-5.16, 1.19]	[-3.96, -1.33]	[-2.83, 3.33]	[-1.27, 0.72]	[-2.77, 1.55]
ROA	0.29	0.179	-6.039	-0.509	1.179	-0.637	-1.965	-0.804	-2.279	0.669
	[0.16, 0.44]	[0.08, 0.28]	[-9.48, -2.55]	[-4.94, 3.83]	[-2.21, 4.67]	[-4.43, 3.14]	[-3.52, -0.39]	[-4.74, 3.09]	[-3.43, -1.13]	[-2.15, 3.42]
Cases Per 100k	-0.115	-0.114	-3.068	-2.987	6.069	-3.004	0.251	-2.061	-0.083	-1.586
	[-0.24, -0.01]	[-0.29, 0.06]	[-7.03, 0.97]	[-8.34, 2.43]	[1.8, 10.31]	[-7.87, 1.8]	[-1.54, 2.08]	[-6.77, 2.77]	[-1.49, 1.33]	[-5.58, 2.35]
Constant	5.735	6.399	1.967	-0.493	0.198	-0.471	2.046	0.318	-0.671	-1.571
	[3.73, 7.65]	[5.55, 7.26]	[-4.2, 8.09]	[-6.64, 5.75]	[-5.87, 6.32]	[-6.5, 5.56]	[-3.9, 7.96]	[-5.83, 6.39]	[-6.44, 5.23]	[-7.63, 4.43]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table I11: Results for profitability and loan growth of participating and non-participating banks in Q3 2020

	NIM(ppt.)		ΔNIM(bps)		CI Gwth(%)		Non-PPP CI Gwth(%)		CRE Gwth(%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)
PPP Loans to Total Loans	-0.506		-0.463		9.544		0.841		0.284	
	[-0.72, -0.23]		[-2.42, 1.6]		[8.23, 10.84]		[0.19, 1.63]		[-0.68, 1.31]	
ln Assets	0.455	-0.295	0.942	-1.906	6.537	-7.254	-0.083	-9.781	0.267	-3.581
	[0.12, 0.75]	[-0.37, -0.22]	[-0.62, 2.44]	[-6.02, 3.07]	[5.39, 7.67]	[-8.61, -5.99]	[-0.7, 0.51]	[-11.48, -8.25]	[-0.67, 1.18]	[-4.5, -2.67]
CI to assets	0.159	-0.016	-1.037	-0.343	-6.724	1.136	-0.229	0.423	0.109	-1.101
	[0.07, 0.23]	[-0.03, 0]	[-1.7, -0.39]	[-1.54, 1.07]	[-7.35, -6.09]	[0.62, 1.67]	[-0.54, 0.04]	[-0.1, 0.93]	[-0.22, 0.42]	[-1.4, -0.81]
Leverage Ratio	-0.186	0.02	-0.887	-0.843	-0.548	0.797	-0.223	1.607	0.226	1.038
	[-0.28, -0.09]	[0, 0.04]	[-1.83, 0.04]	[-2.32, 0.52]	[-1.43, 0.34]	[-0.07, 1.66]	[-0.56, 0.12]	[0.63, 2.62]	[-0.19, 0.67]	[0.46, 1.62]
Liquid Assets to Assets	0.014	-0.027	-0.463	-0.376	-0.739	-0.055	-0.125	0.279	-0.022	-0.259
	[-0.01, 0.04]	[-0.03, -0.02]	[-0.64, -0.29]	[-0.75, 0.01]	[-0.97, -0.5]	[-0.3, 0.19]	[-0.23, -0.02]	[0.01, 0.56]	[-0.11, 0.06]	[-0.42, -0.09]
ALLL to Total Loans	0.087	-0.023	-3.202	-7.644	-2.595	-2.132	-3.153	-1.284	-0.787	-0.891
	[-0.1, 0.3]	[-0.09, 0.04]	[-5.45, -0.95]	[-11.16, -4.08]	[-5.81, 0.62]	[-5.39, 1.01]	[-4.56, -1.75]	[-4.84, 2.2]	[-1.81, 0.25]	[-3.21, 1.36]
ROA	0.255	0.3	-11.97	-0.798	0.812	0.231	-0.694	-1.915	-1.437	0.209
	[0.04, 0.48]	[0.19, 0.41]	[-14.33, -9.62]	[-5.45, 3.96]	[-2.57, 4.19]	[-3.72, 4.09]	[-2.16, 0.8]	[-6.17, 2.41]	[-2.48, -0.38]	[-2.77, 3.15]
Cases Per 100k	0.087	0.039	-1.576	-1.502	2.901	-2.114	-0.134	-1.796	-0.019	-1.046
	[-0.04, 0.24]	[-0.03, 0.11]	[-3.12, -0.09]	[-5.4, 2.36]	[0.56, 5.24]	[-5.07, 0.7]	[-1.08, 0.81]	[-4.98, 1.44]	[-0.67, 0.64]	[-3.16, 0.98]
Constant	1.472	5.923	-1.655	-0.128	-0.063	-1.086	-0.671	-0.599	0.913	-1.42
	[-1.08, 3.89]	[5.07, 6.75]	[-7.74, 4.46]	[-6.28, 5.86]	[-6.23, 6.06]	[-7.34, 4.99]	[-6.18, 4.84]	[-6.71, 5.5]	[-4.94, 6.74]	[-7.57, 4.68]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table I12: Covariance estimates from the Bayesian joint model based on Q2 2020 outcomes

	NIM	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	6.789	6.739	3.544	6.722	6.751
	[6.62, 6.96]	[6.57, 6.92]	[3.06, 3.97]	[6.56, 6.94]	[6.59, 6.93]
COV(participation, bank outcome)	0.524	34.249	64.993	-2.345	-0.655
	[-1.01, 2.08]	[21.34, 48.03]	[56.18, 74.1]	[-12.34, 6.9]	[-7.52, 5.46]
COV(intensity, bank outcome)	3.785	267.811	46.4	-24.87	-5.465
	[-6.9, 14.65]	[180.07, 361.03]	[-36.68, 136.2]	[-92.35, 34.46]	[-53.23, 36.9]
COV(non-participation, bank outcome)	-0.8	15.648	-56.877	-58.002	-34.39
	[-0.98, -0.61]	[-27.4, 44.22]	[-62.14, -51.86]	[-63.35, -52.87]	[-38.25, -30.29]

Table I13: Covariance estimates from the Bayesian joint model based on Q3 2020 outcomes

	NIM	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	6.994	6.911	3.715	-0.378	6.935
	[6.85, 7.15]	[6.73, 7.1]	[3.28, 4.1]	[-1.08, 0.38]	[6.77, 7.11]
COV(participation, bank outcome)	3.538	-10.534	67.787	23.19	-0.454
	[1.65, 5.03]	[-25.21, 3.05]	[62.74, 72.82]	[21.63, 24.66]	[-7.4, 6.29]
COV(intensity, bank outcome)	25.251	-56.874	107.205	-40.042	-3.597
	[11.78, 35.93]	[-161.07, 39.75]	[48.15, 164.43]	[-72.67, -11.88]	[-53.88, 44.4]
COV(non-participation, bank outcome)	-0.777	-7.803	-59.388	-61.262	-36.059
	[-0.99, -0.43]	[-41.08, 32.82]	[-65.07, -54.06]	[-67.31, -55.76]	[-39.86, -32.27]

J 2020:Q4 Results from the Bayesian Model

Table J14 reports the results for participation and intensity from Q4 2020. PPP balances in this quarter reflect total balances from previous quarters, and changes due to forgiveness and repayments. Columns (1), (3), (5), (7), and (9) report results for participation. Larger, and less capitalized banks continue to be associated with greater intensity and participation. However, the relationship between profitability, and PPP participation is weaker than in the main results. Participation in this specification is based on participation in Q2 and Q3 of 2020, and is thereby identical to the outcome in the main specification. The control variables are also identical to the main specifications. Therefore, differences from the main results arise from changes in PPP intensity, and final outcomes.

Columns (2), (4), (6), (8), and (10) report results for the intensity of PPP participation. These results are consistent with the main findings–larger, less capitalized banks were associated with larger PPP loan shares. This suggests that this group of banks retained greater shares of PPP loans even after forgiveness was initiated. As in the case of participation, we find the weaker relationship between ROA and PPP intensity in the Q4. This result entails that banks that were more profitable in 2019 participated more intensively in the earlier rounds, and booked loans that became eligible for forgiveness earlier in the program.

Table J15 reports the results for bank profitability, and loan growth for participants and non-participants. Columns (1), (3), (5), (7), and (9) report the results of bank outcomes for participants. The most notable results are that change in NIM was statistically larger, at 6.28 basis points for participants for every percentage point increase in PPP share intensity. This shows that the downward pressures of PPP on net interest margins were largely transitory. Banks that participated more intensively in the program began to recover margins as forgiveness progressed. Non-PPP C&I growth declined, and CRE growth increased with the share of PPP loans to total loans. Banks that participated intensively in the program in earlier quarters likely began to diversify their portfolio and engage in risk-taking by booking CRE loans.

Columns (2), (4), (6), (8), and (10) report the results for bank profitability, and loan growth among non-participants. These findings are consistent with the results from the main specification. Larger non-participants underwent larger declines in profitability and loan growth. Non-participants with larger capital buffers, and concentrations of C&I loans underwent a growth in this category of loans, but a decline in CRE loan growth. This suggests that non-participants specialized in C&I lending continued to extend this category of loans throughout the pandemic, and the recovery.

Table J16 summarizes the covariances across the four equations in our Bayesian joint model. The estimates are broadly consistent with the main results. Participation and the intensity of participation are positively related, and are also broadly positively related to bank outcomes. The main exception to this finding is that change in NIM is negatively associated with participation, and the intensity of participation. This likely reflects the effects of the forgiveness program, which resulted in the reversal of previous relationships between participation and intensity, with profitability. Banks that were able to access forgiveness and scale down their share of PPP loans earned larger interest margins by recognizing fees along with interest. Unobservables underlying non-participation were negatively related to unobservables related to profitability, and loan growth as in the case of the main results.

Table J14: Results for participation and intensity from the Bayesian joint model in Q4 2020

	NIM		ΔNIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity
Small CI to assets	-0.001		0		-0.003		0.001		-0.003	
	[-0.01, 0.01]		[-0.01, 0.01]		[-0.01, 0.01]		[-0.01, 0.01]		[-0.01, 0]	
COVID-affected employment share		-0.008		0.021		0.049		0.021		0.024
		[-0.01, 0]		[0.01, 0.03]		[0.03, 0.07]		[0.01, 0.03]		[0.01, 0.04]
ln Assets	0.175	1.137	0.185	1.15	0.141	0.88	0.156	1.034	0.166	1.071
	[0.13, 0.21]	[0.97, 1.3]	[0.14, 0.23]	[1, 1.31]	[0.11, 0.17]	[0.71, 1.05]	[0.13, 0.19]	[0.88, 1.18]	[0.13, 0.2]	[0.92, 1.22]
CI to assets	0.04	0.265	0.04	0.266	-0.014	0.329	0.039	0.268	0.04	0.263
	[0.03, 0.05]	[0.24, 0.29]	[0.03, 0.05]	[0.24, 0.29]	[-0.02, 0]	[0.3, 0.36]	[0.03, 0.05]	[0.24, 0.3]	[0.03, 0.05]	[0.23, 0.29]
Leverage Ratio	-0.023	-0.133	-0.02	-0.119	-0.01	-0.103	-0.022	-0.131	-0.026	-0.139
	[-0.04, -0.01]	[-0.2, -0.07]	[-0.03, -0.01]	[-0.18, -0.06]	[-0.02, 0]	[-0.17, -0.04]	[-0.03, -0.01]	[-0.19, -0.07]	[-0.04, -0.01]	[-0.2, -0.08]
Liquid Assets to Assets	0.006	0.052	0.006	0.051	0	0.06	0.006	0.051	0.006	0.05
	[0, 0.01]	[0.04, 0.07]	[0, 0.01]	[0.03, 0.07]	[0, 0]	[0.04, 0.08]	[0, 0.01]	[0.03, 0.07]	[0, 0.01]	[0.03, 0.07]
ALLL to Total Loans	-0.005	0.011	-0.011	-0.002	0.004	0.315	-0.018	-0.014	-0.001	0.051
	[-0.06, 0.05]	[-0.28, 0.31]	[-0.06, 0.04]	[-0.29, 0.29]	[-0.05, 0.06]	[0.01, 0.63]	[-0.07, 0.03]	[-0.28, 0.25]	[-0.05, 0.05]	[-0.23, 0.33]
ROA	0.032	-0.061	-0.004	-0.279	0.045	-0.057	0.047	0.02	0.048	-0.015
	[-0.03, 0.1]	[-0.36, 0.23]	[-0.06, 0.06]	[-0.56, 0.01]	[-0.01, 0.1]	[-0.35, 0.24]	[-0.01, 0.11]	[-0.26, 0.3]	[-0.01, 0.11]	[-0.31, 0.28]
Cases Per 100k	-0.051	-0.421	-0.043	-0.376	-0.026	-0.436	-0.053	-0.414	-0.049	-0.402
	[-0.08, -0.03]	[-0.54, -0.31]	[-0.07, -0.02]	[-0.49, -0.26]	[-0.05, 0]	[-0.55, -0.32]	[-0.08, -0.03]	[-0.53, -0.3]	[-0.07, -0.02]	[-0.52, -0.29]
Constant	-1.226	-9.044	-1.37	-9.82	-0.52	-8.04	-1.005	-8.413	-1.096	-8.881
	[-1.76, -0.66]	[-11.35, -6.71]	[-1.96, -0.81]	[-12.1, -7.63]	[-0.95, -0.1]	[-10.36, -5.73]	[-1.42, -0.6]	[-10.45, -6.35]	[-1.55, -0.64]	[-11.04, -6.72]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table J15: Results for profitability and loan growth of participating and non-participating banks in Q4 2020

	NIM(ppt.)		ΔNIM(bps)		CI Gwth(%)		Non-PPP CI Gwth(%)		CRE Gwth(%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)
PPP Loans to Total Loans	-0.625		6.275		9.475		-1.505		1.157	
	[-0.75, -0.41]		[3.62, 9.05]		[7.04, 12.12]		[-2.82, -0.21]		[0.25, 2.18]	
ln Assets	0.62	-0.161	-1.717	-1.271	5.1	-6.56	0.697	-5.587	-0.098	-2.807
	[0.38, 0.81]	[-0.28, -0.03]	[-3.58, 0.07]	[-5.6, 3.44]	[3.56, 6.45]	[-7.83, -5.31]	[-0.27, 1.71]	[-6.77, -4.43]	[-0.95, 0.7]	[-3.68, -1.96]
CI to assets	0.172	0.007	-2.478	-0.129	-4.915	0.771	0.331	-1.746	-0.068	-1.175
	[0.11, 0.21]	[-0.02, 0.03]	[-3.31, -1.71]	[-1.58, 1.43]	[-5.85, -4.08]	[0.16, 1.27]	[-0.04, 0.71]	[-2.15, -1.36]	[-0.36, 0.2]	[-1.45, -0.91]
Leverage Ratio	-0.094	0.003	-0.091	-1.553	0.164	0.152	0.29	0.753	0.635	0.074
	[-0.14, -0.05]	[-0.02, 0.02]	[-0.94, 0.83]	[-2.88, -0.22]	[-0.55, 0.89]	[-0.63, 0.93]	[-0.12, 0.66]	[0.03, 1.5]	[0.36, 0.93]	[-0.43, 0.58]
Liquid Assets to Assets	0.008	-0.025	-0.937	-0.195	-0.492	-0.073	0.055	-0.316	-0.045	-0.157
	[-0.01, 0.02]	[-0.03, -0.02]	[-1.16, -0.73]	[-0.6, 0.21]	[-0.71, -0.28]	[-0.29, 0.14]	[-0.04, 0.15]	[-0.52, -0.11]	[-0.12, 0.02]	[-0.3, -0.01]
ALLL to Total Loans	0.033	-0.039	-3.286	-7.778	-3.966	-1.97	-3.019	-0.877	-1.317	-0.824
	[-0.16, 0.22]	[-0.1, 0.02]	[-6.39, -0.18]	[-11.75, -3.79]	[-6.74, -1.14]	[-4.96, 0.95]	[-4.44, -1.62]	[-3.62, 1.83]	[-2.34, -0.31]	[-2.77, 1.09]
ROA	0.076	0.181	-13.675	-2.719	0.025	1.925	-2.338	1.699	-2.496	1.31
	[-0.11, 0.26]	[0.1, 0.26]	[-16.78, -10.41]	[-7.28, 1.87]	[-2.72, 2.8]	[-1.3, 5.16]	[-3.65, -1.01]	[-1.52, 4.98]	[-3.47, -1.51]	[-1.01, 3.69]
Cases Per 100k	-0.299	-0.015	2.243	-1.101	-1.75	0.912	-1.086	2.233	0.168	1.016
	[-0.4, -0.2]	[-0.07, 0.04]	[0.5, 4.21]	[-4.28, 2.05]	[-3.52, 0.2]	[-0.92, 2.77]	[-1.98, -0.25]	[0.53, 3.93]	[-0.41, 0.82]	[-0.23, 2.25]
Constant	-0.618	5.409	-0.759	-0.775	-0.157	-0.492	1.069	0.565	0.588	0.255
	[-2.65, 1.45]	[4.54, 6.28]	[-6.79, 5.35]	[-6.9, 5.28]	[-6.3, 5.91]	[-6.66, 5.69]	[-5.03, 7.02]	[-5.6, 6.75]	[-5.23, 6.48]	[-5.66, 6.15]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table J16: Covariance estimates from the Bayesian joint model based on Q4 2020 outcomes

	NIM	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	5.825	5.808	3.779	5.816	5.81
	[5.68, 5.96]	[5.67, 5.95]	[3.09, 4.71]	[5.69, 5.96]	[5.66, 5.95]
COV(participation, bank outcome)	3.672	-45.167	48.141	9.219	-5.732
	[2.43, 4.39]	[-61.41, -29.67]	[38.98, 57.42]	[1.59, 16.82]	[-11.63, -0.5]
COV(intensity, bank outcome)	21.742	-261.156	52.126	51.591	-33.293
	[14.45, 25.99]	[-359.06, -168.82]	[-32.07, 127.43]	[6.84, 96.55]	[-68.21, -2.24]
COV(non-participation, bank outcome)	-0.156	-2.022	-51.442	-50.976	-32.961
	[-0.79, 0.62]	[-40.38, 39.26]	[-56.67, -46.34]	[-56.28, -46.04]	[-36.46, -29.66]

K Robustness: OLS and IV results

As a check on our Bayesian analysis, we estimate our key results using classical OLS and two-stage least squares methods. We consider similar instruments to those used in the joint Bayesian model as described below in the 2SLS model. Our participation and intensity regressions are estimated separately using a logit and OLS framework, respectively. These estimations may be more familiar to readers but require stronger identification assumptions in some cases, such as the requirements on instruments for 2SLS. Broadly, our results using these estimation procedures are similar to those generated by the Bayesian joint model.

K.1 Logit, OLS, and TSLS Estimation Setup

To formally test for participation characteristics, we estimate a logit regression using Call Report data for the second and third quarters of 2020. The dependent variable takes a value of one if the bank reported having PPP loans outstanding as-of quarter end and zero otherwise. We regress this variable on a set of bank characteristics that capture capital levels, funding types, size, and business lending concentration.

We estimate the effect of bank characteristics on PPP participation intensity using an OLS model. The dependent variable in this model is PPP loans outstanding as a share of total loans. We consider similar bank characteristics in this estimation as in the participation logit, namely pre-pandmeic levels of bank capital, funding types, lending concentrations, and size.

Finally, we adopt an instrumental variable framework to address the issue of endogeneity in the intensity of participation relative to observed bank outcomes. The source of this endogeneity is the simultaneous determination of PPP intensity, bank loan growth, and profitability. Banks are likely to have adjusted the size of their loan portfolios and accordingly, determined the extent of participation in the PPP with the ultimate objective of maximizing profits. We address this simultaneity in the determination of bank outcomes and PPP intensity by using an instrument that isolates variation in the intensity of bank participation due to firm demand for loans rather than from bank supply decisions. Specifically, we intend to measure the exogenous variation in firm demand for PPP loans induced by economic disruptions due to the COVID-19 pandemic, and associated containment efforts.

We implement the instrumental variable approach by using two-stage least squares (TSLS). The first stage of this approach estimates the relationship between PPP-intensity and the instrument $Z_{emp,i}$,

$$PPP_i = Z_{emp,i}\pi + W_i'\psi + \nu_i. \tag{10}$$

The second stage estimates the effect of the extent of PPP lending that is explained by the instrument on bank outcomes,

$$Y_i = P\hat{P}P_i\beta + W_i'\gamma + \epsilon_i. \tag{11}$$

where Y_i denotes net interest margins, change in net interest margins relative to 2019, growth in C&I loans, growth in C&I loans outside of the PPP, and growth in CRE loans in separate regressions for each outcome. PPP_i measures the share of PPP loans to total loans and leases of bank i. W_i is a set of control variables consisting of the share of business loans to assets, size, return on assets, leverage ratio, the share of loss allowances to assets, liquid assets, and the deposit-weighted share of COVID cases per 100,000 population in a bank's region of operation.

The main exclusion restriction, $E[\epsilon_i Z_{emp,i}|W_i] = 0$, is that the deposit-weighted share of employment in contact-sensitive sectors does not directly affect bank profitability and loan growth outside of the PPP. This measure disrupts the simultaneity in the determination of bank outcomes and PPP intensity by delineating the variation in participation intensity that arises from firm demand for loans under the program. Bartik et al. [2020] reported survey results that showed that firms in COVID-affected sectors such as retail and hospitality constituted the largest shares of applicants for PPP loans. Crucially, the survey responses indicate that approval rates did not vary substantially by sector, which entails that these sectors were over-represented among recipients of PPP loans. Therefore, the share of COVID-affected sectors in a bank's region of operation manifests demand rather than strategic supply considerations of banks.

Banks' existing loans to COVID-affected sectors expose a potential channel for violating the exclusion restriction. When borrowers are unable to service existing loans, bank profitability and loan growth decline, particularly if the loans remain unpaid to the extent that they are charged off. In this context, the exclusion restriction requires that the deposit-weighted employment in COVID-affected sectors does not mirror the share of existing bank loans to such sectors. This requirement is met as long as certain banks specialize more heavily than others in lending to sectors such as retail and hospitality irrespective of the sectoral composition of firms in their region of operation.

We construct an alternate set of instruments that exploit the terms of the PPP to address endogeneity emanating from bank incentives for participation. We use the fraction of firms with fewer than 500 employees per county weighted by bank deposits to determine the share of eligible firms in a bank's operating region. Other instruments we consider are the share of unused commitments and the share of core deposits to total assets. These measures approximate the presence of existing relationships with firms that would have expedited the PPP application process for borrowers. Li and Strahan [2020] found that both of these measures were important predictors of PPP lending among small banks. This finding supports our use of these measures as relevant instruments for explaining PPP lending. Berger and Udell [1995] uncover the informational value of unused commitments to banks in that over time, these products enable lenders to overcome the problems of asymmetric information in lending to small firms. These instruments have the drawback that they absorb bank incentives to preserve the quality of their loans by lending to existing borrowers. We disentangle the effects of relationship lending and emergency pandemic lending by assessing the variation in treatment effects across instruments.

K.2 Logit Participation Results

Table K17 shows the results of the logit estimation. Column (1) shows no statistically significant association between C&I loan concentration, measured as the share of commercial loans to assets, and PPP participation. Similarly, the relationship between business lending and participation is also not significant when we consider only small C&I loans– outstanding loans with original amounts less than $1 million– in column (2). We do, however, find a strong and statistically significant relationship in column (3) when we consider the share of committed but undrawn C&I loan commitments. In this specification, a percentage point increase in unused C&I commitments relative to assets increases the log odds ratio of participation by about 0.11 points. In column (4), we consider a model that includes all these C&I loan measures which confirms that unused commitments on C&I loans are the best predictor of the three for PPP participation.

Table K17: PPP Participation Determinants

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.000			-0.013	0.002			0.005
	(0.008)			(0.018)	(0.008)			(0.021)
Small CI to assets		-0.008		-0.006		-0.010		-0.025
		(0.009)		(0.020)		(0.009)		(0.022)
Unused CI Commitments to Assets			0.111***	0.128***			0.111***	0.119***
			(0.027)	(0.030)			(0.027)	(0.029)
ln *Assets*	0.721***	0.710***	0.633***	0.611***	0.745***	0.731***	0.664***	0.621***
	(0.045)	(0.046)	(0.051)	(0.053)	(0.048)	(0.049)	(0.053)	(0.057)
ROA	0.308***	0.314***	0.322***	0.331***	0.298***	0.306***	0.312***	0.331***
	(0.063)	(0.063)	(0.064)	(0.064)	(0.063)	(0.063)	(0.064)	(0.064)
Liquid Assets To Assets	-0.011***	-0.012***	-0.009***	-0.011***	-0.011***	-0.012***	-0.008***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Leverage Ratio	-0.071***	-0.072***	-0.069***	-0.070***	-0.066***	-0.067***	-0.064***	-0.066***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ALLL to Total Loans	-0.032	-0.023	-0.032	-0.008	-0.045	-0.032	-0.042	-0.020
	(0.052)	(0.047)	(0.051)	(0.043)	(0.051)	(0.046)	(0.049)	(0.042)
Cases Per 100k	-0.016	-0.014	-0.020	-0.016	-0.013	-0.011	-0.017	-0.014
	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)	(0.042)	(0.041)	(0.041)
Constant	-5.782***	-5.579***	-5.081***	-4.695***	-6.120***	-5.850***	-5.481***	-4.853***
	(0.582)	(0.604)	(0.608)	(0.644)	(0.605)	(0.632)	(0.628)	(0.683)
Observations	7,786	7,786	7,786	7,786	6,854	6,854	6,854	6,854
Loglik	-2,372.52	-2,371.91	-2,351.34	-2,347.62	-2,284.67	-2,283.85	-2,264.95	-2,261.22
Psuedo R^2	0.12	0.12	0.12	0.13	0.10	0.10	0.11	0.11

Notes: Dependent variable is an indicator for PPP loan outstanding at the end of the quarter. Sample is 2020:Q2 and 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Among other characteristics, Table K17 shows that larger and more profitable banks were more likely to participate. A one percentage point increase in bank assets is associated with about an 0.8 point increase in the log odds ratio of PPP participation across specifications. Similarly, a one percentage point increase in a bank's return on assets (ROA) increases the log odds ratio of participation by about 0.3 points across specifications.

Similar to our findings that lending concentrations were important drivers of participation, we also find that banks with greater holdings of liquid assets were less likely to participate. For each 1 percentage point increase in the share of liquid assets to total assets, we find that the probability of participation declines by 0.01 log odd points.

Somewhat counter to our findings that more financially viable banks were likely to participate, we find the opposite result regarding capital and loan loss allowance. In this case, we find that better capitalized banks as measured by higher leverage ratios were less likely to participate. The log odds ratio of participation declines by a somewhat modest 0.07 points for each 1 percentage point increase in the leverage ratio, though this effect is statistically significant. Similarly, banks that have reserved more allowance for loan losses as a share of total loans appear to have been less likely to participate. For each percentage point increase in the allowance stock to total loans, the log odds ratio of participation declines about 0.03 points. This relationship is not statistically significant though.

The COVID crisis itself seems to have had little impact on a bank's decision of whether or not to participate in PPP lending. Across all specifications, the deposit-weighted COVID case variable is statistically insignificant meaning that local COVID cases in a bank's operating area was not an important participation determinant. Columns (5) - (8) confirm that our results hold for the smallest of community banks, those with total assets less than $1 billion. Qualitatively, our results are similar to the full sample with larger and more profitable banks more likely to contribute. However, less capitalized banks and those with greater exposure to business line draws were also more likely to participate. The parameter estimates across these specifications are similar in magnitude to the full sample as well.

K.3 OLS Participation Intensity Results

We next turn to how much participants decided to participate. We use the share of PPP loans outstanding to total loans outstanding to determine a bank's PPP participation intensity. These regressions tell us how the level of PPP participation varied conditional on the set of bank characteristics. The results are shown in Table K18.

Table K18: PPP Participation Intensity Determinants

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.351***			0.125***	0.429***			0.261***
	(0.022)			(0.038)	(0.025)			(0.047)
Small CI to assets		0.440***		0.148***		0.491***		0.047
		(0.042)		(0.054)		(0.040)		(0.059)
Unused CI Commitments to Assets			0.749***	0.557***			0.825***	0.537***
			(0.034)	(0.051)			(0.041)	(0.058)
ln *Assets*	0.770***	1.526***	0.204***	0.473***	1.517***	2.314***	0.843***	1.086***
	(0.072)	(0.086)	(0.079)	(0.104)	(0.106)	(0.119)	(0.115)	(0.135)
ROA	-0.246	-0.422	-0.287	-0.289	-0.415	-0.605**	-0.448	-0.409
	(0.273)	(0.284)	(0.286)	(0.281)	(0.284)	(0.299)	(0.302)	(0.291)
Liquid Assets To Assets	0.103***	0.094***	0.083***	0.104***	0.116***	0.101***	0.088***	0.115***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Leverage Ratio	-0.212***	-0.181***	-0.224***	-0.195***	-0.173***	-0.146***	-0.204***	-0.172***
	(0.034)	(0.036)	(0.033)	(0.033)	(0.034)	(0.036)	(0.033)	(0.033)
ALLL to Total Loans	0.364**	0.406**	0.353**	0.329**	0.192	0.266	0.228	0.181
	(0.164)	(0.167)	(0.175)	(0.168)	(0.165)	(0.170)	(0.183)	(0.170)
Cases Per 100k	0.108	0.146*	0.196**	0.150*	0.181**	0.216**	0.270***	0.213**
	(0.084)	(0.086)	(0.083)	(0.081)	(0.089)	(0.092)	(0.089)	(0.087)
Constant	-4.203***	-12.987***	4.064***	-1.316	-14.140***	-22.930***	-3.795**	-9.330***
	(1.098)	(1.522)	(1.151)	(1.617)	(1.526)	(1.842)	(1.592)	(1.967)
Observations	7,048	7,048	7,048	7,048	6,131	6,131	6,131	6,131
Adjusted R2	0.148	0.107	0.166	0.191	0.185	0.129	0.180	0.220

Notes: Dependent variable is PPP loans as a share of total loans in 2020:Q2 and 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019. COVID cases are county level case counts averaged over counties where the bank operates a branch according to the Summary of Deposit data. Daily county-level COVID case counts are drawn from John Hopkins.
t statistic in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Contrary to the logit model for PPP participation, the concentration of C&I lending on a bank's balance sheet seems to more strongly predict how intensively the bank participated in PPP lending. Columns (1) - (4) repeat the previous exercise of considering each C&I loan exposure measure individually and then jointly. Column (1) shows that a one percentage point increase in a bank's C&I exposure as a share of total assets is associated with about a 35 basis point increase in PPP lending relative to total loans. Similarly, an increase in a bank's share of small C&I lending–

often used as a proxy for small business lending– is associated with about a 44 basis point increase in relative PPP lending. This is slightly higher than the overall C&I lending effect, suggesting that small loans may proxy for existing relationships with eligible PPP customers, a result discussed by Li and Strahan [2020]. Finally, column (3) shows that unused C&I commitments relative to total assets is also a statistically significant predictor of PPP participation intensity and it is qualitatively larger than the coefficients on C&I concentration ratios. We jointly consider all these C&I loan measures in column (4). All the C&I lending concentration measures remain statistically significant and positive, with unused C&I commitments being the strongest predictor of PPP intensity as measured by coefficient size. We interpret this as a signal of the risk-aversion channel that PPP provided because undrawn C&I commitments are an ex-ante measure of C&I liquidity and credit risk.

Regarding other characteristics, similar to the logit regressions on participation, we find that larger banks were more likely to make more PPP loans as a share of total loans. However, more profitable banks were less likely to participate as intensively though this effect is not statistically significant. Banks with larger liquid asset holdings, however, did participate more intensively, contrary to the participation results.

Our remaining regressors provide more evidence of a risk-aversion channel. Banks with more allowance against loan losses were likely to participate more intensively, contrary to our findings on participation alone, while capital ratios remain a negative predictor of participation intensity. Both greater ALLL holdings relative to loans and lower capital ratios provide measures of risk. For ALLL, banks are required to hold larger ALLL stocks when larger losses are more likely. Similarly, banks with smaller capital bases will be more threatened by outsized loan losses emanating from the pandemic's economic effects.

In the next to last row, we consider a bank's local exposure to COVID cases. Across specifications we find that banks with greater local exposure to COVID made more PPP loans as a share of total loans across the period when the program was active. However, in some specifications and samples the finding is only weakly significant or even insignificant. Nonetheless, this result provides yet more evidence that

PPP provided some protection from potential risks related to the pandemic.

Columns (5) - (8) report results for the same specification for banks with less than $1 billion in total assets. The results here are qualitatively similar to the full sample results. Specifically, banks with more C&I loan exposure or those facing more drawdown risk were more likely to make more PPP loans. Similarly, larger banks and those with more liquid asset holdings made relatively more loans. However, more profitable banks and better capitalized banks made fewer loans as a share of total lending. COVID case exposure is a slightly more significant predictor of lending intensity among smaller community banks than it is for the sample as a whole.[16]

K.4 TSLS Balance Sheet Impact Results

We evaluate the effects of increased intensity of participation in the PPP on the balance sheets of participating banks. We examine how participation affected the net interest margins, change in net interest margin, and growth in C&I and CRE loans relative to levels in 2019.

Table K19 reports the results from the first stage regressions. Our main instrument is the deposit-weighted share of employment in COVID-affected industries. This instrument, $Z_{emp,i}$ satisfies the assumption of relevance $\pi \neq 0$. Column (1) shows that the deposit-weighted share of COVID-affected employment is positively associated with PPP intensity and that this relationship is statistically significant. A 1 percent increase in this ratio is associated with a 10 basis point increase in the intensity of PPP participation. The F-test in the last two rows of the table test the model fit after including the instrument. We reject the null hypothesis of a weak instrument at a 1 percent level of significance [Cragg and Donald, 1993; Stock, Yogo, et al., 2005].

Columns (2)-(4) summarize the first stage results for the remaining three instruments that we have considered. Notably, PPP share has a significant negative relationship with the deposit-weighted share of employment in small firms. Columns

[16] In Appendix K, we report the results shown in table K18 disaggregated across 2020:Q2 and 2020:Q3. The results are mostly qualitatively similar to the combined results though COVID cases are a stronger predictor of participation in the later quarter.

(3) and (4) show that core deposit shares and unused commitments, which measure preexisting relationships with small firms, have a positive and significant relationship with PPP participation intensity. In all cases, we reject the null hypothesis of weak instruments.

Table K20 summarizes the results from the second stage of instrumental variable regression based on the share of employment in COVID-affected sectors. The table reports OLS results along with the Hausman test of endogeneity. In all cases, the IV result is larger than the OLS result, indicating that the endogeneity of the OLS estimate biases the effect toward zero. Furthermore, the F statistic from the Hausman test indicates that the OLS results are not consistent, that is we reject the null that the coefficient on residuals generated from a regression of the instrument on all the controls is zero when used in the baseline regression. In all cases, we find that the estimated residuals improve the regression fit except for the case on the change in NIMs.

Notably, PPP participation resulted in a statistically significant decline in the change in NIM. The levels of NIM increased marginally and in line with our expectations, C&I growth increased substantially in response to increased PPP participation. The results in column (2) show that higher participation in the PPP entailed a small, statistically significant improvement in bank NIMs. A one percent increase in PPP loans to total loans generated a 5 basis point rise in NIMs. At the mean level of PPP participation of 8.5 percent, the estimated coefficient predicts a 40 basis point rise in NIM. This is consistent with the terms of PPP loans, which bear an interest of merely 1 percent and result in fee income to banks, which is only fully realized after a loan is forgiven.

Column (4) shows a statistically and economically significant decline of 3.75 basis points in ΔNIM, which the change in the level of NIM in 2020 relative to 2019. Even though this finding may appear at odds with the estimated positive effect of PPP participation on NIM, these two results can be reconciled by considering the interpretation of the two coefficients. The first result indicates that on balance, PPP loans resulted in a small positive increase in NIM. The second result shows that despite the rise in NIMs emanating from participation in the PPP, margins fell relative to levels in 2019. This shows that the growth in NIMs in response to a marginal increase in the share of PPP loans was substantially smaller than the growth in NIMs generated by the bank's asset portfolio from the pre-pandemic period. Because PPP loans displaced regular bank lending, potential growth to NIMs from other loans was shut down.

In column (6), we find that PPP loans generate a statistically and economically significant increase in the growth of C&I loans. A one percent rise in the share of PPP loans to total loans generated 15 percent growth in C&I loans relative to 2019. This outsized effect of PPP participation on C&I growth is explained by the fact that PPP lending contributed directly to bank loan portfolios. In addition, other factors tied to the pandemic also expanded C&I lending. For example, firms rapidly drew down on their lines of credit in response to the panic in March 2020 and thereby converted off-balance sheet commitments into lending reported on bank balance sheets [Li, Strahan, and Zhang, 2020]. Indeed, the introduction of the PPP alleviated this trend as firms that received PPP loans repaid larger shares of the amount that they had drawn down relative to non-PPP recipients [Chodorow-Reich et al., 2020]. Indeed, in column (8) we see that non-PPP C&I lending increased modestly for banks with larger PPP portfolios. However, non-C&I lending, as measured by CRE growth, did not expand with PPP lending which is shown in column (10). We find these result even conditioning on the size of the C&I portfolio shown in the second row.

The third row of Table K20 shows that bank size had differential effects on NIM, the change in NIM and C&I growth. Larger banks underwent a decline in NIM but a rise in the change in NIM relative to 2019 levels. This suggests that non-PPP lending that was forgone during the pandemic had yielded larger margins for smaller banks than larger banks. Finally, we find that both total and non-PPP C&I growth declined with asset size. This result is primarily driven by base effects as loan portfolios grew by a larger percent among small banks for a given change in C&I lending.

Banks with higher shares of liquid assets earned lower NIM and underwent a steeper decline in NIM relative to 2019 levels. Participation in the PPP Liquidity Facility (PPPLF) provides a potential explanation for this observation. This facility carried a low interest rate and was likely tapped by banks that were liquidity-constrained. The low cost of funds from the facility would have supported margins from falling substantially for participating banks.[17]. The weakly negative relationship between liquid assets shares and C&I growth suggests that banks with more liquid assets were also likely more conservative and expanded their loan portfolios to a more limited extent than small banks. Liquid asset shares are not significantly associated with CRE lending.

Banks with larger pre-pandemic ROA earned larger NIM but experienced a larger decline in NIM relative to 2019. This indicates that banks that were more profitable pre-pandemic underwent a greater opportunity cost by forgoing their regular lending activities and instead participating in the PPP. More profitable banks also had lower growth in C&I lending, both overall, and outside the PPP, as well as lower growth in CRE lending.

Likewise, better capitalized banks had greater reductions in net interest margins but more total C&I lending growth. This result differs from our result on PPP intensity because it measures C&I lending relative to the base period whereas our PPP intensity result measures PPP as a share of all loans in that quarter. Thus, better capitalized banks increased C&I lending more but they also increased other lending more as shown by the positive and significant coefficient on CRE growth in column (10).

Table K26 reports the coefficients on PPP share from the second stage of the IV regressions using other instruments in place of the share of employment in COVID-affected industries. Across different instruments, we find that the NIM level effect is inconsistent both in sign and statistical significance. The change in NIMs however is consistently negative across different instruments and statistically significant except for when we use unused commitments as an instrument. Similarly, we find that PPP lending boosted total C&I lending in all specifications but had much smaller or even negative effects on non-PPP C&I lending. Results on CRE growth are also not consistent across instruments with some specifications showing a statistically significant increase and other showing insignificant declines. Thus, we conjecture

[17] We examine participation in PPPLF in Appendix H

that the most consistent result is that PPP increased C&I lending sharply but pushed net interest margins down considerably for the lenders participating most intensively.

K.5 Quarterly Estimates

Tables K21 and K22 provide results for the specifications presented in Table K17 for the quarters 2020:Q2 and 2020:Q3, respectively. The results for each quarter are qualitatively similar to the combined results. In particular, larger and more profitable banks were more likely to participate while more capitalized banks were less likely to participate.

Tables K23 and K24 report specifications on PPP lending intensity but by individual quarter. The results remain qualitatively similar with banks facing more C&I exposure typically making more PPP loans. Large and riskier banks– as measured by leverage capital ratios– were also more likely to participate across quarters. However, one difference does emerge. COVID cases seem to be a better predictor of PPP loan holdings, particularly for smaller banks, only for the third quarter which corresponds to the end of the second funding round. This suggests that loan targeting improved as the program progressed and more controls were added.

K.6 2020:Q4 Bank Outcomes

Table K25 reports the results for 2020:Q4. This quarter was not considered in our primary sample because the PPP was not operational during this time. Thus, any changes in PPP lending are due to sales, purchases, paydowns or forgiveness. On net, we find that banks with greater PPP loan shares had higher levels of NIMs and C&I loan growth in 2020:Q4. There was no statistically singificant change in the decline in NIMs and there was a moderate increase in CRE lending growth for large PPP lenders. While this is only a single cross-section, it suggests that some of our key findings are transitory. Thus, the impact on profitability is likely to be temporary as loans are forgiven. Moreover, revenue generated by PPP lending and efforts to boost post-PPP lending profitability may increase risk-taking in the future. Unfortunately, our data series is too short to make strong statements about these impacts. The PPP began again in 2021:Q1 so 2020:Q4 remains our only quarter since the pandemic began without a PPP program or financial crisis.

Finally, Table K26 shows the results from the IV using all the possible instruments. Just as in the main results, we find disagreement across the estimates on the level of net interest margins. The change in NIM is always negative and mostly significant. PPP boost C&I lending unambiguosly but non-PPP lending results are mixed across instruments. CRE lending increases in some specifications by is negative and insignificant in at least one specification.

Table K19: PPP Intensity Share Determinants

	(1)	(2)	(3)	(4)
COVID-affected employment share	0.106***			
	(0.009)			
Small firm employment share		-0.097***		
		(0.007)		
Core Deposits To Assets			0.072***	
			(0.010)	
Unused CI Commitments to Assets				0.528***
				(0.050)
CI to assets	0.357***	0.332***	0.356***	0.201***
	(0.022)	(0.021)	(0.022)	(0.031)
ln *Assets*	0.602***	0.469***	0.775***	0.289***
	(0.075)	(0.078)	(0.071)	(0.081)
ROA	-0.170	-0.029	-0.407	-0.245
	(0.270)	(0.272)	(0.271)	(0.277)
Leverage Ratio	-0.206***	-0.220***	-0.144***	-0.211***
	(0.033)	(0.033)	(0.035)	(0.032)
ALLL to Total Loans	0.422***	0.498***	0.377**	0.331**
	(0.162)	(0.160)	(0.164)	(0.168)
Liquid Assets To Assets	0.099***	0.102***	0.081***	0.101***
	(0.007)	(0.007)	(0.008)	(0.007)
Cases Per 100k	0.132	-0.152*	0.186**	0.147*
	(0.084)	(0.083)	(0.084)	(0.081)
Constant	-4.256***	5.316***	-9.596***	1.427
	(1.083)	(1.289)	(1.359)	(1.306)
Observations	7,048	7,048	7,048	7,048
F value	114.522	220.220	85.615	346.656
F p-value	0.000	0.000	0.000	0.000

Notes: Dependent variable is PPP loans as a share of total loans in 2020:Q2 and 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019. CRA origination share is calculated using 2019 origination volumes reported on the banks CRA disclosure. Small firm employment share is the share of firms with 500 or fewer employees operating in a county according to the QWI database of the U.S. Census. Share of affected employment is determined at the county level from the share of employment in the most affected industrial sectors. Affected industries are defined as the bottom quartile of total employment change from January to April 2020. See Boyarchenko et al. [2020] for more information. County level variables are weighted by bank branch deposits in each county according to the Summary of Deposit data. County employment shares are from the QCEW database of the Bureau of Labor Statistics.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table K20: Bank Outcomes IV Regression: Employment share in COVID-affected industries

	NIM		Δ NIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
PPP Loans to Total Loans	0.004**	0.048***	-1.214***	-3.375***	11.163***	15.149***	-0.141***	0.737**	0.180***	0.257
	(0.001)	(0.009)	(0.243)	(0.706)	(0.237)	(1.001)	(0.050)	(0.359)	(0.040)	(0.296)
CI to assets	0.003*	-0.013***	-0.531***	0.226	-7.661***	-9.059***	0.122***	-0.186	0.112***	0.085
	(0.001)	(0.004)	(0.101)	(0.270)	(0.282)	(0.446)	(0.043)	(0.130)	(0.037)	(0.109)
ln *Assets*	-0.154***	-0.188***	0.870	2.535***	1.637**	-1.434	-0.630**	-1.307***	0.424**	0.364
	(0.007)	(0.010)	(0.542)	(0.779)	(0.800)	(1.185)	(0.260)	(0.374)	(0.212)	(0.297)
ROA	0.234***	0.245***	-12.234***	-12.766***	-3.754*	-2.771	-2.364***	-2.147***	-1.881***	-1.862***
	(0.015)	(0.021)	(2.049)	(1.741)	(2.003)	(2.164)	(0.599)	(0.612)	(0.534)	(0.537)
Leverage Ratio	-0.022***	-0.012***	-1.448***	-1.906***	0.921**	1.766***	-0.009	0.178	0.272**	0.288**
	(0.003)	(0.004)	(0.224)	(0.279)	(0.370)	(0.447)	(0.129)	(0.145)	(0.116)	(0.134)
ALLL to Total Loans	0.005	-0.011	-3.940***	-3.152**	-5.385***	-6.838***	-2.860***	-3.180***	-0.538	-0.566
	(0.015)	(0.017)	(1.417)	(1.357)	(2.007)	(2.024)	(0.495)	(0.523)	(0.647)	(0.657)
Liquid Assets To Assets	-0.022***	-0.027***	-0.312***	-0.088	-0.638***	-1.050***	0.044	-0.047	-0.032	-0.040
	(0.001)	(0.001)	(0.058)	(0.092)	(0.109)	(0.153)	(0.030)	(0.048)	(0.023)	(0.039)
Cases Per 100k	-0.077***	-0.082***	-9.123***	-8.889***	3.421***	2.990***	0.003	-0.092	0.005	-0.004
	(0.008)	(0.009)	(0.623)	(0.634)	(1.009)	(1.045)	(0.325)	(0.337)	(0.231)	(0.232)
Constant	5.922***	6.109***	20.908***	11.826	56.754***	73.506***	10.911***	14.603***	-0.423	-0.099
	(0.095)	(0.116)	(7.725)	(8.706)	(11.431)	(13.447)	(3.841)	(4.192)	(3.124)	(3.265)
Observations	7,048	7,048	7,048	7,048	7,048	7,048	7,048	7,048	7,048	7,048
Hausman F value		572.24		0.84		45.26		10.11		6.60
Hausman p-value		0.00		0.36		0.00		0.00		0.01

Notes: Instrumental variable is employment share in COVID-affected industries. Sample is 2020:Q2 and 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019. CRA origination share is calculated using 2019 origination volumes reported on the banks CRA disclosure. COVID cases are county level case counts averaged over counties where the bank operates a branch according to the Summary of Deposit data. Daily county-level COVID case counts are drawn from John Hopkins. COVID-affected employment share is employment in industries that underwent the largest decline in employment averaged over counties where the bank operates a branch according to the Summary of Deposit data. County-level employment share in COVID-affected industries is obtained from the QCEW databse of the Bureau of Labor Statistics.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table K21: 2020:Q2 PPP Participation Determinants

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.001			-0.002	0.002			0.009
	(0.011)			(0.026)	(0.011)			(0.030)
Small CI to assets		-0.009		-0.016		-0.010		-0.029
		(0.012)		(0.029)		(0.012)		(0.032)
Unused CI Commitments to Assets			0.102***	0.113***			0.102***	0.108***
			(0.038)	(0.041)			(0.037)	(0.040)
ln *Assets*	0.732***	0.720***	0.653***	0.621***	0.738***	0.723***	0.665***	0.618***
	(0.063)	(0.064)	(0.070)	(0.075)	(0.068)	(0.069)	(0.074)	(0.080)
ROA	0.347***	0.354***	0.355***	0.370***	0.340***	0.348***	0.347***	0.369***
	(0.092)	(0.092)	(0.093)	(0.094)	(0.092)	(0.092)	(0.093)	(0.094)
Liquid Assets To Assets	-0.012***	-0.013***	-0.010**	-0.012***	-0.012***	-0.013***	-0.010**	-0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Leverage Ratio	-0.071***	-0.072***	-0.069***	-0.071***	-0.070***	-0.071***	-0.068***	-0.070***
	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)
ALLL to Total Loans	-0.058	-0.047	-0.056	-0.035	-0.066	-0.053	-0.063	-0.043
	(0.069)	(0.063)	(0.067)	(0.059)	(0.068)	(0.062)	(0.065)	(0.058)
Cases Per 100k	0.051	0.053	0.032	0.036	0.063	0.066	0.043	0.048
	(0.122)	(0.123)	(0.119)	(0.120)	(0.125)	(0.126)	(0.122)	(0.123)
Constant	-5.926***	-5.701***	-5.287***	-4.797***	-6.015***	-5.736***	-5.439***	-4.780***
	(0.800)	(0.832)	(0.839)	(0.905)	(0.851)	(0.886)	(0.883)	(0.959)
Observations	3,896	3,896	3,896	3,896	3,427	3,427	3,427	3,427
Loglik	-1,184.51	-1,184.18	-1,175.54	-1,173.98	-1,146.34	-1,145.90	-1,137.85	-1,136.02
Pseudo R^2	0.12	0.12	0.13	0.13	0.10	0.11	0.11	0.11

Notes: Dependent variable is an indicator for any PPP loans outstanding at quarter end. Sample is 2020:Q2. Regressor balance sheet variables are measured as four quarter averages from 2019.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table K22: 2020:Q3 PPP Participation Determinants

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	-0.000			-0.022	0.002			0.000
	(0.011)			(0.023)	(0.012)			(0.029)
Small CI to assets		-0.008		0.003		-0.009		-0.021
		(0.013)		(0.026)		(0.012)		(0.031)
Unused CI Commitments to Assets			0.120***	0.143***			0.119***	0.130***
			(0.040)	(0.045)			(0.039)	(0.043)
ln *Assets*	0.715***	0.704***	0.618***	0.606***	0.758***	0.744***	0.670***	0.630***
	(0.066)	(0.066)	(0.073)	(0.077)	(0.069)	(0.070)	(0.076)	(0.082)
ROA	0.271***	0.275***	0.291***	0.294***	0.260***	0.265***	0.278***	0.294***
	(0.085)	(0.085)	(0.087)	(0.086)	(0.085)	(0.085)	(0.087)	(0.088)
Liquid Assets To Assets	-0.009**	-0.010**	-0.007	-0.009**	-0.009**	-0.010**	-0.007	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Leverage Ratio	-0.071***	-0.072***	-0.069***	-0.070***	-0.062***	-0.064***	-0.060***	-0.062***
	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)
ALLL to Total Loans	-0.003	0.004	-0.005	0.021	-0.021	-0.009	-0.019	0.005
	(0.081)	(0.074)	(0.081)	(0.066)	(0.079)	(0.070)	(0.077)	(0.063)
Cases Per 100k	-0.052	-0.051	-0.055	-0.049	-0.056	-0.053	-0.059	-0.053
	(0.052)	(0.052)	(0.051)	(0.051)	(0.052)	(0.052)	(0.051)	(0.052)
Constant	-5.663***	-5.481***	-4.904***	-4.627***	-6.265***	-6.006***	-5.567***	-4.976***
	(0.845)	(0.879)	(0.882)	(0.922)	(0.862)	(0.902)	(0.896)	(0.978)
Observations	3,890	3,890	3,890	3,890	3,427	3,427	3,427	3,427
Loglik	-1,186.63	-1,186.37	-1,174.44	-1,172.04	-1,136.93	-1,136.58	-1,125.72	-1,123.83
Pseudo R^2	0.11	0.11	0.12	0.12	0.10	0.10	0.10	0.11

Notes: Dependent variable is an indicator for any PPP loans outstanding at quarter end. Sample is 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table K23: PPP Participation Intensity Determinants: 2020:Q2

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.335***			0.103**	0.409***			0.229***
	(0.029)			(0.044)	(0.033)			(0.052)
Small CI to assets		0.428***		0.162**		0.476***		0.071
		(0.060)		(0.072)		(0.057)		(0.076)
Unused CI Commitments to Assets			0.730***	0.558***			0.802***	0.538***
			(0.045)	(0.067)			(0.055)	(0.077)
ln *Assets*	0.806***	1.532***	0.252**	0.529***	1.553***	2.316***	0.897***	1.157***
	(0.100)	(0.119)	(0.109)	(0.143)	(0.148)	(0.165)	(0.160)	(0.187)
ROA	-0.071	-0.230	-0.125	-0.130	-0.230	-0.401	-0.277	-0.244
	(0.319)	(0.328)	(0.342)	(0.333)	(0.333)	(0.345)	(0.363)	(0.347)
Liquid Assets To Assets	0.104***	0.095***	0.085***	0.105***	0.116***	0.103***	0.090***	0.116***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Leverage Ratio	-0.232***	-0.205***	-0.241***	-0.213***	-0.195***	-0.172***	-0.223***	-0.190***
	(0.045)	(0.047)	(0.043)	(0.044)	(0.045)	(0.047)	(0.044)	(0.044)
ALLL to Total Loans	0.326	0.371	0.315	0.293	0.146	0.223	0.183	0.138
	(0.227)	(0.231)	(0.243)	(0.233)	(0.229)	(0.235)	(0.253)	(0.236)
Cases Per 100k	-0.141	-0.049	-0.090	-0.115	0.229	0.276	0.229	0.219
	(0.256)	(0.256)	(0.249)	(0.247)	(0.284)	(0.284)	(0.274)	(0.273)
Constant	-4.372***	-12.851***	3.663**	-1.763	-14.291***	-22.751***	-4.286*	-9.954***
	(1.514)	(2.100)	(1.589)	(2.273)	(2.096)	(2.526)	(2.189)	(2.779)
Observations	3,523	3,523	3,523	3,523	3,061	3,061	3,061	3,061
Adjusted R2	0.144	0.108	0.166	0.188	0.179	0.129	0.179	0.215

Notes: Dependent variable is PPP loans as a share of total loans in 2020:Q2. Regressor balance sheet variables are measured as four quarter averages from 2019. COVID cases are county level case counts averaged over counties where the bank operates a branch according to the Summary of Deposit data. Daily county-level COVID case counts are drawn from John Hopkins.
t statistic in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table K24: PPP Participation Intensity Determinants: 2020:Q3

	All Banks				Banks < \$1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.366***			0.147**	0.449***			0.292***
	(0.033)			(0.062)	(0.038)			(0.077)
Small CI to assets		0.452***		0.133		0.505***		0.024
		(0.060)		(0.081)		(0.057)		(0.091)
Unused CI Commitments to Assets			0.768***	0.557***			0.849***	0.535***
			(0.050)	(0.076)			(0.061)	(0.086)
ln *Assets*	0.740***	1.520***	0.156	0.418***	1.475***	2.304***	0.776***	1.008***
	(0.103)	(0.123)	(0.114)	(0.152)	(0.152)	(0.172)	(0.166)	(0.194)
ROA	-0.417	-0.605	-0.444	-0.442	-0.583	-0.790*	-0.602	-0.558
	(0.433)	(0.453)	(0.449)	(0.443)	(0.448)	(0.476)	(0.473)	(0.457)
Liquid Assets To Assets	0.103***	0.093***	0.080***	0.102***	0.115***	0.100***	0.085***	0.114***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Leverage Ratio	-0.192***	-0.157***	-0.207***	-0.179***	-0.153***	-0.123**	-0.188***	-0.156***
	(0.050)	(0.054)	(0.049)	(0.048)	(0.051)	(0.054)	(0.050)	(0.048)
ALLL to Total Loans	0.403*	0.439*	0.390	0.366	0.235	0.306	0.270	0.222
	(0.236)	(0.240)	(0.252)	(0.241)	(0.237)	(0.244)	(0.263)	(0.244)
Cases Per 100k	0.156	0.207*	0.303***	0.228**	0.208*	0.257**	0.364***	0.267**
	(0.107)	(0.110)	(0.107)	(0.103)	(0.112)	(0.116)	(0.112)	(0.108)
Constant	-4.086**	-13.150***	4.419***	-0.895	-13.955***	-23.069***	-3.253	-8.663***
	(1.590)	(2.206)	(1.667)	(2.301)	(2.220)	(2.688)	(2.315)	(2.790)
Observations	3,525	3,525	3,525	3,525	3,070	3,070	3,070	3,070
Adjusted R2	0.151	0.106	0.165	0.192	0.190	0.127	0.180	0.224

Notes: Dependent variable is PPP loans as a share of total loans in 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019. COVID cases are county level case counts averaged over counties where the bank operates a branch according to the Summary of Deposit data. Daily county-level COVID case counts are drawn from John Hopkins.
t statistic in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table K25: Bank Outcomes in Q4 2020 IV Regression: Employment share in COVID-affected industries

	(1) NIM	(2) dNIM	(3) C&I Gwth	(4) Non-PPP C&I Gwth	(5) CRE Gwth
PPP Loans to Total Loans	0.109***	-0.850	16.292***	1.155	1.053*
	(0.023)	(1.449)	(1.966)	(0.811)	(0.630)
ln *Assets*	-0.169***	7.589***	-2.956	-2.022***	0.244
	(0.023)	(1.363)	(2.006)	(0.713)	(0.557)
CI to assets	-0.028***	-0.637	-7.238***	-0.429	-0.087
	(0.008)	(0.485)	(0.705)	(0.263)	(0.201)
Leverage Ratio	-0.005	-0.859**	1.161**	0.526***	0.531***
	(0.006)	(0.366)	(0.551)	(0.199)	(0.144)
Liquid Assets To Assets	-0.032***	-0.579***	-0.847***	-0.110	-0.061
	(0.002)	(0.130)	(0.198)	(0.075)	(0.056)
ALLL to Total Loans	-0.009	-3.853	-6.932***	-3.527***	-1.614**
	(0.032)	(2.389)	(2.190)	(0.744)	(0.730)
ROA	0.152***	-18.039***	-1.151	-2.009**	-2.230***
	(0.054)	(2.822)	(3.229)	(0.882)	(0.752)
Cases Per 100k	0.018	-0.186	0.907	0.107	0.207
	(0.014)	(0.914)	(1.159)	(0.487)	(0.376)
Constant	5.653***	-80.332***	78.078***	23.369***	-2.281
	(0.247)	(15.149)	(20.413)	(7.155)	(5.467)
Observations	3,518	3,518	3,518	3,518	3,518
Adjusted R2	-0.517	0.114	0.392	-0.055	-0.042

Notes: Instrumental variable is employment share in COVID-affected industries. Sample is 2020:Q2 and 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019. CRA origination share is calculated using 2019 origination volumes reported on the banks CRA disclosure. COVID cases are county level case counts averaged over counties where the bank operates a branch according to the Summary of Deposit data. Daily county-level COVID case counts are drawn from John Hopkins. COVID-affected employment share is employment in industries that underwent the largest decline in employment averaged over counties where the bank operates a branch according to the Summary of Deposit data. County-level employment share in COVID-affected industries is obtained from the QCEW databse of the Bureau of Labor Statistics.

t statistic in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table K26: Bank Outcomes IV Regression: Effect of PPP share on outcomes

Instrumental Variable	(1) NIM	(2) ΔNIM	(3) C&I Gwth	(4) Non-PPP C&I Gwth	(5) CRE Gwth
Small firm employment share	-0.005	-1.334**	17.258***	0.886***	0.466**
	(0.007)	(0.553)	(0.890)	(0.279)	(0.200)
Core Deposits To Assets	0.063***	-8.488***	4.898***	-1.457***	-0.199
	(0.013)	(1.270)	(1.626)	(0.472)	(0.320)
Unused CI Commitments To Assets	-0.023***	-0.887	6.094***	-0.942***	0.322**
	(0.006)	(0.578)	(0.768)	(0.205)	(0.154)

Notes: Sample is 2020:Q2 and 2020:Q3. Regressor balance sheet variables are measured as four quarter averages from 2019. CRA origination share is calculated using 2019 origination volumes reported on the banks CRA disclosure. Small firm share is employment share in firms with less than 500 employees per county averaged over counties where the bank operates a branch according to the Summary of Deposit data. Employment share in small firms is obtained from the QWI database of the U.S. Census. Employment share in COVID-affected industries is obtained from the QCEW databse of the Bureau of Labor Statistics.
t statistic in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

L 2020:Q1 C&I Loan Draw Effect

This appendix presents results using C&I loan growth and loans from 2020:Q1. During the onset of the pandemic in the first quarter, many banks experienced large draws on existing lines of credit. We hypothesize that banks experiencing greater draws would have been more active in the program because firms may have returned any precautionary draws after receiving the PPP funds. In that way, the PPP helped to reduce credit risk to the banks by transferring the default risk from their own capital to the government balance sheet.

Table L27 shows the impact of these draws on participation, intensity, and the level of net interest margins. Columns (1) - (3) show that draws in the first quarter had no statistically important impact on participation. However, banks with larger C&I loan growth, C&I loan growth in the top quartile, and those with greater usage rates all participated more intensively. However, net interest margins were somewhat larger compared to non-participants though this effect is not statistically important across all our first quarter lending measures.

Table L28 repeats the exercise for the change in net interest margins. The results for participation and intensity are qualitatively similar with the most statistically important effect of loan draws occurring on the intensity of participation in the program. Moreover, the change in net interest margins was larger compared to banks that experienced less C&I loan growth. This effect is statistically important for banks that experienced the highest C&I loan growth impacts.

Table L27: Effect of 2020:Q1 C&I Draws on participation, intensity, and NIM

	Participation			PPP Intensity			NIM (participants)			NIM (non-participants)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CI\,gwth^{2020:Q1}$	0.001			0.008			0.004			-0.001		
	[0, 0]			[0.01, 0.01]			[0, 0.01]			[0, 0]		
$CI\,gwth^{75th}$		0.129			1.028			0.308			-0.061	
		[-0.02, 0.2]			[0.66, 1.39]			[0.19, 0.45]			[-0.21, 0.12]	
$CI\,Usage^{2020:Q1}$			0.004			0.038			0.013			0.002
			[0, 0.01]			[0.01, 0.07]			[0, 0.02]			[-0.01, 0.01]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table L28: Effect of 2020:Q1 C&I Draws on participation, intensity, and ΔNIM

	Participation			PPP Intensity			ΔNIM (participants)			ΔNIM (non-participants)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CI\,gwth^{2020:Q1}$	0.001			0.009			0.066			0.044		
	[0, 0]			[0.01, 0.01]			[0.04, 0.1]			[-0.02, 0.11]		
$CI\,gwth^{75th}$		0.127			1.008			3.061			2.175	
		[0.06, 0.19]			[0.64, 1.37]			[0.36, 5.87]			[-2.55, 7.07]	
$CI\,Usage^{2020:Q1}$			0.003			0.037			0.17			0.184
			[0, 0.01]			[0.01, 0.06]			[-0.04, 0.39]			[-0.27, 0.65]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Tables L29 and L30 report the results on total C&I loan growth and non-PPP C&I growth. These specifiations show that PP participants that experienced the largest C&I loan growth in the first quarter had more total C&I loan growth and more non-PPP loan growth during the subsequent quarters the PPP was active.

Table L29: Effect of 2020:Q1 C&I Draws on participation, intensity, and C&I growth

	Participation			PPP Intensity			CI Gwth (participants)			CI Gwth (non-participants)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CI\ gwth^{2020:Q1}$	0.002			0.008			0.28			0.027		
	[0, 0]			[0, 0.01]			[0.24, 0.32]			[-0.01, 0.07]		
$CI\ gwth^{75th}$		0.123			1.056			16.451			4.846	
		[0.06, 0.19]			[0.7, 1.4]			[13.08, 19.82]			[0.75, 8.93]	
$CI\ Usage^{2020:Q1}$			0.005			0.034			0.615			-0.655
			[0, 0.01]			[0.01, 0.06]			[0.32, 0.91]			[-1.01, -0.3]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Table L30: Effect of 2020:Q1 C&I Draws on participation, intensity, and non-PPP C&I growth

	Participation			PPP Intensity			Non-PPP CI Gwth (participants)			Non-PPP CI Gwth (non-participants)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CI\ gwth^{2020:Q1}$	0.002			0.009			0.196			0.027		
	[0, 0]			[0.01, 0.01]			[0.18, 0.21]			[-0.02, 0.08]		
$CI\ gwth^{75th}$		0.119			1.149			12.965			4.717	
		[0.04, 0.19]			[0.81, 1.49]			[11.43, 14.49]			[0.31, 9.23]	
$CI\ Usage^{2020:Q1}$			0.005			0.033			0.317			-0.685
			[0, 0.01]			[0.01, 0.06]			[0.21, 0.42]			[-1.09, -0.28]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

Finally, Table L31 reports the results for commercial real estate lending (CRE) as a check on spillover effects. We find mixed evidence that participants in the PPP program made more CRE loans. In at least one specification, the sign is negative and statistically unimportant. However, in the other specifications we find positive and statistically important effects. Notably, for non-participants we find negative impacts of first quarter C&I loan growth on CRE lending, suggesting that the capital protection that PPP provided may have encouraged some additional, non-C&I lending for the most active C&I lenders in the first quarter.

Table L31: Effect of 2020:Q1 C&I Draws on participation, intensity, and non-PPP CRE growth

	Participation			PPP Intensity			CRE Gwth (participants)			CRE Gwth (non-participants)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CI\ gwth^{2020:Q1}$	0.001			0.008			0.019			-0.046		
	[0, 0]			[0, 0.01]			[0.01, 0.03]			[-0.07, -0.02]		
$CI\ gwth^{75th}$		0.107			0.981			2.007			-3.539	
		[-0.05, 0.18]			[0.62, 1.33]			[0.89, 3.08]			[-6.85, 1]	
$CI\ Usage^{2020:Q1}$			0.003			0.035			-0.043			-0.015
			[0, 0.01]			[0.01, 0.06]			[-0.12, 0.04]			[-0.24, 0.22]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 11,000 MCMC draws with a burn-in of 1000.

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