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Federal Reserve Bank of Kansas City

Loan Guarantees in a Crisis: An Antidote to a Credit Crunch

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April 11, 2022

Abstract

Credit contractions are costly, but policymakers have limited tools to counter them. In this paper, we examine the efficacy of public credit guarantees as antidotes to a credit crunch by studying the Paycheck Protection Program (PPP). We find that the program averted a historic credit crunch at a time when banks were unlikely to meet firm credit needs by risking their own capital. Our evaluation incorporates selection effects emanating from banks' participation decision on both the extensive and intensive margins. Risk-aversion, rather than profitability, motivated bank participation in the program. Indeed, even as the program boosted loan growth among participants, it attenuated profitability.

JEL Codes: C11, G21, G28, H12

Keywords: Paycheck Protection Program, government loan guarantees, credit crunch, bank liquidity, net interest margins, Bayesian modeling

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1 Introduction

Credit contractions are costly. Indeed, loan supply reductions were a principal contributor to both the Great Depression and the more recent Global Financial Crisis– two of the deepest recessions in U.S. history. Despite the potentially severe costs of credit contractions, however, policymakers have few tools available to boost tight loan supply in the depths of a crisis.

In this paper, we examine a policy tool that is seldom used as an emergency measure during economic crises: the public credit guarantee. Bachas, Kim, and Yannelis [2021] exhaustively uncovered the favorable effect of credit guarantees on bank credit supply during normal times, and prior empirical studies have illuminated the role of credit guarantees in supporting lending when banks are capacity constrained due to impaired balance sheets [Ono, Uesugi, and Yasuda, 2013; Wilcox and Yasuda, 2019; Boeckx, de Sola Perea, and Peersman, 2020]. However, the efficacy of guarantees as a crisis-response measure when banks are not under duress is still an open question. More specifically, we ask do guarantees preserve bank lending in a crisis whose origins were exogenous to the banking system? In theory, public credit guarantees are well suited to such situations because they can help avert a credit market collapse during a crisis that emerges from deteriorating risk perceptions [Mankiw, 1986]. The answer to this question clarifies to policymakers the broader role of guarantees beyond serving as an intervention in banking crises and redressing credit rationing in normal times. But empirical evidence is scant owing to limited instances in which guarantees are used outside of banking crises.

We quantify the effects of public credit guarantees under these circumstances by examining the U.S. Paycheck Protection Program (PPP), a credit guarantee program that was introduced in response to the COVID-19 pandemic– an exogenous health crisis. At its onset, the pandemic and associated containment measures stifled economic activity and undermined business revenue and profit expectations across the United States. U.S. banks, in aggregate, were stable and healthy, but began actively tightening lending standards and setting aside additional provisions in anticipation of credit losses from the pandemic's economic ravages. We find that the PPP, however, offset a potentially large credit crunch through two channels– by stimulating growth in loans directly covered by the guarantee, and by providing a backstop that prevented contractions of non-guaranteed loans on bank balance sheets. Our results also shed light on bank incentives to participate in the program. Risk-aversion, rather than profitability, induced program participation, both along the intensive and extensive margins. Relatedly, we find that the program did not did not enhance bank profitability– PPP loans compressed net interest margins relative to pre-pandemic levels among participating banks– but instead forestalled a contraction in their loan books and averted an even larger decline in their margins.

We design our evaluation of the PPP by recognizing that banks likely selected into the program strategically based on its features[Joaquim and Netto, 2021]. A unique feature of the PPP was 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. This feature of the PPP entailed inherent trade-offs for banks. First, banks had to balance risk and profitability concerns. Although PPP loans carried no credit risk, they yielded a low interest rate of one percent, and processing fees that accrued only over the life of the loan. Second, banks incurred the opportunity cost of funding new loans using their own capital until the loans were fully reimbursed upon forgiveness or default. Participating banks would likely evaluate whether to extend PPP loans at the cost of reducing other non-guaranteed lending or to simultaneously expand both types of loan portfolios. In other words, extending risk-free, but low-yielding PPP loans may have induced banks to rebalance the composition of their risky assets with a view toward maintaining profits.

Addressing bank trade-offs in evaluating the PPP gives rise to two empirical challenges– selection effects and simultaneity in the determination of PPP intensity and bank lending and profits. To address these empirical challenges, we jointly model the decision to participate, the intensity of participation, and bank outcomes in a Bayesian framework. Importantly, the joint model addresses selection effects inherent in a bank's program participation decision and their choice of the extent of participation. In other words, we account for selection effects from both the extensive and intensive margins of participation. We additionally address the simultaneous determination of bank decisions and outcomes by specifying covariances across equations. Identification requires variables that affect PPP participation and intensity without directly affecting bank outcomes. Accordingly, we require variables that influence the bank's PPP participation decisions but are otherwise uncorrelated with lending or profitability outcomes.

We use pre-pandemic technological efficiency to measure exogenous variation in the probability of bank participation. Banks' technology platforms were especially salient in processing PPP loans, in no small part due to the SBA's digital application processing requirements. In addition, high borrower demand for PPP loans required banks to process large application volumes expeditiously. Banks reliant on manual application processing would have likely found their processes to be inadequate for participation. Once the participation decision was made, however, technological efficiency did not directly influence participation intensity because banks may book large- or small-denominated loans with the same processing platform. One may also be concerned that the state of a bank's technology may be correlated with long-term bank profitability and balance sheet characteristics as well. We address these correlations by controlling for pre-pandemic profitability and balance sheet measures.

We next address a bank's choice of the intensity of participation in the PPP. In this case, we use the deposit-weighted share of employment in COVID-affected industries, such as hospitality and retail, to isolate demand for PPP loans from supply effects. We turn to the core principle underlying the PPP's enactment– to protect jobs at small businesses– in measuring the demand for PPP loans. Because jobs in contact-intensive sectors were most at risk from pandemic-abatement measures such as lockdowns and social-distancing, firms from these sectors faced an immediate need for support under the program to retain workers and to survive the economic disruption. Indeed, studies that evaluated the design and roll-out of the program noted that firms in COVID-affected sectors were over-represented in the pool of PPP applicants [Bartik, Cullen, Glaeser, Luca, Stanton, and Sunderam, 2020b; Balyuk, Prabhala, and Puri, 2021]. Our measure of the predominance of COVID-affected sectors in a bank's region of operation is thereby closely related to the pandemic-induced demand for PPP loans. Moreover, our measures of bank outcomes, lending and profits, become directly related to these exposures only if the share of existing bank loans to these sectors mirror their share in a bank's operating region. In this setting, participation in the PPP, lending growth, and profitability would simultaneously increase with the presence of contact-sensitive sectors in the bank's operating area. However, sector-specific lending specialization by banks [Blickle, Parlatore, and Saunders, 2021; Paravisini, Rappoport, and Schnabl, 2015] precludes such a one-to-one mapping between geographic concentration of industries and their respective balance sheet loan share, breaking the direct relationship between our COVID-affected employment measure and bank outcomes.

Our results indicate that selection effects were present despite widespread participation in the program. We find that larger and more profitable lenders, who were consequently better positioned to originate and hold loans until forgiveness, were more likely to participate in the program. These findings have been confirmed by others in the emerging PPP literature [Anbil, Carlson, and Styczynski, 2021; Lopez and Spiegel, 2021], however, our model additionally highlights that risk-aversion emerged as the more dominant concern when banks weighed risk and profitability considerations. Banks with larger C&I loan portfolio concentrations and greater 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 bank participation, we find that banks that were riskier ex-ante, as measured by lower leverage capital ratios, were both more likely to participate and originate more PPP loans relative to the size of their total lending portfolio.

Our observation that banks were driven to participate in the PPP by risk-aversion rather than profitability is further confirmed by our results on bank outcomes. We estimate that a one percentage point increase in PPP participation intensity resulted in a 4 basis point decline in NIM, or a 10 percent decline relative to 2019 levels for the average bank, during the quarters when the program was active. This result is driven by the fact that the PPP was not immediately profitable for participating banks because the loans offered low interest rates and deferred fee recognition. We also find that participating banks expanded their business loan portfolios due to PPP lending, but not outside the program. Banks grew their overall C&I loan portfolio by

10 percent but their non-PPP C&I portfolio declined modestly on a year-over-year basis per percentage point increase in PPP intensity. Incremental participation in the PPP also did not induce risk-taking in the form of growth in Commercial Real Estate (CRE) loans.

Counterfactual results from our joint model further clarify the PPP's effects on bank lending and profits by depicting participants' outcomes in the event they had not participated in the program. Using counterfactual lending growth, we evaluate whether the program crowded out private capital or provided an additional boost to business lending. We estimate that absent PPP lending, C&I loan growth would have contracted during the second half of 2020. Our results suggest that the counterfactual average decline of 78 percent in commercial loans, would have been similar to the runoff rates observed for the worst hit loan portfolios during the Global Financial Crisis. We additionally find some evidence of spillover effects across the loan book with PPP participation precluding a large runoff in commercial real estate loans. In total, our results show that participation in the PPP forestalled a large contraction in business lending outside the program, and by doing so, provided a modest boost to net interest margins at participating banks.

Most importantly, our counterfactual results indicate that the PPP helped avert a credit crunch primarily by facilitating lending by riskier banks. Chodorow-Reich, Darmouni, Luck, and Plosser [2021] document that the PPP offset a pandemic driven credit crunch among commercial borrowers, particularly among small firms obtaining capital from large banks. We complement these findings by both quantifying how severe that credit crunch might have been and identifying the lender attributes that drove the contraction in private credit. Indeed, a decomposition of our loan growth counterfactual result shows a clear pattern of risk aversion as the main driver of a potential credit crunch. The PPP's effectiveness lies in inducing participation among such risk-averse banks that might have otherwise contracted lending. Specifically, 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. That said, our results also suggest a role for the importance of relationship lending at community banks– a role emphasized by Li and Strahan [2021] and Balyuk et al. [2021]. Banks with larger C&I loan concentrations, and thus those with more prior relationships, were more likely to participate in the PPP, and to do so more intensively. Our counterfactual results, however, illustrate the limitations of relationship lending and the importance of supplementary loan guarantees during a crisis. In the absence of the PPP's loan guarantees, banks would have retrenched lending during the unprecedented pandemic-led crisis, even if they had long-standing relationships with borrowers.

Our results point to the interventionary role for credit guarantees following a large economic shock. Previous work has shown that credit rationing is costly and credit guarantees can be welfare-improving when they increase lending to optimal levels in normal times [Stiglitz and Weiss, 1981; Gale, 1990; Mankiw, 1986]. We demonstrate the effectiveness of credit guarantees as emergency measures during crises. The experiences from the PPP illustrate that public guarantees can be especially effective in forestalling a credit crunch during a crisis that sharply exacerbates banks' uncertainty about borrowers' ability to repay. Avoiding credit rationing during such a crisis supports the eventual recovery by limiting the severity of the economic downturn [Bernanke, 1983; Chodorow-Reich, 2014]. Consequently, in crises that emerge outside the banking sector, guarantees support credit supply by fostering banks' willingness to lend, even when their ability to lend is not directly impaired.

The rest of the paper proceeds as follows: Section 2 describes the PPP program parameters, the Bayesian model setup, and the data and identification restrictions needed to estimate the model. Section 3 examines the question of which bank characteristics predicted PPP participation. Section 4 examines the effect of PPP lending on bank balance sheets and income. Section 5 estimates lending counterfactuals absent PPP program participation to assess whether PPP lending crowded out other borrowing. Section 6 provides robustness exercises, and Section 7 concludes.

2 Institutional Background and Methodology

2.1 The Paycheck Protection Program

At the onset of the COVID-19 pandemic, businesses faced the prospect of unprecedented revenue shortfalls and potential closure from the direct health effects of the pandemic as well as public health measures that were introduced to curtail its spread. Employment at firms with fewer than five hundred employees fell by 18 percent during the first quarter of 2020, and small firms had cash reserves to cover only two weeks of expenses early in the crisis [Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton, 2020a]. The Paycheck Protection Program was designed to enable small businesses to endure these economic ravages without having to downsize their workforce.[1]

The PPP provided forgivable, low-cost, government guaranteed loans via the Small Business Administration (SBA) to enhance small businesses' survival prospects and help retain workers. PPP loans were generally to U.S. small businesses with 500 or fewer employees, however, eligibility was determined based on the SBA's firm size standards which can vary across industries. Forgiveness rules required the bulk of the funds be used to cover payroll expenses, but payments toward utilities, state and local taxes, interest and rent on existing mortgages and leases were also permitted to a limited extent. Overall, the PPP was a fiscal tool designed to use forgivable loans to preserve employment at small businesses that may have otherwise been lost to the economic disruption from the pandemic.

Banks and other financial institutions funded and disbursed PPP loans to businesses, and participation in the program was entirely subject to lenders' discretion. Because PPP loans were risk-free, lenders received a modest interest rate of 1 percent.[2] In addition, banks received processing fees on a sliding scale, which were entirely paid by the SBA and were recognized as interest income over the term of the loan. During most of the program, loans had five year maturities, and payments

[1]The Paycheck Protection Program (PPP) was created as part of broader legislation that provided fiscal support program enacted under the Coronavirus Aid, Relief, and Economic Security (CARES) Act passed on March 27, 2020.

[2]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.

were deferred until forgiveness or approximately sixteen months after disbursal if borrowers did not apply for forgiveness in the intervening period. The revenue stream on PPP loans therefore depended on borrowers' choice of timing in applying for forgiveness and the speed with which the SBA processed forgiveness applications. [3]

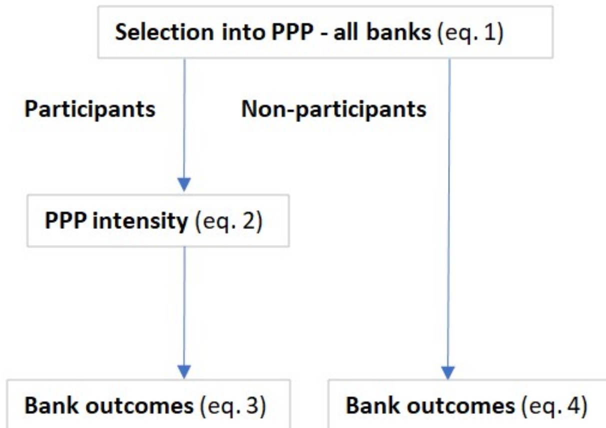
Because banks funded and held PPP loans on their balance sheet until repayment or forgiveness, the Federal Reserve established the Paycheck Protection Program Liquidity Facility (PPPLF) to address lenders' liquidity and capital constraints. The PPPLF provided low cost liquidity to banks by lending funds at 35 basis points against whole PPP loans as collateral. The facility also eased capital constraints for banks by excluding loans used as collateral in the PPPLF from the calculation of the leverage ratio. In setting aside capital for PPP loans, banks were likely to be constrained by the leverage ratio rather than the risk-based capital ratio because PPP loans were assigned a zero risk weight under the CARES Act. Analogous to the PPP, participation in the PPPLF was voluntary. This facility was established to expand participation by banks and other financial institutions that may not have had sufficient liquidity or capital space to disburse PPP loans.

2.2 Bayesian Joint Model Setup

We measure the effect of the PPP on bank loan growth and profits by controlling for changes in these measures that arise from bank decisions rather than the program's features. Banks decided whether and how much to participate in the PPP due to the voluntary nature of the program. These decisions introduce a selection bias, and render the main treatment variable– PPP loans to total loans– endogenous. We address these econometric challenges by modeling banks' decisions to participate in the PPP, and their choice of PPP intensity, jointly with the effect of PPP on bank outcomes. Figure 1 illustrates the structure of our statistical model. Equation (1) defines the decision to participate in the PPP, equation (2) models the intensity of participation, equation (3) models the financial outcomes of participants, and equation (4) models the outcomes of non-participants.

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

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



By modeling participation and intensity in two separate equations, we allow for the possibility that bank characteristics may distinctively affect the two decisions. Our model follows the multivariate structure in Vossmeyer [2016] for sample selection and treatment, but specifies a continuous treatment instead of a censored treatment specified in the former study. An alternative modeling structure consists of collapsing equations 1 and 2 into a single equation and specifying PPP intensity as a censored outcome that takes values of zero among non-participants. This setup assumes that bank propensity to participate and extent of participation respond identically to balance sheet constraints and program characteristics. Instead, we adopt a more general modeling approach where we estimate distinct parameters associated with PPP participation and intensity.

The model structure in Figure 1 is formally represented by Equations 1 - 4. The control variables $\mathbf{x_i'}$ are common to all four equations and consist of pre-determined bank and operating region characteristics discussed below. We specify a multivariate normal distribution, $\mathcal{N}_4(0, \mathbf{\Omega})$, for the errors $\epsilon_i = (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}, \epsilon_{i4})$.

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

Equation 1 represents the probability of each bank participating in the PPP. The outcome y_{i1}^{*} in this equation is a continuous latent variable that represents bank i's underlying net utility from participating in the program relative to non-participation. Bank participation signifies that this net utility is positive. The observed binary outcome, y_{i1}, is accordingly related to the latent variable through the indicator operator, $y_{i1} = \mathbf{1}(y_{i1}^{*} > 0)$. The covariates in this equation are bank-level controls, $\mathbf{x_{i1}'}$, and a covariate, z_{i1}, that is correlated with particpation, but not with the errors, PPP intensity, or bank outcomes given the covariates.

Equation 2 describes banks' decision rule to determine the intensity of participation in the PPP, y_{i2}, measured as the ratio of PPP loans to total loans. The covariates consist of bank-level controls, $\mathbf{x_{i1}'}$, and an instrument, z_{i2}, that is independent of the errors and bank outcomes but related to the treatment, y_{i2}, as specified in Li and Tobias [2014] and Greenberg [2012].

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

One of the main advantages of undertaking a joint modeling approach is that it allows us to incorporate covariances between outcomes across Equations 1 - 4. The covariance matrix $\mathbf{\Omega}$ depicts the relationships between unobservables $\epsilon_i = (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}, \epsilon_{i4})$.

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

The term Ω_{12} measures the covariance between unobservables underlying the decision to participate and the intensity of participation. The covariance terms Ω_{13} and Ω_{14} record the relationship between unobservables pertaining to 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 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 obtain the likelihood for this model by partitioning the equations into outcomes and covariates pertaining to participants and non-participants, as described in Appendix D. We denote N_p and N_{np} as the set of participant and non-participant banks in the sample. The complete-data likelihood function for the full sample of observations combines the elements pertaining to each group of banks,

$$f(y, y_1^* | \mathbf{x_i}, \theta, \Omega_p, \Omega_{np}) = \prod_{i \in N_p} \left[f_{\mathcal{N}}(\boldsymbol{y}_{i,p} | \mu_{i,p}, \Omega_p) \right] \prod_{i \in N_{np}} \left[f_{\mathcal{N}}(\boldsymbol{y}_{i,np} | \mu_{i,np}, \Omega_{np}) \right]. \tag{5}$$

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.

$$f(\theta, \Omega_p, \Omega_{np}, y_1^* | y) \propto f(y, y_1^* | \mathbf{x_i}, \theta, \Omega_p, \Omega_{np}) f(\theta) f(\Omega_p) f(\Omega_{np}) \tag{6}$$

The Markov Chain Monte Carlo (MCMC) algorithm used to estimate this model utilizes the estimation approach for incorporating multiple selection mechanisms in Li [2011] and Vossmeyer [2016]. The steps underlying the algorithm and the results from simulation exercises are provided in Appendix D. To evaluate the effect of the exclusion restriction in Equation 1, our simulation exercises consider a setting in which we specify an instrument in the selection equation and another, when there is no instrument. We recover the true values of parameters within a 95 percent posterior credibility interval in both cases.

2.2.1 Data and Identification

We require data on bank balance sheets, PPP lending activity, and various local measures of both the pandemic's impact as well as the economic well-being of the local area. Data on bank balance sheets and PPP lending are drawn from the FFIEC call reports.[4] We determine a bank's local market using the Summary of Deposits (SOD) data, which is an annually collected FDIC data set that reports the location and holdings of bank branches and their booked deposits. We also collect data on local macroeconomic and health conditions. Data on local COVID case counts are collected from Johns Hopkins University's COVID database.Local employment by industry is drawn from the Current Employment Statistics database from the Bureau of Labor and Statistics.

Our bank sample considers only community banks, defined as banks with less than $10 billion in total assets. The majority of the nearly 5,000 banks operating in the U.S. are below this asset level, providing the widest possible source of variation. The community bank focus also provides us with a set of banks focused on business lending as a core activity. Larger banks often have less uniform business models

[4]Call reports 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 and counts of PPP loans outstanding. PPP loans pledged to the PPPLF are also reported. Specifically, 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. We use these items in our PPPLF analysis reported in the appendix.

that can be more complex or specialized. Inclusion of these banks would complicate the analysis.[5] Overall program participation was 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 achieve identification of our model by specifying exclusion restrictions in the selection and intensity equations. In principle, we can obtain identification in the selection step by relying on the functional form of the normal distribution.[6] But identification is enhanced by the exclusion restriction. Leung and Yu [1996] show that the absence of an exclusion restriction in the sample selection model primarily exacerbates collinearity and results in a deterioration in prediction rather than in parameter biases. Our main interest from the estimation of equations 1 through 4 lies in the estimates of the parameters rather than predicted outcomes. Moreover, results from our simulation exercises in Appendix D show that we recover true values of parameters both with and without the exclusion restriction, but arrive at more precise estimates in the former case.

We use two main instruments to estimate equations 1 - 4, corresponding to the variables denoted as z_{i1} and z_{i2} in equations 1 and 2. The variable for z_{i1} should be related to PPP lending through its impact on participation while z_{i2} should be related to bank outcomes through its effect on intensity.

We specify technical expenses relative to assets as the exogenous variable z_{i1} in the equation for participation that is excluded from subsequent equations. Specifically,

[5] We also exclude non-deposit trusts from our sample due to their unique business model. Non-deposit trusts do not operate as typical deposit banks and instead primarily conduct fiduciary business and hold only limited deposit types. See U.S. DOL's or more information. Non-deposit trusts dis not participated in the PPP.

[6] Identification by functional form can be understood by contrasting the sample selection model with Heckman's two-step procedure, a classical alternative that requires an exclusion restriction. Because the difference between the two methods is the specification of the normal likelihood, identification without an exclusion restriction arises mainly from this distributional assumption [Cameron and Trivedi, 2005].

we consider pre-pandemic payments toward data processing and telecommunications expenses to third-party vendors. Higher expenses per dollar of assets represent likely inefficiencies from lower prior investments on technology and the inability to develop in-house technical platforms.[7] Technical efficiency likely enhanced bank PPP participation. We hypothesize that a key driver of banks' PPP participation was an ability to build loan processing platforms internally. Loan processing ability was particularly important given high borrower demand and the quickness with which competitor banks originated loans. Pandemic-related branch closures and the reduced willingness of borrowers to visit bank branches that were opened also likely required banks to have at least some ability to reach customers virtually. For these reasons, banks already equipped with efficient technical platforms would have had the capability to participate in the program. That said, technical efficiency should not affect lending intensity. Participating banks could book large or small-denominated loans with the same processing platform. Indeed, the FDIC's Quarterly Report noted that "banks with greater technology investment made a larger share of loans of all sizes" [FDIC, 2021]. Because technology expenses directly relate to participation, and only indirectly to loan amounts through participation, we exclude this variable from the equation for participation intensity.

We implement the exclusion restriction on z_{i2} by defining it as a measure of pandemic-induced demand for the PPP, unrelated to bank supply considerations. In particular, this variable is the deposit-weighted share of COVID-affected employment in a bank's region of operation, which represents an aggregate measure of potential pandemic-related demand for PPP loans. We construct this variable as shown by equation 7 where 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. The main exclusion restriction is that the share of employment in contact-sensitive sectors such as hospitality and retail does not directly affect bank profitability and loan growth outside of the PPP, which are outcomes in subsequent

[7] Call report instructions for these items are open to banks' interpretation. However, discussions with bank examination teams reveal that these items mostly capture outsourcing of technology needs to third-parties, consistent with our requirements to measure lack of in-house technological ability. Examples provided were expenses to build and maintain a website or to cover general IT needs.

equations. This measure disrupts the simultaneity in the determination of bank outcomes and PPP intensity by isolating the variation in participation intensity that arises from firm demand for loans under the program. Indeed, in their evaluation of the PPP, Bartik et al. [2020b] and Balyuk et al. [2021] noted that firms in COVID-affected sectors were over-represented in the pool of PPP applicants. Glancy [2021] found that PPP loans predominantly flowed to firms located close to bank branches. Taken together, the predominance of COVID-affected sectors in a bank's region of operation is closely related to the pandemic-induced demand for PPP loans.

$$Z_{emp,i} = \frac{\sum_{j=1}^{J} Emp_j d_{i,j}}{\sum_{j=1}^{J} d_{i,j}}, \tag{7}$$

Exposure to pandemic-affected sectors is only indirectly associated with banks' profits and loan growth through PPP intensity. Bank outcomes become directly related to exposure to pandemic-affected sectors if the share of pre-existing bank loans to these sectors mirror their share in a bank's operating region. In this setting, the presence of contact-sensitive sectors in a bank's operating area would simultaneously determine its participation in the PPP, lending growth and profitability. These co-movements would arise from strategic bank objectives to preserve the health of existing borrowers by issuing them government-guaranteed loans. However, studies on sectoral specialization in bank lending [Blickle et al., 2021; Paravisini et al., 2015] have shown that banks typically specialize in lending to specific sectors, that may not necessarily conform to the sector's employment share in a bank's operating region. Since the specialized nature of bank lending disrupts the direct relationship between our measure of COVID-affected employment and bank outcomes, we exclude this measure from subsequent equations for bank lending growth and interest margins.

The control variables specified by the vector $\mathbf{x'_{i1}}$ include bank controls– asset size, share of business loans, capital and liquid asset ratios, and profitability– and local health conditions measured by COVID cases per capita. Local health conditions are constructed based on local bank deposit weights similar to the local employment measure using equation 7.[8]

[8] COVID case data are reported daily at the county level. We average these daily counts by

2.3 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. Banks with higher PPP shares also underwent larger technical expenses to assets, and were more exposed to COVID-affected employment share. Post pandemic, we see that high participating banks had slightly lower 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. CRE growth was higher for banks with larger PPP loan shares. 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. Non-participants grew their CRE portfolios less than the two participating groups.

3 Who Participated in the PPP and How Much?

The first step in our empirical model, and the PPP loan origination process consists of banks deciding whether they want to participate in the program. In the second step, banks that opted to lend PPP loans determine the intensity of participation. We show that the selection effects from these bank decisions were non-ignorable. Banks' risk-aversion, and their capacity to fund PPP loans determined their participation on the intensive and extensive margins.

Table 2 reports the determinants of bank participation and intensity of participa-

county to determine quarterly exposure rates that can be linked to the quarterly bank data.

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						
Tech Exp. to Assets	0.20	(0.13)	0.18	(0.14)	0.21	(0.19)
COVID-affected emp. share	19.69	(6.99)	17.05	(8.38)	18.33	(10.12)
C&I to Assets	10.85	(6.93)	7.57	(5.33)	8.27	(9.81)
C&I Commitments to Assets	15.42	(9.78)	9.84	(6.69)	10.09	(11.00)
Unused C&I Commitments to Assets	4.57	(3.87)	2.26	(2.32)	1.83	(2.96)
Small C&I to Assets	6.22	(4.00)	5.31	(3.81)	6.42	(8.42)
Core Deposits to Assets	71.62	(10.29)	68.09	(10.45)	67.50	(13.25)
Liquid Assets to Total Assets	20.63	(11.90)	19.09	(11.38)	25.17	(15.21)
ALLL to Total Loans	1.32	(0.64)	1.34	(0.59)	1.50	(1.21)
Total Assets ($ Millions)	0.68	(1.02)	0.42	(0.87)	0.23	(0.63)
ln(Total Assets)	12.78	(1.10)	12.20	(1.09)	11.59	(1.05)
Leverage Ratio	10.90	(2.20)	11.85	(3.21)	12.77	(4.44)
Tier 1 Ratio	15.60	(5.80)	17.57	(7.05)	21.49	(10.36)
$ROA^{2019\ Avg}$	1.19	(0.61)	1.19	(0.57)	0.96	(0.70)
Post-Pandemic Outcomes						
PPP Share	13.15	(6.98)	3.91	(1.83)	0.00	(0.00)
NIM	3.46	(0.59)	3.49	(0.62)	3.38	(0.78)
ΔNIM	-50.06	(49.65)	-39.57	(38.07)	-48.65	(47.38)
CI Gwth	129.97	(118.09)	51.47	(62.72)	10.14	(36.46)
CI Gwth Less PPP	-3.70	(22.15)	-2.64	(25.11)	10.14	(36.46)
Total Banks	1,824		1,689		378	

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.

tion in the PPP. The results represent estimates for equations 1 and 2, respectively. The results are based on the specification where change in NIM relative to 2019 levels is the outcome variable. The results from the remaining specifications, where the outcomes are C&I growth, C&I growth outside of the PPP, and CRE growth, are qualitatively similar and are provided in Appendix D.3.

Column (1) reports the determinants of a bank's decision to participate in the PPP. Technologically efficient banks were more likely to opt into the program in that participation is negatively associated with technology expenses relative to assets. The posterior distribution shows that this coefficient takes negative values with a probability of 90 percent. As discussed in Section 2, because these expenses denote

Table 2: PPP Participation and Intensity Determinants

	Participation	Intensity
	(1)	(2)
Tech expenses to assets	-0.08	
	[-0.2, 0.04]	
COVID-affected employment share		0.04
		[0.03, 0.05]
ln *Assets*	0.17	1.15
	[0.14, 0.19]	[1.01, 1.29]
ROA	0.09	0.32
	[0.04, 0.14]	[0.04, 0.6]
C&I to assets	0.03	0.30
	[0.03, 0.04]	[0.28, 0.33]
Leverage Ratio	-0.05	-0.33
	[-0.06, -0.04]	[-0.38, -0.27]
ALLL to Total Loans	-0.02	0.13
	[-0.06, 0.02]	[-0.12, 0.38]
Liquid Assets to Assets	0.01	0.07
	[0, 0.01]	[0.06, 0.09]
Cases Per 100k	0.03	0.13
	[-0.01, 0.06]	[-0.05, 0.31]
Constant	-0.98	-8.70
	[-1.34, -0.62]	[-10.63, -6.79]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000. The results are based on the specification that uses C&I loan growth as the main outcome variable.

payments to third-party vendors, this ratio is lower for banks that have already invested in efficient, internal technology divisions. Bank funding capacity served as a constraint on PPP participation–larger and more profitable banks were more likely to participate in the program. These relationships are statistically important as the 95 percent credibility intervals for bank size and ROA are entirely on the positive real line. An additional factor that induced PPP participation was bank risk aversion. Banks with larger exposures to business loan risks, as determined by more concentrated shares of total C&I loans, were more likely to participate in the PPP. Relatedly, banks with lower leverage capital ratios were more likely to participate in the PPP, providing evidence of a risk-neutralizing effect of the program. Banks that were more vulnerable to coming up against capital requirements likely viewed the PPP as a means to expand lending without taking on credit risk. Other bank controls consisting of reserved loan loss allowance relative to total loans and liquid asset shares are not statistically important. Finally, exposure to the pandemic in the bank's operating region was not statistically important in explaining PPP participation.

Column (2) represents the determinants of participation intensity. Banks responded to local demand factors by lending a larger share of PPP loans in the presence of greater COVID-affected employment in their operating region. The coefficient of 4 basis points implies that at the average level of COVID-affected employment of 19.7 percent, this demand-based measure explained nearly 80 basis points of the participation intensity in the PPP. Bank risk aversion and funding capacity, which were important drivers of bank participation also influenced participation intensity. Larger and more profitable banks were more likely to make PPP loans at greater relative volumes. Additionally, banks facing greater exposure to C&I lending losses and those with lower capital ratios participated more intensively, on average. These findings suggest that PPP loans likely allowed capital-constrained banks to transfer risks to the government–a PPP loan could meet borrower loan demand while preventing the need for the borrower to draw on existing lines of credit, which would put additional bank capital at risk. Banks with larger shares of liquid assets participated more intensively, which further underlines the role of pre-existing bank funding capacity. Loss reserves and COVID cases in banks' operating region did not influence intensity in a statistically important manner.

In related work, Li and Strahan [2021] also find a strong association between existing C&I lending and relative PPP lending volumes similar to our own results.[9]

[9]Estimation methods also differ across these two papers. We model PPP lending intensity using a multi-stage model that instruments for participation using expenses on technology while Li and Strahan [2021] use a reduced form approach.

However, our results differ in subtle, but important ways. Namely, our joint model uncovers a stronger positive association between bank capital and PPP intensity than Li and Strahan found for small banks. When combined with our C&I exposure results, we interpret our findings as a risk-aversion channel–banks participated in the PPP more intensively when they were already exposed to potential losses on business loans, and when they faced capital constraints. PPP loans permitted banks to extend loans without risking capital to future credit losses. We rely on this evidence to highlight that risk-aversion, rather than relationship lending, was a stronger driver of PPP participation. Our results, nevertheless reconcile with results from Li and Strahan as banks likely relied on their existing relationships to identify potential PPP borrowers.

3.1 The PPPLF Alleviated Capital Constraints

Our results on participation and intensity of participation reveal the remarkable finding that more leveraged banks participated in the PPP and disbursed larger shares of loans. A direct explanation for this behavior, as we previously discussed, is that PPP loans offered a channel to transfer risks from capital-constrained banks to the federal government. In this subsection, we show that the features of the Federal Reserve's PPPLF, which was established to enhance PPP participation, also contributed to increased participation by leveraged banks. Whereas PPP loans carried a zero risk weight and thereby did not weigh on risk-based capital ratios, they depressed issuing banks' leverage ratio. In this context, the PPPLF alleviated potential capital constraints. PPP loans pledged to the facility were exempt from the bank's leverage ratio. Other studies of the PPPLF have examined the role of the PPPLF in alleviating liquidity consitraints [Anbil et al., 2021]. Our analysis highlights the PPPLF's role in fostering participation in the PPP by alleviating capital constraints.

Table 3 shows the determinants of banks' participation decision in the PPPLF based on estimates of logit models. We focus on the effects of leverage ratio and C&I exposure, but have considered a range of other controls related to liquidity, profitability, and provisions. Exemption on the leverage ratio was an important driver of bank participation in the PPPLF. The estimate in column (1) shows that banks with lower leverage ratios were more likely to participate in the PPPLF. This effect remains statistically significant even after controlling for measures of C&I exposure in column (5). In this specification, both the share of undrawn commitments and on-balance sheet exposures drive PPPLF participation higher. Banks with substantial C&I exposure could potentially forestall additional drawdowns and credit losses, both sources of pressure on capital, by lending PPP loans. Exposed banks could then maintain their capital level by financing PPP loans through the PPPLF. Together, the coefficients on leverage and C&I lending suggest that the exclusion of loans pledged to the PPPLF from leverage ratio were important in driving bank participation in the PPP.

Table 3: PPPLF Participation Determinants

	(1)	(2)	(3)	(4)	(5)
Leverage Ratio	-0.116***				-0.114***
	(0.020)				(0.020)
C&I to assets		0.058***			0.034***
		(0.005)			(0.009)
Small C&I to assets			0.078***		0.013
			(0.009)		(0.013)
Unused C&I Commitments to Assets				0.103***	0.060***
				(0.010)	(0.013)
Observations	7,022	7,022	7,022	7,022	7,022
Loglik	-2,630.09	-2,583.72	-2,612.38	-2,596.61	-2,551.76
Bank controls	Yes	Yes	Yes	Yes	Yes
Psuedo R^2	0.07	0.08	0.07	0.08	0.10

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We next turn to the determinants of how much banks decided to rely on the PPPLF in Table 4. The results represent estimates from a linear regression of the share of PPP loans pledged to the PPPLF on bank characteristics. Our findings on PPPLF intensity mirror those on the PPPLF participation decision. Columns (1) through (5) show that capital constrained banks and those with a larger exposure to C&I loans pledged larger shares of loans to the PPPLF facility.

Table 4: PPPLF Participation Intensity Determinants

	(1)	(2)	(3)	(4)	(5)
Leverage Ratio	-0.609***				-0.541***
	(0.098)				(0.097)
C&I to assets		0.518***			0.598***
		(0.059)			(0.114)
Small C&I to assets			0.581***		-0.199
			(0.090)		(0.144)
Unused C&I Commitments to Assets				0.605***	-0.017
				(0.103)	(0.136)
Observations	6,940	6,940	6,940	6,940	6,940
Adjusted R2	0.041	0.056	0.046	0.044	0.059
Bank controls	Yes	Yes	Yes	Yes	Yes

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Absent the PPPLF, many banks may have found PPP loans unprofitable given their low interest rate relative to funding costs or may been concerned about the capital space used by PPP loans that might put them too close to their regulatory minimums. By alleviating these concerns, the PPPLF made the PPP more successful among community banks than it otherwise would have been.

4 How did the PPP Affect Bank Lending and Profits?

We quantify the effect of the PPP on bank profits and lending after conditioning on the selection effects modeled in the previous section. Notably, incremental participation in the PPP diluted bank profitability on account of its low interest rates and gradual recognition of fees. Nearly all of the lending growth the PPP generated was directly within the program. The program did not induce non-PPP C&I lending or risk-taking under CRE categories. The countervailing effect of the PPP on bank profits, and negligible effects on risk-taking reinforce our finding from the previous section–risk-aversion was salient in motivating banks to participate in the program.

Table 5 reports the estimates for equation 3, which models bank outcomes for PPP participants. The first row reports the main treatment effects of incremental participation in the PPP on profitability and loan growth. In column (1), a one percent higher participation intensity lowered NIM by 4.3 basis points relative to 2019 levels. At the mean PPP intensity rate of 8.5 percent, this estimate explains the full decline of 33 basis points in NIM experienced by participating banks since 2019. C&I lending grew by 10.5 percent on a year-over-year basis in response to a one percent higher intensity of PPP lending as shown in column (2). However, all of the lending growth emanated from within the program–we find no statistically important effect on lending growth outside the PPP in column (3). Similarly, incremental participation in the PPP did not result in statistically important effects on risk-taking as measured by growth in CRE loans in column (4).

We report the estimates for bank controls that reflect funding capacity and exposure to losses, namely bank size and loan and loan loss allowances in Table 5.[10] We trace the effect of these characteristics on bank profits and loan growth as funding capacity and exposure to losses were salient in determining participation and intensity decisions. The PPP was more profitable and generated higher C&I growth among larger community banks. Previously, we had found that larger banks were more likely to participate in the program, and with greater intensity. Taken together, these findings suggest that larger banks that were able to participate materially in the program were likely overcame the limiting effect of the program's low interest rates and generated profits from originating large volumes of loans.

Banks that had reserved larger shares of their loan portfolios for loan loss allowances underwent larger declines in profits and loan 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 depicted in column (1). 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. While lending declined across C&I and CRE categories in columns (2)-(4), much of this decline was concen-

[10]We report the estimates for the full set of control variables in Tables D.3 and D.4 in Appendix D.3

Table 5: Profitability and Loan Growth Outcomes at Participant Banks

	ΔNIM (bps)	C&I Growth(%)	Non-PPP C&I Growth(%)	CRE Growth(%)
	(1)	(2)	(3)	(4)
PPP Loans to Total Loans	-4.27	10.52	-0.46	0.23
	[-6.03, -2.7]	[9.26, 11.87]	[-1.46, 0.57]	[-0.54, 1.01]
$\ln Assets$	3.98	6.20	0.13	0.36
	[2.72, 5.33]	[5.18, 7.19]	[-0.82, 1.04]	[-0.48, 1.2]
ALLL to Total Loans	-3.29	-3.67	-2.72	-0.53
	[-5.28, -1.32]	[-6.2, -1.15]	[-3.65, -1.78]	[-1.23, 0.18]

Table 6: Profitability and Loan Growth Outcomes at Non-Participant Banks

	ΔNIM (bps)	C&I Growth(%)	Non-PPP C&I Growth(%)	CRE Growth(%)
	(1)	(2)	(3)	(4)
$\ln Assets$	-0.91	-7.47	-6.64	-3.72
	[-4.99, 3.55]	[-8.46, -6.49]	[-7.57, -5.72]	[-4.41, -3.02]
ALLL to Total Loans	-9.60	-2.06	0.02	-0.93
	[-12.19, -6.98]	[-4.6, 0.44]	[-2.42, 2.44]	[-2.55, 0.68]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

trated in non-PPP C&I where banks would be fully exposed to inherent credit risks. This finding is consistent with the heightened risk aversion among banks exposed to losses from business loans, which we encountered in their participation and intensity decisions.

Table 6 reports the coefficient estimates for non-participants. Notably, the direction of coefficients associated with bank size is the opposite to that of participants. Larger banks experienced a steeper decline in margins and a sharper contraction in lending. This suggests that smaller non-participants expanded their loan portfolio and exposed their capital to potential credit losses even as larger banks curtailed lending, likely reflecting pandemic support from the smallest banks based on relationship-lending. As in the case of participants, increased loan loss allowances at non-participants was associated with a larger decline in NIM as well as a contraction in C&I lending. Since these allowances represent higher expected credit losses, they limited lenders' ability to use their resources to disburse risky loans and to maintain profits. Table 7 characterizes the direction and magnitude of covariances across the steps in the joint model–bank participation, intensity and outcomes on profitability and lending. [11] Overall, the covariances illustrate that selection effects from bank decisions were salient–banks that were better positioned to expand their loan portfolios and to earn higher net interest margins strategically opted into the program. The first row shows that participation was positively related to intensity–banks that were most likely to participate in the PPP expended larger shares of their loanable funds on the program. The second and third rows show that unobserved factors related to bank participation, and intensity were positively related to the unobserved component of bank profitability and loan growth. Finally, in line with our expectations, the relationships between non-participation and bank outcomes in the bottom row move in an approximately opposite direction to those in the second row between participation and outcomes. These results support our hypothesis that bank decisions related to the PPP were endogenous – banks that were more likely to expand their loan portfolio and earn higher profits participated more intensively in the program. Banks less likely to expand loans and profit from the program withheld

[11] The underlying numerical estimates are presented in Table E.1 in Appendix E.

participation.

Table 7: Covariance Estimates from the Bayesian Joint Model

	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
	(1)	(2)	(3)	(4)
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 E.1 in the Appendix.

We investigate the timing of the PPP's effects on bank outcomes in Table 8. While early access to the program was critical for firms to withstand the disruptions from the pandemic[Balyuk et al., 2021; Doniger and Kay, 2021], we find that the timing of PPP lending was also relevant to banks' profitability. We split our sample period into subsamples for 2020:Q2 and 2020:Q3, the quarters when the program was most active. [12] The first column shows that the decline in NIM we had previously reported occurred almost entirely in the second quarter of 2020. Lending growth, however, did not vary across the two quarters. C&I lending consistently grew year-over-year in both quarters as shown by column (2). Similarly, columns (3) and (4) show that the program had only a modest effect on lending outside of the program in both quarters. Our results suggest that banks' margins declined when they swiftly disbursed a large number of loans early in the pandemic, when economic activity was restricted, and financial markets were in turmoil. But, as economic activity increased and demand for loans stabilized, banks likely developed the capacity to process applications by assessing their impact on profit margins. In addition, the

[12] Additional details about the individual quarter estimates are available in Appendix G. Results for the fourth quarter of 2020, which is not considered in our main sample, are presented in Appendix I.

latter rounds of the PPP involved smaller loan amounts, which carried a higher percent of fees, further supporting bank margins.

Table 8: Quarterly Treatment Effects by Outcome

	ΔNIM(bps)	C&I Gwth(%)	Non-PPP C&I Gwth(%)	CRE Gwth(%)
	(1)	(2)	(3)	(4)
Baseline	-4.27	10.52	-0.46	0.23
	[-6.03, -2.7]	[9.26, 11.87]	[-1.46, 0.57]	[-0.54, 1.01]
Q2 2020	-6.91	10.72	0.36	0.20
	[-9.15, -4.92]	[8.65, 12.92]	[-0.89, 1.71]	[-0.71, 1.09]
Q3 2020	-0.19	9.53	-0.33	0.41
	[-2.54, 2.39]	[7.18, 12.04]	[-2.33, 1.54]	[-0.76, 1.61]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Finally, we reevaluate treatment effects by controlling for the sharp rise in credit line drawdowns that banks experienced in the first quarter of 2020. Table 9 reports our baseline result for PPP intensity from Table 5 as well as estimates from a model that includes an indicator for banks in the top quartile of C&I growth in 2020:Q1. We find that on controlling for large drawdowns, the negative effect of the PPP on profit margins is only slightly attenuated. This finding suggests that the decline in NIM from the PPP was not inadvertently reporting the effect of a sudden expansion of the asset base from drawdowns. Growth in total C&I lending was higher in the specification that included large C&I drawdowns. Columns (3) and (4) show that the effect of the PPP on lending outside of the program remained muted even after controlling for credit line drawdowns. Therefore, the effects of the PPP on lending growth remain broadly unchanged even after addressing the conversion of off-balance sheet commitments into on-balance sheet exposures from firm usage of credit lines. [13]

[13] Appendix K summarizes the direct effect of drawdowns on participation, intensity, and bank outcomes controlling for other characteristics. We find that banks that experienced large drawdowns were more likely to participate in the PPP, as well as undergo larger growth in C&I loans and larger change in NIM relative to 2019.

Table 9: C&I Loan Draw Effects

	ΔNIM(bps)	C&I Gwth(%)	Non-PPP C&I Gwth(%)	CRE Gwth(%)
	(1)	(2)	(3)	4)
Baseline	-4.27	10.52	-0.46	0.23
	[-6.03, -2.7]	[9.26, 11.87]	[-1.46, 0.57]	[-0.54, 1.01]
Baseline + CI gwth top qrtile	-3.92	12.13	0.20	0.29
	[-5.45, -2.37]	[10.67, 13.61]	[-0.78, 1.17]	[-0.46, 0.99]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

5 Did the PPP Crowd Out Lending or Avert A Credit Crunch?

The PPP will ultimately be deemed successful if the program met small businesses' demand for funds that would have otherwise been unaddressed by the private sector. Alternatively, the program would be considered inefficient if it instead crowded out private lending by banks and hindered their prospects for growth and earnings. Would banks have been willing to extend loans at a time when firms' need for funds was intense, but ability to repay was uncertain? To answer this question, we generate counterfactual rates at which lending would have grown at participating banks in the event they had not participated in the PPP. This counterfactual analysis is different from the potential outcome of banks had the PPP itself not been introduced. The latter is not estimable because 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 sub-category of institutions had been ineligible to participate in the program.

Since no major sub-class of financial intermediaries were excluded from participating in the PPP, we evaluate counterfactuals by using outcomes of banks that were unaffiliated with the program by their own choice–namely, non-participant banks. Accordingly, our estimates represent lending and profits that participating banks would have incurred, had they chosen not to participate in the PPP. To evaluate counterfactuals, we multiply the estimates that correspond to outcomes for non-participants

(Equation 4) with the financial characteristics pertaining to participants($\mathbf{x_i}$).

Figure 3a shows that had participating banks not engaged in the PPP, they would have contracted their loan portfolio substantially. The blue and green lines respectively denote the average realized levels of C&I loan growth for participants and non-participants. The yellow density represents the posterior distribution of the counterfactual C&I growth for PPP participants. Participating banks experienced exceptional year-over-year growth of 92%, whereas non-participants grew their loan books by a more modest, but notable rate of 10%. If participating banks had not associated with the program, their C&I loans would have likely contracted by 78 percent. This contraction is statistically important since the full density lies on the negative real line. Participating banks would have substantially reduced lending and allowed portfolio runoffs if they had not entered the PPP. This finding reveals that the PPP served as a backstop to the banking system by preventing a contraction in bank lending.

Our counterfactual estimate of a decline of nearly 80 percent in C&I loan books is striking. However, Figure 2 demonstrates that our estimates align with declines across loan portfolios during the Global Financial Crisis (GFC), especially among loan categories directly afflicted by the crisis. In that crisis, community banks experienced shocks to commercial real estate portfolios, and specifically to construction and land development loans [Bassett and Marsh, 2017; Friend, Glenos, and Nichols, 2013]. Figure 2 shows that peak-to-trough declines in C&I and CRE loans at community banks registered at about 15 and 20 percent respectively. Most of the run-off in CRE loans was due to declines in the most affected portfolio, construction and land development (CLD), which contracted by nearly 70 percent in total. Notably, the declines in loan balances that began during the GFC persisted for several years after the NBER recession ended.

While our results suggest that lending would have contracted more precipitously than during the GFC, a larger and more rapid contraction in lending is consistent with the nature of the COVID shock. The onset of the pandemic induced widespread panic in financial markets[Acharya and Steffen, 2020], and a sudden and deep recession that was ultimately short-lived. At its genesis, however, the pandemic looked

Figure 2: GFC Growth Rates at Community Banks

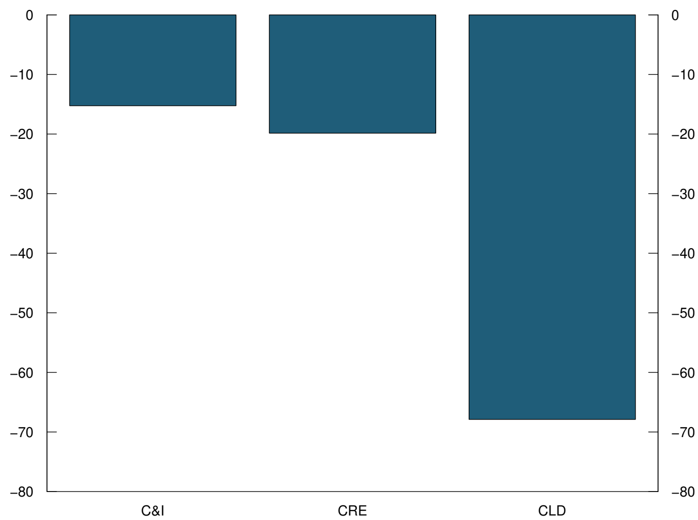


Chart shows peak-to-trough growth rates of selected loan portfolios at community banks from the Global Financial Crisis. Peak date is 2007:Q3, the start of the NBER recession period, for all portfolios. Trough dates are the last quarter when aggregate growth was negative. Trough dates by portfolio are: C&I, 2011:Q1; CRE, 2012:Q3; and CLD, 2013:Q1.
Source: Call Reports.

likely to rival and even surpass the Global Financial Crisis in terms of economic costs.[14] Due to the starkly weaker outlook at the onset of the pandemic, we should expect that loan growth would decline suddenly and dramatically in the ensuing period as our estimates suggest, rather than over a period of several years as seen in the Global Financial Crisis. Accordingly, our findings are in line with the results from Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) that provided evidence of a severe and sudden tightening of lending standards.[15] 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

[14]The U.S. economy shed about 8 million jobs during the Great Recession of 2008, and over 20 million jobs during the COVID-19 recession. Source: Authors' calculations from Total Nonfarm Employees from the U.S. Bureau of Labor Statistics.

[15]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

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].

The PPP not only forestalled contraction in C&I lending, the program also pre-empted lending declines in the commercial real estate portfolio. Figure 3b shows that CRE lending would have declined 52 percent if participants had forgone the PPP program compared to a realized growth rate of 7 percent. This substantial difference between realized and counterfactual growth further supports our finding that the PPP served as a backstop to bank lending.

Consistent with the loan declines the PPP averted, we find that, on average, bank profitability was also supported by program participation. Figure 3c shows that participants had a realized decline in net interest margins of 33 basis points. Absent program participation however, average net interest margins were projected to decline more than 40 basis points. Although the posterior interval around this estimate spans zero, the mass of the distribution lies on the negative real line. These findings reconcile easily with results from Section 4. Even though incremental participation compressed margins due to low interest rates, the program averted a larger decline in NIM that would have arisen from a freeze in bank lending and runoffs in loan portfolios. Undoubtedly, the PPP helped to minimize credit losses, which supported margins, but it also upheld margins by inducing banks to continue, rather than retrench lending.

In Table 10, we examine the main drivers underlying the remarkable decline in counterfactual lending and margins for program participants.[16] To this end, we evaluate a measure of the average contribution of each covariate to the counterfactual, namely, the product of the mean value of the covariate across participants with the estimated coefficient of that covariate for non-participants. This denoted as $\bar{\mathbf{x}}_{p,j}\beta_{4j}^{(g)}$, $g = 1, 2, ..., 50,000$, where $\bar{\mathbf{x}}_{p,j}$ is the mean value of each covariate j across participants and $\beta_{4j}^{(g)}$ is the g^{th} posterior draw of the associated coefficient from equation 4. The table reports the mean and 95 percent credibility interval of this product across the 50,000 posterior draws.

[16]We provide the full set of results from the decomposition in Table H.1 in Appendix H.

Table 10: Decomposition of predicted counterfactual outcomes for participants

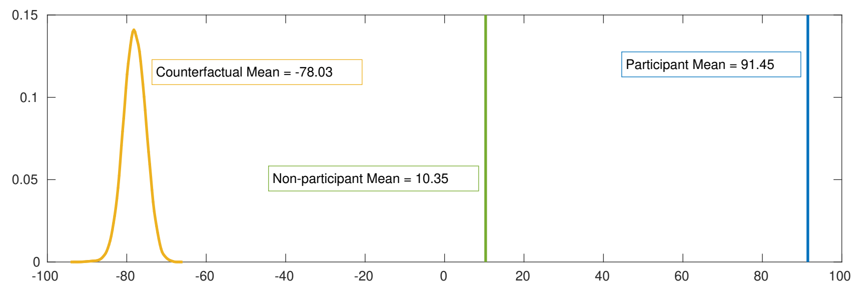
	ΔNIM	C&I Gwth	CRE Gwth
	(1)	(2)	(3)
ln Assets	-32.69	-91.32	-44.71
	[-68.92, 10.89]	[-103.66, -79.68]	[-53.63, -36.27]
ALLL to Total Loans	-12.66	-2.95	-1.1
	[-16.05, -9.32]	[-6.25, 0.29]	[-3.21, 1.01]

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 55,000 MCMC draws with a burn-in of 5000.

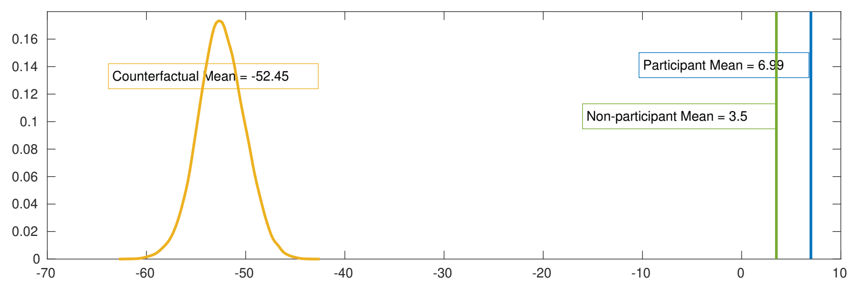
Our decomposition of the counterfactual outcomes reveals two important findings. First, bank size and loan loss allowances predominantly explain the full magnitude of counterfactual lending and margins. Second, the relationship between bank characteristics and outcomes is fundamentally different across participants and non-participants. Together with the differences in the pre-pandemic characteristics across the two groups of institutions, these differences in relationships explain why participating banks would have contracted their loan portfolios and faced greater margin compression if they had not engaged in the PPP, compared to the banks that actually opted out of the program.

Bank size largely explains the sharply lower counterfactual margins and loan growth for participants relative to their realized outcomes. Contrary to participants, margins and lending growth declined with size among non-participants. Moreover, participating banks are larger than non-participants. Taken together, the model predicts that the mean participants' asset size would have contributed to a decline in NIM of 32 basis points relative to 2019, and a reduction in C&I and CRE loan portfolios by 91 percent and 45 percent respectively, had they not participated in the PPP. This result points to the differences in the way small and large community banks responded to the crisis. Smaller banks, which were less likely to participate in the program, continued to lend loans using their own capital. The larger banks were more likely to participate in the PPP, and those that did not engage in the program

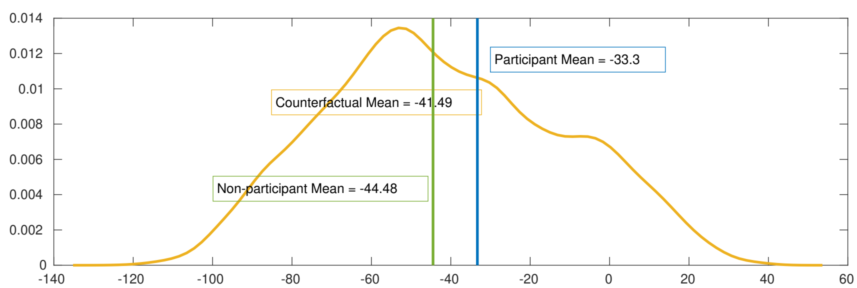
Figure 3: Estimated Counterfactual Values



(a) C&I Loan Growth



(b) CRE Loan Growth



(c) ΔNIM

Charts show the posterior density of counterfactual YoY growth in C&I loans, average YoY growth in C&I loans outside of the PPP, average YoY growth in CRE loans outside of the PPP, and average change in NIM, respectively, for participating banks in the event of non-participation. The blue and green lines represent the realized average values for these categories for participants and non-participants, respectively, over year ending in Q2 and Q3 2020.
Source: Authors' calculations.

curtailed lending. Therefore, participating banks, which were relatively larger in size, would have retrenched lending and undergone further compression in margins if they had not engaged in the PPP.

The second salient factor underlying participants' counterfactuals is the ratio of loan loss allowances to total loans. Participating banks with average ALLL ratios were likely to undergo a 13 basis point decline in NIM relative to 2019, and declines of 3 and 1 percentage points in C&I and CRE loan growth respectively. Loan loss allowances, were on average higher among non-participants, and were associated negatively with loan growth and margins among participants and non-participants. Our results show that if participants had foregone the PPP, banks already exposed to potential losses would have withheld lending to mitigate further losses, even at the cost of additional margin compression.

The counterfactual values for bank lending are consistent with our finding that bank participation in the PPP was motivated by risk-aversion. Banks that participated in the PPP would not have expanded lending to address business credit needs had they not participated in the program. This means the PPP, crucially, did not crowd out private lending. Instead, the PPP offset what would have been a sharp decline in bank lending. Notably, the PPP served as a backstop to bank lending. Minoiu, Zarutskie, and Zlate [2021] identified that the Main Street Lending Progam (MSLP) functioned as a backstop by stimulating lending outside of the program. The PPP, instead, provided a backstop by preventing declines in non-PPP loan portfolios. Further, our counterfactual results highlight the limitation of relationship lending during crises. Our counterfactual results confirm that, in fact, absent the PPP, bank lending to businesses would have contracted substantially. While existing relationships measured by C&I lending exposures would have mitigated this effect to some degree, they do not fully offset the credit crunch that would have occurred absent the PPP.

6 Robustness

We verify that our results are not sensitive to model misspecification issues by generating related, but distinct, exogenous variables for PPP intensity. This corresponds to reestimating the joint Bayesian model by replacing the variable $z_{i,2}$ with alternatives. We consider three additional variables. First, we calculate the share of small firm employment from the QWI data. This variable is constructed in the same fashion as the variable measuring COVID-affected employment share. We weight the share of firms with less than 500 employees in a county by a bank's deposit share in that county. The 500 employee cutoff roughly corresponds to the firm eligibility criteria in the PPP. This variable acts as an alternative to the PPP demand instrument created using COVID-affected sector employment. Second, we use a bank's core deposits to assets ratio as the exogenous variable. This variable measures a bank's ability to fund PPP loans without additional capital market activity. Finally, we consider the share of unused commitments to total assets. This variable captures a bank's exposure to potential pandemic-induced drawdowns. In our risk-aversion interpretation of the model results, banks should be more willing to generate PPP loans during periods of heightened uncertainty for customers that have unused commitments because they can fully capture the benefits of the government guarantee while retaining their customer relationships without risking their own capital.

While we find these exogenous variables acceptable, they are not preferable to our main excluded variable. COVID-affected sector employment is exogenous to both the broader economy and bank lending. COVID's differential effect across sectors was unrelated to economic activity and firm access to bank funding. For these reasons, we find this variable to be most suitable for identification. Alternatively, while we have no reason to believe PPP's employment eligibility cutoff was not set arbitrarily, it could have been set in response to financing needs or COVID's expected impact. While we still find the share of eligible firms to be a convincing variable for identification, it is not as strongly exogenous as COVID-affected employment. Finally, the bank measures are least suitable as exogenous variables. First, balance sheet characteristics will affect both profitability and lending outcomes. Second, while we measure these variables as-of 2019, or during the pre-pandemic period, bank balance sheets changed dramatically during the pandemic which also affects outcomes for banks. For this reason, it is unclear, ex-ante, that pre-pandemic balance sheet measures are useful indicators for predicted decision making during the pandemic, especially when considering the sizable changes in deposit and loan growth beginning in 2020:Q1.

Table 11 shows the standardized coefficient estimates for the PPP intensity equation using the COVID-affected employment variable and the three alternative variables. Small firm employment is negatively related to PPP intensity suggesting that firm size is not an adequate demand control. The bank balance sheet measures, however, are consistent with our expectations. Banks with greater core deposit funding and more unused commitments as a share of assets were more intensive PPP lenders. These results reemphasize the selection effects across banks and show that banks better positioned to lend, or those that faced higher loss probabilities, were more likely to participate in the program. All these estimates are statistically important.

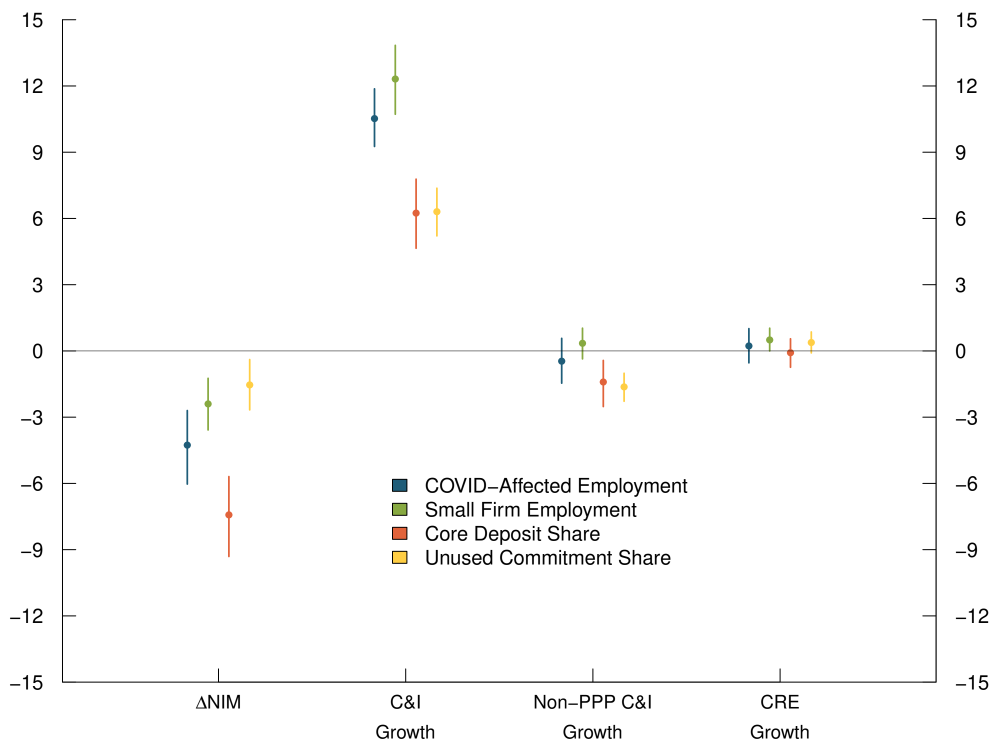
Table 11: Alternative Instrument Effects

	COVID-affected Employment	Small firm Employment	Core Deposit Ratio	Unused C&I Cmmt Ratio
	(1)	(2)	(3)	(4)
Mean	0.093	-0.135	0.106	0.263
	[0.07, 0.11]	[-0.16, -0.11]	[0.09, 0.13]	[0.24, 0.29]

Note: Table shows standardized coefficients for each exogenous variable on PPP intensity. Coefficients are estimated using the Bayesian joint model shown in equations 1 - 4. 95% credibility intervals are shown in brackets.

Figure 4 shows the coefficients on PPP intensity, namely, the treatment effects of the PPP on participants using each of the instruments. We find that the point estimates for the change in net interest margins range from about -1 to -8 basis points across each set of instruments. Most all the point estimates from our main specification are within the range of estimates generated using alternative instruments, suggesting that our main findings are robust to model specification changes. For example, all the net interest margin estimates are negative, statistically important, and closely clustered, regardless of the exogenous variable used. C&I loan growth estimates are similarly grouped. C&I lending increased between 6 and 12 percent, and the estimates are statistically important across all model specifications. We find only small effects for non-PPP C&I lending and CRE growth across specifications. These estimates are not always statistically important either. This reconfirms our result that spillovers across portfolios were limited.

Figure 4: Treatment effects by instrument



Source: Call Reports.

As an alternative to our Bayesian joint estimation, we use our exogenous variable set to estimate outcomes using a classical frequentist two-stage least square approach. In this setup, we model PPP intensity in the first stage and the outcome in the second stage. We instrument PPP intensity using our preferred instrument, COVID-affected employment share in a bank's local market. The two stage least square results are shown in Table 12. The first row reports the coefficients on PPP intensity on various bank outcomes from the baseline, Bayesian joint model. Our OLS and IV estimates of the PPP intensity coefficient are reported in rows 2 and 3 respectively.[17] We find that using OLS or instrumenting PPP intensity with COVID-affected employment both show negative effects on NIMs and strong positive effects on total C&I lending. The IV estimates, which account for selection of PPP intensity, are larger than the OLS estimates in both cases. Bayesian estimates account for both, selection into the PPP and intensity of participation. The magnitude of the treatment effect on profitability in the Bayesian setting is larger than the IV estimate. These results reveal the salience of selection effects and the need to appropriately model them to generate valid estimates of treatment effects. Treatment effects on non-PPP lending portfolios are small, limited, and not always statistically important. These results are consistent with our Bayesian model estimates and suggest that the effects of the program predominantly operated through the C&I portfolio.

Table 12: OLS and Two-stage Least Squares Estimation

	ΔNIM(bps)	C&I Gwth(%)	Non-PPP C&I Gwth(%)	CRE Gwth(%)
	(1)	(2)	(3)	(4)
Baseline	-4.27	10.52	-0.46	0.23
	[-6.03, -2.7]	[9.26, 11.87]	[-1.46, 0.57]	[-0.54, 1.01]
OLS	-1.22***	11.26***	-0.10*	0.18***
	(-5.00)	(47.74)	(-2.10)	(4.41)
IV	-3.25***	15.07***	0.77*	0.26
	(-4.61)	(15.15)	(2.15)	(0.87)

Notes: Table shows estimates of PPP intensity on bank profitability and balance sheet outcomes from the Bayesian joint model ("Baseline") as well as a standard OLS and a two-stage least squares model. The two-stage least squares model uses the share of COVID-affected employment in a bank's local market as the instrument. For the baseline model, 95% credibility intervals are shown in brackets. T-statistics are shown in parenthesis for the OLS and two-stage least squares estimates.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[17] Additional details on the logit, IV and OLS results are presented in Appendix J.

7 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 not only supported businesses, but also the banks that disbursed the loans. 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 mid-sized 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. One of the reasons for the widespread take-up of the PPP was likely the broader guarantee implicit in the program relative to standard loan guarantee programs. European guarantee programs that were set up contemporaneously with the PPP, and prior programs in Japan did not convert loans to grants by means of a forgiveness procedure [Ono et al., 2013; Core and De Marco, 2021]. Indeed, other programs provided only partial guarantees for loans above a threshold. Despite the more generous nature of the PPP's loan guarantees, which likely induced greater bank and firm participation, other features of the program placed costs on participating banks and checked excessive transfer of risk to the federal government. 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.

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ONLINE APPENDIX MATERIALS

A Key Paycheck Protection Program Dates

Table A.1 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 A.1: 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 B.1 describes the PPP loan terms.

Table B.1: 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 C.1 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 C.1: 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 the estimation algorithm, we 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,

$$\boldsymbol{y}_{i,p} = \begin{pmatrix} y^*_{i1} \\ y_{i2} \\ y_{i3} \end{pmatrix}, \quad \boldsymbol{y}_{i,np} = \begin{pmatrix} y^*_{i1} \\ y_{i4} \end{pmatrix}. \tag{8}$$

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

$$\mu_{i,p} = \begin{pmatrix} \mathbf{x_i'}\beta_\mathbf{1} + z_{i1}\gamma_1 \\ \mathbf{x_i'}\beta_\mathbf{2} + z_{i2}\gamma_2 \\ \mathbf{x_i'}\beta_\mathbf{3} + y_{i2}\delta \end{pmatrix}, \quad \mu_{i,np} = \begin{pmatrix} \mathbf{x_i'}\beta_\mathbf{1} + z_{i1}\gamma_1 \\ \mathbf{x_i'}\beta_\mathbf{4} \end{pmatrix}. \tag{9}$$

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,

$$\Omega_p = \begin{pmatrix} 1 & \Omega_{12} & \Omega_{13} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} \end{pmatrix}, \quad \Omega_{np} = \begin{pmatrix} 1 & \Omega_{14} \\ \Omega_{41} & \Omega_{44} \end{pmatrix}. \tag{10}$$

Subsequently, 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

The likelihood and priors we have specified generate conditional conjugacy. We thereby develop the following Gibbs sampler to estimate the model.[18]

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.

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.

[18] The trace plots for the results in Section 3 and the simulation study are available upon request.

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, $y_{i1}^*|\theta, y, \Omega \sim \mathcal{TN}_{(-\infty,0)}\left(\mu_{i,np|\setminus 1}, \Omega_{np|\setminus 1}\right)$ for $i \in N_{np}$ and $y_{i1}^*|\theta, y, \Omega \sim \mathcal{TN}_{(0,\infty)}\left(\mu_{i,p|\setminus 1}, \Omega_{p|\setminus 1}\right)$ 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 D.1 presents the results of the simulation study. 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 $\boldsymbol{\beta} = \{\beta_1, \beta_2, \beta_3, \beta_4\}$.

Table D.1: 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.

D.3 Additional Results for Participation and Intensity

See Table D.2.

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

	C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)
	Part.	Intensity	Part.	Intensity	Part.	Intensity
Tech exp. to assets	-0.17		-0.09		0.02	
	[-0.26, -0.07]		[-0.17, -0.01]		[-0.07, 0.11]	
COVID-affected employment share		0.08		0.03		0.03
		[0.06, 0.1]		[0.02, 0.04]		[0.02, 0.04]
ln Assets	0.14	0.81	0.15	1.12	0.19	1.25
	[0.12, 0.16]	[0.68, 0.95]	[0.13, 0.17]	[0.99, 1.24]	[0.17, 0.21]	[1.12, 1.38]
CI to assets	-0.02	0.38	0.04	0.31	0.03	0.30
	[-0.03, -0.02]	[0.36, 0.41]	[0.03, 0.04]	[0.28, 0.33]	[0.03, 0.04]	[0.27, 0.32]
Leverage Ratio	-0.02	-0.26	-0.04	-0.30	-0.04	-0.30
	[-0.03, -0.01]	[-0.32, -0.21]	[-0.05, -0.03]	[-0.36, -0.25]	[-0.05, -0.03]	[-0.36, -0.25]
Liquid Assets to Assets	0.00	0.09	0.01	0.07	0.01	0.07
	[0, 0]	[0.08, 0.1]	[0, 0.01]	[0.06, 0.09]	[0, 0.01]	[0.06, 0.09]
ALLL to Total Loans	0.00	0.45	-0.03	0.09	-0.02	0.12
	[-0.03, 0.04]	[0.19, 0.7]	[-0.07, 0.01]	[-0.15, 0.33]	[-0.06, 0.03]	[-0.12, 0.37]
ROA	0.07	0.10	0.08	0.28	0.07	0.25
	[0.03, 0.12]	[-0.16, 0.37]	[0.03, 0.12]	[0.02, 0.54]	[0.03, 0.12]	[-0.01, 0.52]
Cases Per 100k	0.03	0.11	0.01	0.09	0.02	0.11
	[0, 0.06]	[-0.06, 0.28]	[-0.02, 0.04]	[-0.08, 0.27]	[-0.02, 0.05]	[-0.07, 0.28]
Constant	-0.41	-6.75	-0.82	-8.38	-1.25	-10.01
	[-0.67, -0.15]	[-8.59, -4.91]	[-1.07, -0.56]	[-10.07, -6.67]	[-1.54, -0.96]	[-11.77, -8.24]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Table D.3: Profitability and Loan Growth Outcomes at Participant Banks

	ΔNIM(bps)	CI Gwth(%)	Non-PPP CI Gwth(%)	CRE Gwth(%)
	(1)	(2)	(3)	(4)
PPP Loans to Total Loans	-4.27	10.52	-0.46	0.23
	[-6.03, -2.7]	[9.26, 11.87]	[-1.46, 0.57]	[-0.54, 1.01]
ln *Assets*	3.98	6.20	0.13	0.36
	[2.72, 5.33]	[5.18, 7.19]	[-0.82, 1.04]	[-0.48, 1.2]
C&I to assets	0.42	-7.18	0.22	0.10
	[-0.09, 0.97]	[-7.77, -6.63]	[-0.1, 0.54]	[-0.14, 0.34]
Leverage Ratio	-2.48	-0.23	-0.09	0.28
	[-3.33, -1.71]	[-0.94, 0.49]	[-0.5, 0.34]	[-0.04, 0.59]
Liquid Assets to Assets	-0.05	-0.80	0.07	-0.03
	[-0.2, 0.1]	[-0.99, -0.61]	[-0.02, 0.15]	[-0.1, 0.03]
ALLL to Total Loans	-3.29	-3.67	-2.72	-0.53
	[-5.28, -1.32]	[-6.2, -1.15]	[-3.65, -1.78]	[-1.23, 0.18]
ROA	-10.48	1.38	-2.12	-1.84
	[-12.56, -8.3]	[-1.24, 4.03]	[-3.14, -1.09]	[-2.61, -1.08]
Cases Per 100k	-8.42	2.79	-0.07	0.02
	[-9.76, -7.05]	[0.98, 4.6]	[-0.7, 0.56]	[-0.45, 0.5]
Constant	0.03	-0.64	2.55	0.03
	[-5.94, 6.06]	[-6.61, 5.35]	[-3.27, 8.41]	[-5.89, 5.91]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Table D.4: Profitability and Loan Growth Outcomes at Non-Participant Banks

	ΔNIM(bps)	CI Gwth(%)	Non-PPP CI Gwth(%)	CRE Gwth(%)
	(1)	(2)	(3)	(4)
ln *Assets*	-0.91	-7.47	-6.64	-3.72
	[-4.99, 3.55]	[-8.46, -6.49]	[-7.57, -5.72]	[-4.41, -3.02]
C&I to assets	-0.10	1.42	-1.86	-1.07
	[-1.13, 1.04]	[1.06, 1.79]	[-2.17, -1.56]	[-1.28, -0.87]
Leverage Ratio	-0.26	0.84	1.98	1.06
	[-1.54, 0.92]	[0.21, 1.46]	[1.36, 2.61]	[0.67, 1.45]
Liquid Assets to Assets	-0.41	-0.06	-0.47	-0.24
	[-0.68, -0.12]	[-0.23, 0.11]	[-0.64, -0.3]	[-0.36, -0.13]
ALLL to Total Loans	-9.60	-2.06	0.02	-0.93
	[-12.19, -6.98]	[-4.6, 0.44]	[-2.42, 2.44]	[-2.55, 0.68]
ROA	-1.54	-0.03	-0.39	0.27
	[-5.5, 2.45]	[-3.16, 3.11]	[-3.48, 2.74]	[-1.87, 2.4]
Cases Per 100k	-3.77	-2.46	-1.74	-0.43
	[-6.83, -0.69]	[-4.75, -0.21]	[-4.02, 0.54]	[-2.03, 1.13]
Constant	-0.60	-1.27	0.68	-2.00
	[-6.7, 5.48]	[-7.35, 4.8]	[-5.32, 6.71]	[-7.84, 3.87]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

E Covariances from the Bayesian Joint Model

Estimated covariances from the Bayesian Joint Model are presented in Table E.1.

Table E.1: Covariance estimates from the Bayesian joint model

	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	6.87	3.72	6.89	6.89
	[6.74, 6.99]	[3.38, 4.04]	[6.77, 7.01]	[6.77, 7.01]
COV(participation, bank outcome)	17.50	64.72	3.35	-0.09
	[6.48, 29.58]	[59.16, 69.6]	[-3.83, 10.19]	[-5.53, 5.22]
COV(intensity, bank outcome)	143.31	63.71	18.49	-2.11
	[67.09, 228.09]	[6.64, 116.31]	[-31.82, 66.78]	[-40.18, 35.36]
COV(non-participation, bank outcome)	-0.13	-61.53	-62.38	-36.18
	[-33.01, 35.67]	[-65.52, -57.74]	[-66.37, -58.52]	[-39.21, -33.22]

E.1 Interpreting Marginal and Conditional Estimates

To interpret the differences in the estimated coefficients of C&I loans to assets across columns (4) and (6) in Table 5 and 6, we must consider the implications of using a joint modeling structure represented in Equations 1-4. First, estimates for each equation represent moments from the marginal distribution, after marginalizing out the remaining outcomes from the remaining equations. Second, covariances between selection, and outcomes for participants and non-participants introduce dependence between estimates for the two groups. Below, we consider conditional estimates instead of marginal estimates for non-participants, to perform a more direct comparison across specifications in columns (4) and (6).

Consider the outcomes, mean and covariances for non-participants represented in Equations 8, 9, and 10. The joint model for the two outcomes pertaining to non-participants is represented by,

$$\begin{pmatrix} y_{i1}^{*} \\ y_{i4} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mathbf{x_i}'\beta_{\mathbf{1}} + z_{i1}\gamma_1 \\ \mathbf{x_i}'\beta_{\mathbf{4}} \end{pmatrix}, \begin{pmatrix} 1 & \Omega_{14} \\ \Omega_{41} & \Omega_{44} \end{pmatrix}\right). \tag{11}$$

This joint Gaussian distribution results in the following expression for the mean of bank outcomes y_{i4}^{*} conditional on non-participation[Poirier, 1995].

$$E\left[y_{i4} | y_{i1}^{*}, \beta, \Omega\right] = \mathbf{x_i}'\left(\beta_{\mathbf{4}} - \Omega_{14}\beta_{\mathbf{1}}\right) + \Omega_{14} y_{i1}^{*} - \Omega_{14} z_{i1}\gamma_1. \tag{12}$$

We obtain the posterior conditional mean of the coefficient of C&I loans to assets and 95 percent credible intervals by using the estimates of $\beta_{\mathbf{1}}, \beta_{\mathbf{4}}$, and Ω_{14} from Tables 2, 5, 6, and E.1 in Equation 12.

The conditional moments of the coefficient of C&I assets are qualitatively similar when the outcome is C&I loans or C&I loans excluding PPP. C&I loans increase by 0.25 percentage points for a percent increase in C&I concentration. The 95 percent probability intervals for this estimate are -0.10 and 0.62 percentage points. Under the specification with C&I loans outside the PPP, the conditional mean estimate is 0.49 percentage points with a probability interval of 0.19 and 0.79. Therefore, the seemingly large difference between the marginal estimates of 1.4 and -1.8 percentage points are resolved upon evaluating their corresponding conditional estimates.

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, Kovner, and Shachar [2020].

Figure F.1: Change in employment

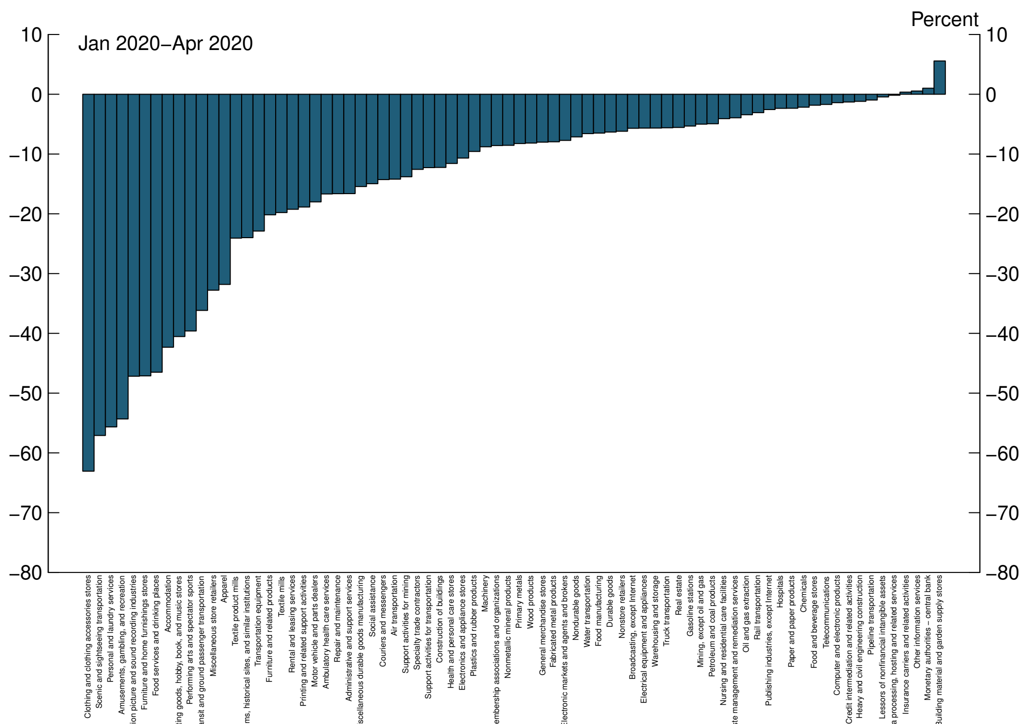

Chart shows percent change in employment over Jan - Apr 2020 across industries.
Source: CES data from the Bureau of Labor Statistics.

G Quarterly Results from the Bayesian Model

Tables G.1 and G.2 provide results for bank outcomes in the quarters 2020:Q2 and 2020:Q3, respectively. Columns (1), (3), (5), and (7) report the results for participation in the program. The results for each quarter are qualitatively similar to the combined results. In particular, larger, and more liquid 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.

Table G.1: Results for participation and intensity from the Bayesian joint model in Q2 2020

	ΔNIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity
Tech exp. to assets	-0.128		-0.204		-0.145		-0.032	
	[-0.31, 0.05]		[-0.33, -0.07]		[-0.27, -0.02]		[-0.18, 0.1]	
COVID-affected employment share		0.039		0.086		0.04		0.039
		[0.02, 0.06]		[0.06, 0.11]		[0.02, 0.06]		[0.02, 0.06]
ln Assets	0.178	1.213	0.122	0.786	0.141	1.054	0.191	1.222
	[0.14, 0.22]	[1.04, 1.39]	[0.09, 0.15]	[0.6, 0.97]	[0.11, 0.17]	[0.87, 1.23]	[0.16, 0.22]	[1.04, 1.4]
CI to assets	0.033	0.294	-0.024	0.368	0.034	0.297	0.032	0.289
	[0.03, 0.04]	[0.26, 0.33]	[-0.03, -0.02]	[0.33, 0.4]	[0.03, 0.04]	[0.26, 0.33]	[0.03, 0.04]	[0.26, 0.32]
Leverage Ratio	-0.046	-0.327	-0.025	-0.292	-0.042	-0.328	-0.044	-0.324
	[-0.06, -0.03]	[-0.4, -0.25]	[-0.04, -0.01]	[-0.37, -0.21]	[-0.06, -0.03]	[-0.41, -0.25]	[-0.06, -0.03]	[-0.4, -0.25]
Liquid Assets to Assets	0.006	0.074	-0.001	0.09	0.006	0.07	0.006	0.071
	[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	-0.026	0.136	0.007	0.389	-0.038	0.051	-0.03	0.046
	[-0.09, 0.04]	[-0.21, 0.48]	[-0.04, 0.06]	[0.04, 0.74]	[-0.09, 0.01]	[-0.28, 0.38]	[-0.09, 0.03]	[-0.3, 0.39]
ROA	0.116	0.562	0.092	0.277	0.093	0.483	0.1	0.478
	[0.04, 0.19]	[0.19, 0.93]	[0.03, 0.16]	[-0.09, 0.65]	[0.03, 0.16]	[0.12, 0.85]	[0.03, 0.17]	[0.1, 0.85]
Cases Per 100k	0.026	0.034	0.042	-0.095	-0.004	-0.148	-0.015	-0.132
	[-0.07, 0.13]	[-0.47, 0.54]	[-0.03, 0.12]	[-0.6, 0.41]	[-0.09, 0.08]	[-0.64, 0.35]	[-0.11, 0.08]	[-0.65, 0.38]
Constant	-1.096	-9.708	-0.159	-6.048	-0.624	-7.399	-1.233	-9.483
	[-1.59, -0.6]	[-12.01, -7.47]	[-0.54, 0.21]	[-8.51, -3.57]	[-1.01, -0.23]	[-9.8, -4.96]	[-1.66, -0.81]	[-11.91, -7.06]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Table G.2: Results for participation and intensity from the Bayesian joint model in Q3 2020

	ΔNIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity
Tech exp. to assets	-0.108		-0.143		-0.083		0.048	
	[-0.29, 0.07]		[-0.3, 0.01]		[-0.26, 0.07]		[-0.11, 0.2]	
COVID-affected employment share		0.035		0.081		0.061		0.045
		[0.02, 0.05]		[0.06, 0.11]		[0.01, 0.13]		[0.02, 0.11]
ln Assets	0.161	1.106	0.147	0.739	0.173	0.84	0.188	1.074
	[0.12, 0.2]	[0.91, 1.3]	[0.12, 0.18]	[0.55, 0.93]	[0.13, 0.23]	[0.34, 1.24]	[0.15, 0.24]	[0.45, 1.33]
CI to assets	0.034	0.317	-0.02	0.398	0.018	0.346	0.029	0.321
	[0.03, 0.04]	[0.28, 0.35]	[-0.03, -0.01]	[0.36, 0.43]	[-0.01, 0.04]	[0.29, 0.41]	[0, 0.04]	[0.28, 0.4]
Leverage Ratio	-0.043	-0.315	-0.02	-0.249	-0.036	-0.249	-0.041	-0.289
	[-0.06, -0.03]	[-0.4, -0.23]	[-0.03, -0.01]	[-0.33, -0.17]	[-0.05, -0.02]	[-0.36, -0.12]	[-0.05, -0.03]	[-0.38, -0.14]
Liquid Assets to Assets	0.006	0.073	-0.001	0.089	0.001	0.084	0.005	0.076
	[0, 0.01]	[0.05, 0.09]	[0, 0]	[0.07, 0.11]	[-0.01, 0.01]	[0.06, 0.12]	[-0.01, 0.01]	[0.05, 0.11]
ALLL to Total Loans	-0.021	0.163	0.001	0.455	-0.022	0.267	-0.007	0.23
	[-0.08, 0.04]	[-0.2, 0.53]	[-0.05, 0.05]	[0.1, 0.81]	[-0.08, 0.04]	[-0.15, 0.72]	[-0.07, 0.06]	[-0.15, 0.64]
ROA	0.056	0.009	0.059	-0.058	0.08	-0.083	0.057	-0.007
	[-0.02, 0.13]	[-0.4, 0.41]	[0, 0.12]	[-0.42, 0.31]	[0.01, 0.16]	[-0.66, 0.43]	[-0.01, 0.14]	[-0.54, 0.41]
Cases Per 100k	0.022	0.132	0.03	0.144	0.015	0.148	0.01	0.142
	[-0.02, 0.07]	[-0.11, 0.37]	[-0.01, 0.07]	[-0.08, 0.37]	[-0.03, 0.06]	[-0.09, 0.39]	[-0.04, 0.06]	[-0.1, 0.38]
Constant	-0.88	-8.062	-0.529	-5.927	-0.81	-6.05	-1.157	-8.159
	[-1.39, -0.37]	[-10.7, -5.4]	[-0.92, -0.15]	[-8.46, -3.39]	[-1.21, -0.39]	[-10.18, -1.04]	[-1.59, -0.69]	[-11.22, -2.52]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Columns (2), (4), (6), and (8) 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, more liquid 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, as in the case of participation, this relationship was weaker in Q3 2020.

Tables G.3 and G.4 report results for Q2 and Q3 2020 respectively, under the specifications presented in Tables 5 and 6. Columns (1), (3), (5), and (7) 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 do not persist into Q3. Banks experienced a larger decline in profitability during the first round when firms rushed to obtain PPP funding and when banks processed large volumes of applications. By the second round, profit margins were likely cushioned by fees and interest accrued from the first round as well as the smaller size of loans relative to the first round on account of larger firms gaining early access, and small firms gaining access subsequently [Balyuk et al., 2021].[19] Banks that participated more intensively in the PPP experienced substantial growth in their overall C&I loan portfolio and weaker growth in non-PPP C&I loans. 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.

[19]The sliding scale in fees resulted in a larger percent of loan amount paid out as fees for small loans compared to large loans. Details of fee structure available here.

Table G.3: Results for profitability and loan growth of participating and non-participating banks in Q2 2020

	ΔNIM(bps)		CI Gwth(%)		Non-PPP CI Gwth(%)		CRE Gwth(%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)
PPP Loans to Total Loans	-6.914		10.717		0.363		0.202	
	[-9.15, -4.92]		[8.65, 12.92]		[-0.89, 1.71]		[-0.71, 1.09]	
ln Assets	5.278	-1.501	5.898	-6.707	-0.384	-6.081	0.444	-3.728
	[3.73, 7.02]	[-6.44, 3.69]	[4.38, 7.35]	[-7.93, -5.51]	[-1.5, 0.67]	[-7.28, -4.93]	[-0.45, 1.34]	[-4.63, -2.86]
CI to assets	1.446	-0.284	-7.209	1.308	0.009	-1.618	0.08	-1.032
	[0.78, 2.19]	[-1.54, 1]	[-8.09, -6.35]	[0.82, 1.81]	[-0.41, 0.39]	[-2.05, -1.21]	[-0.19, 0.36]	[-1.32, -0.76]
Leverage Ratio	-3.736	0.249	-0.114	0.656	0.218	1.667	0.34	0.939
	[-4.95, -2.65]	[-1.23, 1.64]	[-1.2, 1]	[-0.12, 1.43]	[-0.34, 0.83]	[0.84, 2.49]	[-0.07, 0.75]	[0.42, 1.47]
Liquid Assets to Assets	0.267	-0.45	-0.759	-0.106	0.021	-0.446	-0.052	-0.19
	[0.05, 0.51]	[-0.8, -0.11]	[-1.04, -0.48]	[-0.33, 0.12]	[-0.09, 0.13]	[-0.68, -0.21]	[-0.13, 0.03]	[-0.34, -0.04]
ALLL to Total Loans	-2.992	-8.652	-3.881	-1.711	-2.714	0.518	-0.259	-0.511
	[-6.1, 0.14]	[-11.93, -5.28]	[-7.17, -0.59]	[-4.8, 1.33]	[-4.01, -1.39]	[-2.56, 3.59]	[-1.26, 0.73]	[-2.69, 1.65]
ROA	-6.035	-1.985	1.521	-0.204	-1.899	-0.666	-2.229	0.236
	[-9.43, -2.48]	[-6.75, 2.78]	[-1.99, 5.04]	[-4.02, 3.6]	[-3.43, -0.43]	[-4.47, 3.15]	[-3.36, -1.1]	[-2.55, 3.03]
Cases Per 100k	-3.176	-2.896	5.757	-2.377	0.059	-1.562	-0.088	-1.184
	[-7.16, 0.79]	[-8.26, 2.52]	[1.59, 9.9]	[-7.11, 2.3]	[-1.77, 1.91]	[-6.37, 3.28]	[-1.48, 1.29]	[-5.23, 2.75]
Constant	1.904	-0.577	-0.137	-0.608	1.95	0.32	-0.878	-1.476
	[-4.25, 8.07]	[-6.74, 5.55]	[-6.18, 5.89]	[-6.69, 5.48]	[-3.9, 7.75]	[-5.77, 6.45]	[-6.72, 5.03]	[-7.51, 4.56]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Table G.4: Results for profitability and loan growth of participating and non-participating banks in Q3 2020

	ΔNIM(bps)		CI Gwth(%)		Non-PPP CI Gwth(%)		CRE Gwth(%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)
PPP Loans to Total Loans	-0.185		9.529		-0.331		0.41	
	[-2.54, 2.39]		[7.18, 12.04]		[-2.33, 1.54]		[-0.76, 1.61]	
ln Assets	0.751	-1.128	6.672	-7.459	0.35	-8.115	0.279	-3.887
	[-1.12, 2.46]	[-5.33, 3.93]	[5.17, 8.17]	[-8.82, -6.14]	[-0.63, 1.58]	[-11.48, -5.49]	[-0.67, 1.24]	[-5.94, -2.78]
CI to assets	-1.138	-0.213	-6.826	1.198	0.149	-0.91	0.058	-0.856
	[-1.98, -0.37]	[-1.32, 1.13]	[-7.89, -5.81]	[0.69, 1.71]	[-0.52, 0.81]	[-2.29, 0.89]	[-0.42, 0.45]	[-1.28, 0.2]
Leverage Ratio	-0.781	-0.968	-0.585	0.769	-0.274	1.785	0.204	1.029
	[-1.83, 0.33]	[-2.41, 0.37]	[-1.68, 0.5]	[-0.15, 1.68]	[-0.82, 0.22]	[0.77, 2.78]	[-0.23, 0.65]	[0.46, 1.61]
Liquid Assets to Assets	-0.465	-0.456	-0.764	-0.041	0.007	-0.103	-0.039	-0.199
	[-0.67, -0.27]	[-0.81, -0.09]	[-1.06, -0.47]	[-0.29, 0.21]	[-0.22, 0.21]	[-0.62, 0.55]	[-0.21, 0.07]	[-0.4, 0.21]
ALLL to Total Loans	-3.169	-7.649	-2.558	-2.166	-2.738	-0.768	-0.886	-1.282
	[-5.46, -0.89]	[-11.17, -4.14]	[-5.8, 0.75]	[-5.52, 1.12]	[-4.23, -1.27]	[-4.36, 2.67]	[-2.1, 0.2]	[-3.88, 1.06]
ROA	-12.066	-0.988	0.924	0.134	-1.768	-0.793	-1.232	-0.253
	[-14.44, -9.69]	[-5.66, 3.73]	[-2.41, 4.28]	[-3.85, 4.08]	[-3.76, 0.44]	[-5.68, 3.72]	[-2.44, 0.59]	[-3.5, 2.79]
Cases Per 100k	-1.685	-1.322	2.678	-1.649	-0.038	-1.16	-0.023	-0.729
	[-3.25, -0.15]	[-5.08, 2.45]	[0.33, 5.06]	[-4.51, 1.18]	[-1.02, 0.94]	[-4.26, 1.88]	[-0.71, 0.65]	[-2.85, 1.44]
Constant	-1.364	-0.157	-0.253	-1.046	0.337	-0.453	0.286	-1.328
	[-7.45, 4.78]	[-6.37, 5.99]	[-6.31, 5.83]	[-7.19, 5.02]	[-5.81, 6.75]	[-6.58, 5.69]	[-7.13, 6.77]	[-7.35, 4.68]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Columns (2), (4), (6), and (8) report the coefficient estimates for non-participants. The results continue to be consistent with overall results in Tables 5 and 6. 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 G.5 and G.6 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 E.1. 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 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 continues 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 G.5: Covariance estimates from the Bayesian joint model based on Q2 2020 outcomes

	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	6.70	3.56	6.76	6.75
	[6.51, 6.88]	[3.12, 4.01]	[6.59, 6.93]	[6.58, 6.92]
COV(participation, bank outcome)	34.58	64.82	-2.43	-0.09
	[20.65, 50.25]	[56.31, 72.31]	[-11.6, 6.14]	[-6.13, 6.08]
COV(intensity, bank outcome)	276.33	46.73	-23.83	-2.26
	[182.62, 382.21]	[-42.5, 132.84]	[-87.54, 34.95]	[-43.89, 40.44]
COV(non-participation, bank outcome)	-3.11	-56.67	-58.07	-34.66
	[-43.06, 38.25]	[-61.98, -51.63]	[-63.74, -52.74]	[-38.85, -30.79]

Table G.6: Covariance estimates from the Bayesian joint model based on Q3 2020 outcomes

	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	6.92	3.72	3.99	5.98
	[6.75, 7.1]	[3.31, 4.13]	[-0.73, 7.08]	[-0.5, 7.09]
COV(participation, bank outcome)	-12.46	67.92	14.16	1.67
	[-30.2, 3.92]	[57.82, 77.12]	[-0.06, 23.38]	[-7.27, 15.76]
COV(intensity, bank outcome)	-71.08	112.42	17.75	-8.82
	[-198.82, 44.93]	[4.58, 214.17]	[-65.61, 114.26]	[-61.05, 47.27]
COV(non-participation, bank outcome)	-2.99	-61.76	-63.08	-36.19
	[-35.84, 38.18]	[-67.6, -56.46]	[-69.02, -57.32]	[-40.38, -32.39]

H Decomposition of Counterfactual Results

We examine the drivers of the predicted counterfactuals for participants in Table H.1. To this end, we evaluate $\bar{\mathbf{x}}_{p,j}\beta_{4j}^{(g)}$, $g = 1, 2, ..., 50,000$, 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 95 percent credibility interval of this product across the 50,000 posterior draws.

Bank size is the primary determinant of the lower counterfactual change in NIM and loan growth for participants. Participants with asset size at the mean of the group 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 negative coefficient on bank size among non-participants. Small, non-participant banks continued to lend C&I and CRE loans over the course of the pandemic while large non-participants curtailed such lending as depicted in Tables 5 and 6. Large non-participant banks underwent greater declines in NIM relative to small non-participants. Accordingly, if participants had used the decision rules of non-participants, they would have largely cut back lending and earned lower profits as they were, on average, larger than non-participants.

The second most important factor driving the predicted decline in counterfactual profitability and loan growth is the ratio of loan loss allowances to total loans. Participating banks with average levels of this ratio were likely to undergo a 13 basis point decline in change in NIM, and a decline of nearly 3 percentage points to C&I loan growth. Loan loss allowances, therefore, served as a constraint on loan growth and earnings. Moreover, as banks set aside larger reserves when they expect bigger losses, large loan loss allowances are suggestive of riskier loan portfolios. Our results thereby reveal that banks exposed to potential losses would have likely withheld lending on account of risk-aversion, which in the aggregate, would have contributed to a credit crunch.

Unlike bank size and the ratio of loss allowances to total loans, other characteristics do not predict as large a decline in margins and lending, but reflect the realities of increased risk taking in a crisis. For example, better capitalized banks, which have greater space to absorb additional losses, would have increased their lending by more than their less capitalized peers. Banks with greater exposure to C&I loans, and more liquid banks would have increased C&I lending, but curtailed CRE loan growth. And finally, we find that COVID exposure, and thus greater loan risk, would have further reduced C&I and CRE loan growth. Interestingly, previous profitability was not statistically important in determining counterfactual outcomes, suggesting that the precarious outlook for borrowers would have likely outweighed banks' ability to generate pre-pandemic earnings in driving lending declines. These results are all consistent with elevated risk-aversion and the importance of sizable capital buffers in a crisis.

Table H.1: Decomposition of predicted counterfactual outcomes for participants

	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
	(1)	(2)	(3)	(4)
ln Assets	-32.69	-91.32	-127.43	-44.71
	[-68.92, 10.89]	[-103.66, -79.68]	[-141.69, -113.81]	[-53.63, -36.27]
CI to assets	-4.48	12.52	5.02	-10.96
	[-11.98, 4.2]	[9.03, 16.04]	[1.58, 8.45]	[-12.95, -9.01]
Leverage Ratio	1.17	9.24	19.65	11.77
	[-10.69, 12.12]	[2.41, 16.05]	[12, 27.42]	[7.45, 16.24]
Liquid Assets to Assets	-7.82	-1.29	6.05	-5.26
	[-12.91, -2.59]	[-4.75, 2.14]	[2.01, 10.22]	[-7.52, -3.02]
ALLL to Total Loans	-12.66	-2.95	-1.71	-1.1
	[-16.05, -9.32]	[-6.25, 0.29]	[-5.33, 1.94]	[-3.21, 1.01]
ROA	-1.78	-0.56	-4.48	0.86
	[-6.23, 2.67]	[-4.29, 3.15]	[-8.62, -0.4]	[-1.67, 3.37]
Cases Per 100k	-3.24	-2.4	-2	-0.51
	[-5.68, -0.85]	[-4.27, -0.52]	[-4.22, 0.14]	[-1.78, 0.76]
Constant	-0.57	-1.17	-0.24	-2.29
	[-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 55,000 MCMC draws with a burn-in of 5000.

I 2020:Q4 Results from the Bayesian Model

Table I.1 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.

Table I.1: Results for participation and intensity from the Bayesian joint model in Q4 2020

	ΔNIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Part.	Intensity	Part.	Intensity	Part.	Intensity	Part.	Intensity
Tech exp. to assets	-0.072		-0.082		-0.049		-0.048	
	[-0.22, 0.08]		[-0.22, 0.05]		[-0.18, 0.09]		[-0.18, 0.09]	
COVID-affected employment share		0.022		0.032		0.019		0.024
		[0.01, 0.03]		[0.01, 0.05]		[0.01, 0.03]		[0.01, 0.04]
ln Assets	0.196	1.167	0.157	0.967	0.166	1.053	0.182	1.072
	[0.16, 0.23]	[1.02, 1.32]	[0.13, 0.19]	[0.8, 1.13]	[0.14, 0.2]	[0.91, 1.2]	[0.15, 0.21]	[0.92, 1.23]
CI to assets	0.038	0.265	-0.001	0.32	0.038	0.267	0.036	0.263
	[0.03, 0.04]	[0.24, 0.29]	[-0.02, 0.02]	[0.29, 0.35]	[0.03, 0.04]	[0.24, 0.3]	[0.03, 0.04]	[0.23, 0.29]
Leverage Ratio	-0.035	-0.206	-0.029	-0.203	-0.038	-0.222	-0.04	-0.23
	[-0.05, -0.02]	[-0.27, -0.14]	[-0.04, -0.02]	[-0.27, -0.13]	[-0.05, -0.03]	[-0.29, -0.16]	[-0.05, -0.03]	[-0.3, -0.16]
Liquid Assets to Assets	0.007	0.055	0.003	0.06	0.007	0.056	0.007	0.053
	[0, 0.01]	[0.04, 0.07]	[0, 0.01]	[0.04, 0.08]	[0, 0.01]	[0.04, 0.07]	[0, 0.01]	[0.04, 0.07]
ALLL to Total Loans	0.01	0.131	0.024	0.363	0.001	0.104	0.014	0.159
	[-0.04, 0.06]	[-0.16, 0.42]	[-0.03, 0.07]	[0.05, 0.67]	[-0.05, 0.05]	[-0.18, 0.38]	[-0.04, 0.07]	[-0.13, 0.45]
ROA	-0.006	-0.229	0.053	0.088	0.053	0.112	0.043	0.058
	[-0.07, 0.06]	[-0.54, 0.09]	[-0.01, 0.11]	[-0.22, 0.4]	[-0.01, 0.12]	[-0.19, 0.42]	[-0.02, 0.11]	[-0.26, 0.38]
Cases Per 100k	-0.041	-0.349	-0.036	-0.388	-0.048	-0.383	-0.047	-0.377
	[-0.07, -0.02]	[-0.46, -0.23]	[-0.06, -0.01]	[-0.5, -0.27]	[-0.07, -0.02]	[-0.5, -0.27]	[-0.07, -0.02]	[-0.49, -0.26]
Constant	-1.365	-9.484	-0.639	-8.218	-0.991	-8.095	-1.144	-8.253
	[-1.87, -0.87]	[-11.66, -7.41]	[-1.06, -0.23]	[-10.41, -6.03]	[-1.4, -0.58]	[-10.18, -6.04]	[-1.57, -0.72]	[-10.42, -6.1]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

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 I.2 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.

Table I.2: Results for profitability and loan growth of participating and non-participating banks in Q4 2020

	ΔNIM(bps)		CI Gwth(%)		Non-PPP CI Gwth(%)		CRE Gwth(%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)	(part.)	(non-part.)
PPP Loans to Total Loans	5.759		7.427		-1.924		0.922	
	[3.43, 8.26]		[4.04, 9.63]		[-3.55, -0.44]		[-0.25, 2.17]	
ln Assets	-1.619	-0.869	6.188	-6.7	1.06	-5.537	0.086	-2.967
	[-3.44, 0.09]	[-4.87, 3.75]	[4.72, 8.09]	[-8.02, -5.38]	[-0.08, 2.27]	[-6.75, -4.35]	[-0.95, 1.07]	[-3.86, -2.09]
CI to assets	-2.356	-0.323	-4.418	0.11	0.432	-1.599	-0.013	-1.116
	[-3.11, -1.66]	[-1.51, 1.05]	[-5.18, -3.48]	[-0.76, 0.89]	[0.01, 0.89]	[-1.99, -1.22]	[-0.35, 0.3]	[-1.39, -0.85]
Leverage Ratio	0.23	-1.835	-0.616	0.819	-0.359	1.16	0.383	0.431
	[-0.73, 1.28]	[-3.28, -0.43]	[-1.59, 0.28]	[-0.04, 1.66]	[-0.93, 0.16]	[0.39, 1.94]	[-0.01, 0.81]	[-0.1, 0.96]
Liquid Assets to Assets	-0.966	-0.282	-0.341	-0.204	0.088	-0.332	-0.05	-0.209
	[-1.19, -0.76]	[-0.7, 0.14]	[-0.55, -0.1]	[-0.45, 0.04]	[-0.02, 0.2]	[-0.54, -0.13]	[-0.13, 0.02]	[-0.36, -0.07]
ALLL to Total Loans	-3.176	-6.629	-3.176	-2.234	-2.183	-1.357	-1.291	-1.069
	[-6.24, -0.07]	[-10.48, -2.77]	[-5.94, -0.4]	[-5.2, 0.69]	[-3.64, -0.74]	[-4.04, 1.33]	[-2.3, -0.28]	[-3.02, 0.88]
ROA	-13.664	-1.193	0.869	2.147	-0.811	2.166	-1.379	1.347
	[-16.9, -10.35]	[-6.04, 3.69]	[-2.1, 3.81]	[-1.56, 5.83]	[-2.3, 0.7]	[-1.34, 5.7]	[-2.43, -0.34]	[-1.32, 4]
Cases Per 100k	1.695	-1.22	-2.512	1.46	-1.144	1.756	0.057	0.966
	[0.09, 3.41]	[-4.22, 1.84]	[-4.42, -0.93]	[-0.36, 3.27]	[-2.09, -0.28]	[0.12, 3.39]	[-0.58, 0.74]	[-0.25, 2.16]
Constant	-0.944	-0.512	0.543	-0.331	1.606	0.452	0.894	0.234
	[-7.11, 5.18]	[-6.66, 5.58]	[-5.55, 6.56]	[-6.46, 5.83]	[-4.52, 7.71]	[-5.66, 6.53]	[-5.05, 6.92]	[-5.76, 6.3]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

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 I.3 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 I.3: Covariance estimates from the Bayesian joint model based on Q4 2020 outcomes

	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	5.73	4.81	5.74	5.73
	[5.6, 5.86]	[3.99, 5.45]	[5.6, 5.88]	[5.6, 5.87]
COV(participation, bank outcome)	-41.93	43.78	11.32	-4.33
	[-56.16, -28.67]	[30.81, 54.74]	[2.76, 20.77]	[-11.58, 2.44]
COV(intensity, bank outcome)	-236.32	114.25	62.91	-25.28
	[-319.47, -157.9]	[42.85, 223.33]	[13.11, 117.37]	[-67.35, 14.07]
COV(non-participation, bank outcome)	-1.39	-52.70	-48.76	-32.07
	[-32.89, 37.82]	[-58.02, -47.45]	[-54, -43.81]	[-35.81, -28.49]

J 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.

J.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 $Z_{emp,i}$,

$$PPP_i = Z_{emp,i}\pi + W_i'\psi + \nu_i. \tag{13}$$

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

$$Y_i = P\hat{P}P_i\beta + W_i'\gamma + \epsilon_i. \tag{14}$$

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. [2020b] 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 [2021] 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.

J.2 Logit Participation Results

Table J.1 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 J.1: PPP Participation Determinants

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	-0.000			-0.013	0.001			0.004
	(0.008)			(0.018)	(0.008)			(0.021)
Small CI to assets		-0.009		-0.006		-0.010		-0.025
		(0.009)		(0.020)		(0.009)		(0.022)
Unused CI Commitments to Assets			0.110***	0.127***			0.110***	0.118***
			(0.027)	(0.030)			(0.027)	(0.029)
ln *Assets*	0.723***	0.711***	0.636***	0.614***	0.749***	0.733***	0.668***	0.625***
	(0.046)	(0.046)	(0.051)	(0.054)	(0.049)	(0.049)	(0.053)	(0.057)
ROA	0.307***	0.313***	0.321***	0.330***	0.297***	0.305***	0.310***	0.330***
	(0.063)	(0.063)	(0.064)	(0.064)	(0.063)	(0.063)	(0.064)	(0.064)
Liquid Assets To Assets	-0.011***	-0.012***	-0.008***	-0.011***	-0.010***	-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***	-0.071***	-0.066***	-0.068***	-0.064***	-0.067***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ALLL to Total Loans	-0.034	-0.025	-0.034	-0.010	-0.046	-0.033	-0.044	-0.021
	(0.051)	(0.047)	(0.050)	(0.043)	(0.050)	(0.045)	(0.049)	(0.042)
Cases Per 100k	-0.020	-0.018	-0.024	-0.020	-0.017	-0.015	-0.022	-0.018
	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)	(0.042)	(0.041)	(0.041)
Constant	-5.789***	-5.579***	-5.100***	-4.708***	-6.139***	-5.863***	-5.512***	-4.878***
	(0.584)	(0.606)	(0.611)	(0.647)	(0.608)	(0.634)	(0.631)	(0.686)
Observations	7,786	7,786	7,786	7,786	6,853	6,853	6,853	6,853
Loglik	-2,362.48	-2,361.80	-2,341.77	-2,337.91	-2,274.61	-2,273.69	-2,255.32	-2,251.48
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 J.1 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.

J.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 J.2.

Table J.2: PPP Participation Intensity Determinants

	All Banks				Banks < \$1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.359***			0.119***	0.442***			0.253***
	(0.022)			(0.038)	(0.025)			(0.047)
Small CI to assets		0.467***		0.174***		0.523***		0.078
		(0.042)		(0.054)		(0.037)		(0.058)
Unused CI Commitments to Assets			0.763***	0.568***			0.844***	0.549***
			(0.033)	(0.050)			(0.040)	(0.057)
ln *Assets*	0.733***	1.522***	0.163**	0.463***	1.466***	2.308***	0.787***	1.071***
	(0.071)	(0.086)	(0.078)	(0.105)	(0.105)	(0.119)	(0.115)	(0.135)
ROA	-0.268	-0.452	-0.302	-0.317	-0.437	-0.635**	-0.461	-0.438
	(0.273)	(0.283)	(0.286)	(0.281)	(0.284)	(0.299)	(0.303)	(0.291)
Liquid Assets To Assets	0.106***	0.097***	0.085***	0.107***	0.118***	0.105***	0.090***	0.118***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Leverage Ratio	-0.211***	-0.176***	-0.226***	-0.193***	-0.171***	-0.141***	-0.207***	-0.168***
	(0.034)	(0.036)	(0.033)	(0.033)	(0.034)	(0.036)	(0.033)	(0.033)
ALLL to Total Loans	0.368**	0.409**	0.360**	0.334**	0.195	0.271	0.236	0.187
	(0.164)	(0.167)	(0.176)	(0.168)	(0.165)	(0.170)	(0.183)	(0.170)
Cases Per 100k	0.117	0.157*	0.209**	0.162**	0.192**	0.228**	0.283***	0.225***
	(0.084)	(0.086)	(0.083)	(0.081)	(0.089)	(0.092)	(0.089)	(0.086)
Constant	-3.826***	-13.144***	4.541***	-1.344	-13.654***	-23.116***	-3.165**	-9.343***
	(1.096)	(1.536)	(1.148)	(1.630)	(1.523)	(1.830)	(1.592)	(1.965)
Observations	7,022	7,022	7,022	7,022	6,104	6,104	6,104	6,104
Adjusted R2	0.152	0.112	0.169	0.196	0.190	0.134	0.184	0.226

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 [2021]. 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.[20]

J.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 J.3 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 and Yogo, 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 (3) and (4) show that core deposit shares and unused commitments, which measure

[20] In Appendix J, we report the results shown in table J.2 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.

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 J.4 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., 2021]. 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 J.4 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. 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 J.10 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 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.

J.5 Quarterly Estimates

Tables J.5 and J.6 provide results for the specifications presented in Table J.1 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 J.7 and J.8 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.

J.6 2020:Q4 Bank Outcomes

Table J.9 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 significant 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 J.10 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 J.3: PPP Intensity Share Determinants

	(1)	(2)	(3)	(4)
COVID-affected employment share	0.105***			
	(0.009)			
Small firm employment share		-0.098***		
		(0.007)		
Core Deposits To Assets			0.071***	
			(0.009)	
Unused CI Commitments to Assets				0.535***
				(0.050)
CI to assets	0.365***	0.340***	0.364***	0.206***
	(0.022)	(0.021)	(0.022)	(0.031)
ln *Assets*	0.564***	0.427***	0.738***	0.248***
	(0.074)	(0.077)	(0.071)	(0.080)
ROA	-0.191	-0.052	-0.424	-0.265
	(0.270)	(0.272)	(0.271)	(0.277)
Leverage Ratio	-0.205***	-0.219***	-0.144***	-0.211***
	(0.033)	(0.033)	(0.035)	(0.032)
ALLL to Total Loans	0.425***	0.505***	0.380**	0.336**
	(0.162)	(0.160)	(0.164)	(0.168)
Liquid Assets To Assets	0.101***	0.104***	0.084***	0.103***
	(0.007)	(0.007)	(0.008)	(0.007)
Cases Per 100k	0.141*	-0.148*	0.194**	0.158*
	(0.084)	(0.083)	(0.084)	(0.081)
Constant	-3.866***	5.851***	-9.107***	1.869
	(1.081)	(1.289)	(1.355)	(1.304)
Observations	7,022	7,022	7,022	7,022
F value	114.472	227.765	82.293	351.182
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 J.4: Bank Outcomes IV Regression: Employment share in COVID-affected industries

	Δ NIM		C&I Gwth		Non-PPP C&I Gwth		CRE Gwth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
PPP Loans to Total Loans	-1.223***	-3.246***	11.257***	15.066***	-0.104**	0.768**	0.176***	0.258
	(0.244)	(0.704)	(0.236)	(0.995)	(0.049)	(0.357)	(0.040)	(0.297)
CI to assets	-0.534***	0.194	-7.821***	-9.190***	0.118***	-0.195	0.118***	0.088
	(0.103)	(0.275)	(0.274)	(0.448)	(0.043)	(0.132)	(0.038)	(0.112)
ln *Assets*	0.808	2.292***	1.942**	-0.851	-0.574**	-1.213***	0.403*	0.343
	(0.542)	(0.757)	(0.786)	(1.126)	(0.260)	(0.362)	(0.213)	(0.290)
ROA	-12.211***	-12.754***	-3.564*	-2.542	-2.294***	-2.060***	-1.872***	-1.850***
	(2.053)	(1.758)	(2.006)	(2.155)	(0.597)	(0.614)	(0.536)	(0.540)
Leverage Ratio	-1.470***	-1.897***	0.912**	1.715***	-0.004	0.180	0.265**	0.283**
	(0.224)	(0.277)	(0.371)	(0.443)	(0.128)	(0.145)	(0.116)	(0.134)
ALLL to Total Loans	-3.918***	-3.173**	-5.345***	-6.746***	-2.839***	-3.160***	-0.520	-0.550
	(1.411)	(1.357)	(2.006)	(2.025)	(0.489)	(0.517)	(0.646)	(0.657)
Liquid Assets To Assets	-0.295***	-0.081	-0.655***	-1.058***	0.038	-0.054	-0.030	-0.038
	(0.058)	(0.093)	(0.110)	(0.155)	(0.029)	(0.048)	(0.023)	(0.039)
Cases Per 100k	-9.180***	-8.943***	3.303***	2.856***	-0.097	-0.199	0.026	0.016
	(0.625)	(0.634)	(1.008)	(1.040)	(0.318)	(0.330)	(0.232)	(0.233)
Constant	21.743***	14.000	53.560***	68.136***	9.764**	13.101***	-0.189	0.125
	(7.752)	(8.595)	(11.413)	(13.190)	(3.821)	(4.113)	(3.127)	(3.238)
Observations	7,022	7,022	7,022	7,022	7,022	7,022	7,022	7,022
Hausman F value		0.70		44.48		8.47		5.83
Hausman p-value		0.40		0.00		0.00		0.02

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 J.5: 2020:Q2 PPP Participation Determinants

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.001			-0.003	0.001			0.009
	(0.011)			(0.026)	(0.011)			(0.029)
Small CI to assets		-0.009		-0.016		-0.011		-0.029
		(0.012)		(0.029)		(0.012)		(0.032)
Unused CI Commitments to Assets			0.101***	0.113***			0.102***	0.108***
			(0.038)	(0.041)			(0.037)	(0.040)
ln *Assets*	0.734***	0.721***	0.655***	0.623***	0.741***	0.725***	0.668***	0.622***
	(0.063)	(0.064)	(0.070)	(0.076)	(0.068)	(0.069)	(0.074)	(0.080)
ROA	0.348***	0.355***	0.355***	0.370***	0.340***	0.349***	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)
Leverage Ratio				0.000				
				(.)				
ALLL to Total Loans	-0.060	-0.049	-0.058	-0.036	-0.067	-0.054	-0.064	-0.044
	(0.068)	(0.063)	(0.066)	(0.059)	(0.067)	(0.062)	(0.065)	(0.058)
Cases Per 100k	0.044	0.046	0.025	0.029	0.055	0.058	0.036	0.041
	(0.121)	(0.122)	(0.119)	(0.119)	(0.124)	(0.125)	(0.121)	(0.122)
Constant	-5.941***	-5.711***	-5.310***	-4.817***	-6.038***	-5.755***	-5.472***	-4.810***
	(0.802)	(0.834)	(0.842)	(0.907)	(0.853)	(0.888)	(0.885)	(0.962)
Observations	3,895	3,895	3,895	3,895	3,426	3,426	3,426	3,426
Loglik	-1,180.57	-1,180.20	-1,171.72	-1,170.10	-1,142.41	-1,141.92	-1,134.03	-1,132.16
Pseudo R^2	0.12	0.12	0.13	0.13	0.11	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 J.6: 2020:Q3 PPP Participation Determinants

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	-0.001			-0.022	0.002			0.000
	(0.011)			(0.023)	(0.012)			(0.029)
Small CI to assets		-0.008		0.003		-0.010		-0.021
		(0.013)		(0.026)		(0.012)		(0.031)
Unused CI Commitments to Assets			0.118***	0.142***			0.117***	0.129***
			(0.040)	(0.045)			(0.039)	(0.043)
ln *Assets*	0.718***	0.706***	0.623***	0.610***	0.762***	0.748***	0.676***	0.635***
	(0.066)	(0.067)	(0.074)	(0.077)	(0.069)	(0.070)	(0.076)	(0.082)
ROA	0.268***	0.273***	0.289***	0.291***	0.257***	0.263***	0.275***	0.291***
	(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	-0.072***	-0.073***	-0.069***	-0.070***	-0.063***	-0.064***	-0.061***	-0.063***
	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)
ALLL to Total Loans	-0.005	0.002	-0.007	0.019	-0.023	-0.011	-0.021	0.003
	(0.080)	(0.073)	(0.080)	(0.065)	(0.077)	(0.069)	(0.076)	(0.062)
Cases Per 100k	-0.060	-0.058	-0.062	-0.056	-0.064	-0.061	-0.066	-0.061
	(0.051)	(0.052)	(0.051)	(0.051)	(0.052)	(0.052)	(0.051)	(0.051)
Constant	-5.664***	-5.474***	-4.920***	-4.637***	-6.282***	-6.016***	-5.599***	-5.002***
	(0.849)	(0.882)	(0.886)	(0.926)	(0.867)	(0.906)	(0.900)	(0.982)
Observations	3,891	3,891	3,891	3,891	3,427	3,427	3,427	3,427
Loglik	-1,180.44	-1,180.15	-1,168.60	-1,166.14	-1,130.70	-1,130.29	-1,119.81	-1,117.86
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 J.7: PPP Participation Intensity Determinants: 2020:Q2

	All Banks				Banks < $1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.344***			0.097**	0.422***			0.221***
	(0.028)			(0.044)	(0.032)			(0.052)
Small CI to assets		0.455***		0.187***		0.508***		0.101
		(0.059)		(0.072)		(0.053)		(0.075)
Unused CI Commitments to Assets			0.745***	0.570***			0.821***	0.551***
			(0.044)	(0.066)			(0.053)	(0.076)
ln *Assets*	0.770***	1.529***	0.210*	0.518***	1.502***	2.310***	0.840***	1.139***
	(0.099)	(0.120)	(0.109)	(0.144)	(0.147)	(0.165)	(0.160)	(0.188)
ROA	-0.100	-0.267	-0.147	-0.166	-0.259	-0.438	-0.297	-0.279
	(0.319)	(0.328)	(0.343)	(0.334)	(0.333)	(0.345)	(0.364)	(0.348)
Liquid Assets To Assets	0.107***	0.099***	0.088***	0.108***	0.119***	0.106***	0.093***	0.120***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Leverage Ratio	-0.231***	-0.201***	-0.243***	-0.211***	-0.193***	-0.166***	-0.225***	-0.187***
	(0.045)	(0.047)	(0.043)	(0.044)	(0.045)	(0.046)	(0.044)	(0.044)
ALLL to Total Loans	0.340	0.384*	0.332	0.307	0.159	0.238	0.203	0.155
	(0.227)	(0.231)	(0.244)	(0.233)	(0.229)	(0.235)	(0.253)	(0.235)
Cases Per 100k	-0.129	-0.032	-0.082	-0.102	0.244	0.294	0.236	0.231
	(0.256)	(0.256)	(0.249)	(0.247)	(0.285)	(0.284)	(0.274)	(0.273)
Constant	-4.019***	-13.025***	4.139***	-1.786	-13.819***	-22.945***	-3.652*	-9.952***
	(1.513)	(2.121)	(1.585)	(2.296)	(2.094)	(2.509)	(2.191)	(2.781)
Observations	3,509	3,509	3,509	3,509	3,047	3,047	3,047	3,047
Adjusted R2	0.148	0.112	0.169	0.194	0.184	0.134	0.183	0.221

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 J.8: PPP Participation Intensity Determinants: 2020:Q3

	All Banks				Banks < \$1 billion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CI to assets	0.374***			0.141**	0.462***			0.284***
	(0.033)			(0.062)	(0.038)			(0.077)
Small CI to assets		0.479***		0.159**		0.537***		0.056
		(0.059)		(0.081)		(0.052)		(0.090)
Unused CI Commitments to Assets			0.781***	0.567***			0.867***	0.547***
			(0.048)	(0.075)			(0.059)	(0.085)
ln *Assets*	0.702***	1.515***	0.115	0.408***	1.424***	2.297***	0.720***	0.993***
	(0.102)	(0.124)	(0.113)	(0.152)	(0.150)	(0.172)	(0.165)	(0.194)
ROA	-0.431	-0.628	-0.451	-0.463	-0.598	-0.814*	-0.607	-0.580
	(0.432)	(0.452)	(0.450)	(0.443)	(0.447)	(0.475)	(0.474)	(0.457)
Liquid Assets To Assets	0.104***	0.095***	0.082***	0.105***	0.117***	0.103***	0.087***	0.116***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Leverage Ratio	-0.191***	-0.153***	-0.210***	-0.176***	-0.151***	-0.116**	-0.191***	-0.152***
	(0.050)	(0.054)	(0.049)	(0.048)	(0.051)	(0.054)	(0.050)	(0.048)
ALLL to Total Loans	0.396*	0.432*	0.388	0.361	0.228	0.300	0.268	0.218
	(0.236)	(0.240)	(0.253)	(0.242)	(0.237)	(0.244)	(0.263)	(0.244)
Cases Per 100k	0.170	0.222**	0.324***	0.246**	0.224**	0.274**	0.385***	0.286***
	(0.107)	(0.110)	(0.107)	(0.103)	(0.113)	(0.116)	(0.112)	(0.108)
Constant	-3.685**	-13.286***	4.897***	-0.926	-13.452***	-23.241***	-2.622	-8.684***
	(1.586)	(2.223)	(1.661)	(2.317)	(2.211)	(2.670)	(2.312)	(2.783)
Observations	3,513	3,513	3,513	3,513	3,057	3,057	3,057	3,057
Adjusted R2	0.155	0.111	0.168	0.197	0.195	0.133	0.184	0.230

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 J.9: 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 J.10: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

K 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 K.1 shows the impact of these draws on participation, intensity, and 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 K.1: 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			0.07			0.022		
	[0, 0]			[0.01, 0.01]			[0.04, 0.1]			[-0.03, 0.08]		
$CI\ gwth^{75th}$		0.091			1			3.32			1.204	
		[0.03, 0.16]			[0.64, 1.36]			[0.58, 6.11]			[-3.6, 6.07]	
$CI\ Usage^{2020:Q1}$			0.005			0.036			0.159			0.103
			[0, 0.01]			[0.01, 0.06]			[-0.05, 0.38]			[-0.36, 0.57]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Tables K.2 and K.3 report the results on total C&I loan growth and non-PPP C&I growth. These specifications show that PPP 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 K.2: 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			0.275			0.027		
	[0, 0]			[0.01, 0.01]			[0.24, 0.31]			[-0.02, 0.07]		
$CI\,gwth^{75th}$		0.113			1.108			15.59			4.687	
		[0.05, 0.17]			[0.76, 1.45]			[12.14, 19.01]			[0.57, 8.79]	
$CI\,Usage^{2020:Q1}$			0.005			0.032			0.642			-0.72
			[0, 0.01]			[0.01, 0.06]			[0.35, 0.94]			[-1.07, -0.38]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Table K.3: 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)
$CI\,gwth^{2020:Q1}$	0.001			0.008			0.218			0.077		
	[0, 0]			[0.01, 0.01]			[0.2, 0.23]			[0.04, 0.12]		
$CI\,gwth^{75th}$		0.103			1.081			14.498			5.154	
		[0.04, 0.16]			[0.74, 1.42]			[12.94, 16.03]			[1.12, 9.17]	
$CI\,Usage^{2020:Q1}$			0.005			0.037			0.383			-0.685
			[0, 0.01]			[0.01, 0.06]			[0.28, 0.49]			[-1.04, -0.33]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.

Finally, Table K.4 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 K.4: 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)
$CI\,gwth^{2020:Q1}$	0.000			0.010			0.013			-0.018		
	[0, 0]			[0.01, 0.01]			[0, 0.02]			[-0.05, 0.01]		
$CI\,gwth^{75th}$		0.083			0.998			2.068			-2.803	
		[0.02, 0.15]			[0.65, 1.35]			[0.9, 3.24]			[-5.84, 0.18]	
$CI\,Usage^{2020:Q1}$			0.005			0.034			-0.048			-0.028
			[0, 0.01]			[0.01, 0.06]			[-0.13, 0.03]			[-0.26, 0.21]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000.