The Role of Skilled Labor in Income-based Government-directed Bank Lending*

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Abstract

We show that when governments direct banks to lend based on income, the outcomes differ by how closely capital matches the availability of skilled labor in the target population. We document that when skilled labor in the target area is high, additional credit is absorbed in small businesses and future welfare outlays are reduced. In contrast, if skilled labor is relatively low, then capital flows to mortgages and results in housing price growth. Our results point towards the importance of developing skilled labor, alongside credit-provision, for overall development of under-privileged communities.

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To attain socio-economic objectives, governments direct banks to lend to target communities to bridge credit gaps. The underlying justification is that market frictions can limit credit access to some communities, creating gaps between credit demand and supply. In the U.S., the Community Reinvestment Act (CRA) of 1977 encourages depository institutions to extend credit to low and moderate income (LMI) communities. By design, such income based allocation deviates from market-driven lending, which seeks to match capital to its most productive use.

In this paper, we show that when capital is allocated based on income, the outcomes are still affected by how closely capital allocation matches intrinsic productivity of the target community. When capital is steered through directed lending towards communities with relatively more skilled labor, then banks make relatively more business loans. Such business lending leads to greater improvement in economic conditions, and reduces future government welfare expenses. In comparison, when income based lending is directed to areas with less skilled labor, banks provide more residential lending. Such mortgage lending leads to higher house price gains. Higher house prices benefit existing homeowners. At the same time, prospective homeowners and renters may find housing less affordable with rising prices.

The literature on how government policies affect bank lending is vast.[1] Eminent researchers have investigated the effects of CRA on bank lending as well.[2] In this paper, we contribute by showing that matching skill to capital remains the underlying mechanism that drives the outcomes of government-directed lending. Thus, to bridge credit gaps in communities, improving the availability of skilled labor in target areas is important.

[1]For example, Kroszner and Rajan (1994) investigate the effect of Glass-Steagall Act on lending; Jayaratne and Strahan (1996) investigate the real effects of deregulation on bank lending. Recent literature discusses how banks allocate capital in presence of unconventional monetary policy (see, for example, Di Maggio, Kermani, and Palmer, 2019; Heider, Saidi, and Schepens, 2019; Luck and Zimmermann, 2020; Chakraborty, Goldstein, and MacKinlay, 2020).

[2]CRA has led to more mortgage lending (Bhutta, 2011; Agarwal et al., 2012; Saadi, 2020; Begley and Purnanandam, 2021; Ringo, 2022) as well as more small business lending (Bostic and Lee, 2017; Black and Hackney, 2019; Ding, Lee, and Bostic, 2020). Researchers have also noted that banks tend to offer riskier loans due to CRA (Agarwal et al., 2012; Black and Hackney, 2019; Saadi, 2020; Ringo, 2022). Begley and Purnanandam (2021) show that instances of fraud and poor customer service by retail banks is higher in area targeted by the act.

While many proxies could be appropriate, we use the fraction of college graduates (among the population aged 25 or older) as our measure of skilled labor. This measure of the intrinsic productivity—or in other words, the human capital of a community—is simple and transparent. Seminal research on growth and productivity has used same or similar proxies (see, for example, Lucas, 1988, 1990; Gennaioli et al., 2013).

As mentioned above, we focus on the CRA to identify the effect of government-directed lending conditional on skilled labor. The CRA is a long-running and important government directed lending program. In additional results, we also investigate the short but enormous Paycheck Protection Program (PPP). For PPP as well, we show that government-directed lending is more effective when capital is steered towards areas with more skilled labor.

We start by corroborating the findings in the literature regarding the effects of CRA on lending. We use a difference-in-differences research design at the census-tract level.[3] To reduce selection bias concerns, as one step, we limit the census tracts used in our analysis to a narrow income band around the CRA eligibility threshold. We confirm that before CRA eligibility, treatment and control tracts received similar amounts of lending. Panel estimates for CRA show that small business lending rises by 0.6% and mortgage lending rises by 2.9% on average in census tracts that gain CRA eligibility. These results on CRA confirm the findings of the literature on CRA.[4]

We extend the literature by showing that the availability of skilled labor in a target community determines how banks lend due to CRA and what real effects follow. In target areas with higher fraction of college graduates, banks provide more CRA eligible small business loans. When two census tracts with different levels of skilled labor become eligible for CRA loans, the tract with

[3]Under CRA, census tracts are periodically reclassified as lending targets by the Office of Management and Budget (see Table D.II). This identification strategy has been used by Bhutta (2011) and Ding, Lee, and Bostic (2020), among others. Our sample period for CRA is from 2009–2019, i.e., after the financial crisis and before the pandemic.

[4]Regarding mortgages, Bhutta (2011) finds that the CRA caused an increase in mortgage lending from 1997–2002, but not from 2004–06. Saadi (2020) also finds that in the period 1996–2006 and Ringo (2022) finds around the year 2003 that CRA leads to more mortgage lending. Agarwal et al. (2012) show that mortgage lending done around CRA exams default more often. Saadi (2020) and Ringo (2022) also find that CRA leads to more and riskier mortgages. Compared to these papers on mortgages, we consider the period after the financial crisis. Regarding small business lending and CRA, Bostic and Lee (2017), Black and Hackney (2019), Ding, Lee, and Bostic (2020), and Kim, Lee, and Earle (2021) find evidence that CRA increases small business lending.

10 percentage point (pp.) more college graduates receives 0.298% more small business loans per capita at the mean. In contrast, when relatively less skilled labor is available in an area, banks provide relatively more government-directed capital as mortgages. The tract with 10 pp. lower college graduates receives 2.64% more mortgage loans per capita at the mean. Again, we confirm that there was no differential effect in lending patterns conditional on skilled labor before treatment tracts became CRA eligible.

To clarify, the results above suggest that compared to their respective mean levels of lending, as skilled labor rises, small business lending rises and mortgage lending falls. Our results do not suggest that there is unit substitution between small business loans and mortgages in CRA eligible tracts. We understand that banks have a large investment opportunity set including commercial and industrial loans to larger firms, commercial real estate lending, investing in mortgage backed securities, among others. Also, banks are not restricted to lending trade-off decisions within the same geographical region.

Next, we investigate whether government-directed bank lending improves economic conditions of the target population. To estimate the effects, while many alternative exist, we consider the Supplemental Nutrition Assistance Program (SNAP) program. Other than Medicaid, SNAP is the largest U.S. welfare program—with 35.7 million participants at a cost of $60 Billion in 2019 before COVID—that targets the lower income population. Baseline results show that for each dollar of CRA lending, SNAP outlays decline by about 3.55 cents.

The benefits of government-directed lending to low income households, as proxied by the reduction of SNAP usage, are strongest for counties with higher fraction of college graduates. The SNAP outcome variable is at the county-level. We find that if 10 pp. tracts of a county becomes CRA eligible, a county with 10 pp. more than mean college graduates reduces SNAP usage by 0.17%. Thus, availability of skilled labor remains important in determining the efficacy of income based government directed lending.

Regarding house prices, baseline results show that if a tract becomes eligible for CRA lending, then housing prices increase by 0.25% more annually over the next three years compared to the previous three years. Turning to our focus in this paper—on interaction of government-directed lending and skilled labor—when a tract with 10 pp. less college graduates than the mean becomes eligible to receive CRA loans, housing prices increase by 77.5 basis points (bps) more per year for the next three years in this tract.

Our results suggests a government-directed credit elasticity of housing price of 0.22. Bringing the results on mortgage credit supply and housing price elasticity together, we note that census tracts with 10 pp. lower skilled labor than the mean will receive 2.64% more mortgage backed lending and house prices will rise 0.58% more in such areas.

While we cannot completely address the potential selection concerns associated with skilled labor, we attempt to mitigate these concerns in several ways. In particular, to obtain results described above, we take steps to alleviate concerns regarding two sources of selection bias. The first source is an omitted variable bias: areas with more college graduates are inherently different from other areas. A reader may be concerned that income level or population may deliver the observed differential program response to skilled labor. For example, more populated areas, may attract more skilled labor—even though our measure, fraction of college graduates, already has population in the denominator. Similarly, higher income areas may have more skilled workers—even though our CRA treatment is in areas that are relatively lower income compared to their MSA. Hence, we run our analyses by flexibly controlling for income and population of a geography using income and population quintiles interacted with program treatment. Our results remain robust to this test. In addition, we show that after controlling for tract or county fixed effects that we always employ in our analyses, the relevant tract and county characteristics are not statistically different between geographies that differ on skilled labor (see Greenstone, Mas, and Nguyen, 2020, for a similar approach).

Another econometric concern is selection bias regarding program target areas: government-directed lending treated areas are very different from non-treated control areas. To alleviate such selection bias concerns, similar to researchers before us (Saadi, 2020; Begley and Purnanandam, 2021), we conduct robustness analyses using samples matched on relevant and available characteristics where both treated and control groups are within the same larger geographical unit. Our results remain robust to these different approaches of alleviating selection bias concerns.

The difference-in-differences approach that we employ utilizes a two way fixed effect specification. If some tracts get treated much earlier than others, the resulting heterogeneity of treatment effects across time can lead to biased treatment estimates (Goodman-Bacon, 2021; Borusyak, Jaravel, and Spiess, 2021; Roth et al., 2022). Our data structure provides a way to sidestep these concerns. Almost all tracts that gain CRA eligibility do so in two years, 2012 and 2017 (see Table D.II). Hence, to reduce heterogeneity of treatment effects across time, we use a three-year window before and after a tract becomes newly eligible to estimate our effects. The control group in our analysis consists of tracts that are similar in income to the treated tracts but did not gain program eligibility. Our approach thus alleviates concerns regarding estimation bias by reducing comparison between treated observations in 2017 with already treated observations from 2012.

In additional robustness tests, we check if our results are driven by geographical outlier tracts. We exclude census tracts that are either mostly residential or mostly commercial, and find similar results. Further, for our analysis, we obtain identification from instances when tracts gain eligibility and get treated. This is because CRA is a binding constraint on banks when areas becomes eligible.[5]

In additional results, we provide corroborating evidence of our skilled labor channel using PPP. During 2020, when the COVID disruption was at its peak, counties with higher number of college graduates experience a larger decline in SNAP usage in the presence of more PPP lending. Note

[5]Banks are not required to stop lending if a tract loses eligibility. Thus, banks make an endogenous economic decision to lend or not in recently ineligible areas. Including such areas may thus introduce selection bias in our analysis. Nevertheless, in the Appendix, we test the effects of losing CRA eligibility on bank lending (Table D.VI).

that the PPP results are cross-sectional given data constraints. Nevertheless, given the size of the program and the importance of the question, we believe that the PPP results can be useful.

In sum, our results suggest that even when government-directed lending is determined by income, available skilled labor affects ultimate outcomes. The importance of skilled labor has been underscored before by economists in the context of national development (Lucas, 1988, 1990; Mankiw, Romer, and Weil, 1992; Gennaioli et al., 2013).[6] Our results suggest that skilled labor remains important when we investigate within country development of underprivileged communities.

The macroeconomic calculations in the literature have focused on cross-country comparisons of output based on skilled labor. In Appendix A, we develop a stylized model using U.S. tract-level government-directed CRA lending data. The model estimates that the value of the human capital externality parameter as in Lucas (1988) is close to 2.2% in the U.S. in the last decade. In other words, one percent increase in skilled labor, i.e., human capital in an area increases output by about 0.02 percent.

A stream of literature has shown that CRA has led to more mortgage lending (Bhutta, 2011; Agarwal et al., 2012; Saadi, 2020; Begley and Purnanandam, 2021; Ringo, 2022). Literature has also shown that CRA leads to more small business lending (Bostic and Lee, 2017; Black and Hackney, 2019; Ding, Lee, and Bostic, 2020). Researchers have also noted that banks tend to offer riskier loans due to CRA (Agarwal et al., 2012; Black and Hackney, 2019; Saadi, 2020; Ringo, 2022). In addition, Saadi (2020) finds that during the boom period before the financial crisis, house price growth was higher in the eligible census tracts because of the shift in mortgage supply of regulated banks. Begley and Purnanandam (2021) show that instances of fraud and poor customer service by retail banks is higher in area targeted by the act. We extend the above literature

[6]Our work draws inspiration from the macroeconomic cross-country literature that investigates the determinants of economic growth across the world. Lucas (1988, 1990) and recently Gennaioli et al. (2013) note the importance of skilled labor in accounting for regional differences in development across the world. Mankiw, Romer, and Weil (1992) show that an augmented Solow model that includes accumulation of human as well as physical capital explains cross-country variation on economic growth. Further, Barro (1997, 2001) and recently, Hanushek and Woessmann (2012) emphasize the role of education and distinguishes the quantity from the quality of education.

by noting the effect of CRA-driven bank lending varies based on the presence of skilled labor in the target community.

Our paper thus also relates to the general literature that investigates the allocation of bank credit to mortgages compared to firms (Chaney, Sraer, and Thesmar, 2012; Adelino, Schoar, and Severino, 2015; Chakraborty, Goldstein, and MacKinlay, 2018; Martín, Moral-Benito, and Schmitz, 2021). We contribute by investigating lending decisions due to CRA. Recent research also investigates the effect of the paycheck protection program on employment and small businesses.[7] As mentioned above, our focus is on the differential effect of government-directed lending conditional on skilled labor.

I Background and Identification Strategy

We start with a brief description of the Community Reinvestment Act as well as the Paycheck Protection Program in Section I.A. Section I.B discusses the identification challenges and our strategy to address them.

I.A The Policies and Data Sources

We discuss the two large government-directed lending policies and data sources next.

[7] Autor et al. (2022a,b) estimate that the PPP boosted employment at eligible firms by 2–5 percent at its peak in mid-2020, with this effect waning to 0–3 percent throughout the remainder of the year. Granja et al. (2022) find that employment effects of the program were small compared to the size of the program. Chernenko and Scharfstein (2022) uncover significant racial disparities in borrowing through the Paycheck Protection Program (PPP). They find that black-owned establishments are significantly less likely to receive bank PPP loans in counties with more racial bias. The program was "rebooted" in January 2021, and Fairlie and Fossen (2022) find that the rebooted PPP that ran from January to May 2021 seems to have disbursed to minority communities as intended.

I.A.1 Two large government directed lending policies

The Community Reinvestment Act of 1977 is a federal law designed to encourage federally insured banks to lend in communities where they operate, specifically communities in low- and moderate-income (LMI) neighborhoods (see Figure D.1). Federal regulators with supervisory responsibility of a depository institution periodically examine the bank to ascertain the degree to which the institution's lending serves the community. Banks covered by the act report loans to the regulators each year at the census tract level. The regulators assign a rating to the institution based on quantitative and qualitative measures of performance. Regulatory approval of applications (such as for opening new branches, mergers etc.) from the institution may be withheld if the bank fails to meet CRA performance measures.

To determine performance, the act stipulates three tests in each assessment area for a banking institution. The lending test, which is 50% of the points, assesses the lending activity of banks for various types of loans: home mortgages, small businesses lending, and small farm loans. The criteria in this case include geographical and demographic distribution of lending as well as flexibility of lending practices to address credit needs of LMI individuals or areas. The remaining points are based on service quality and investments in the community of the assessment area.[8] Ultimately, a bank is assigned one rating per assessment area by adding up the points in the three tests, and a final rating at the bank certification level which includes multiple assessment areas.

Turning to the second policy, as part of the Coronavirus Aid, Relief and Economic Security (CARES) Act, the Paycheck Protection Program (PPP) began to distribute forgivable loans to small businesses in April 2020. In two phases, the disbursement continued till July 2021 (see Figure D.2). More than 90% of the approximately $800 billion of PPP loans disbursed were forgiven by June 2022.

[8] The investment test considers the amount of investment including grants given in the assessment area or a broader regional area. The service test considers the quality of retail banking services provided by the bank to LMI persons or areas, with criteria such as distribution of bank branches, automated teller machines, etc.

The uncollateralized loans were non-recourse and were 100% guaranteed by the U.S. Small Business Administration (SBA) guarantee. If borrowers certified that the funds were used within a specified period for payroll, utilities, rent or mortgage payments and that certain employment targets were maintained, then the loans were forgiven.[9]

I.A.2 Data Sources and Summary Statistics

The paper utilizes data from multiple sources. The main datasets for lending are CRA disclosures provided by the Federal Financial Institutions Examination Council (FFIEC) and mortgage data from the Home Mortgage Disclosure Act (HMDA) flat files provided by the Consumer Finance Protection Bureau (CFPB). Tract and county-level education data are from the American Community Survey (ACS). We use the Federal Housing Finance Agency's (FHFA) Housing Price Index (HPI). For monthly housing prices, we use data from Zillow. Appendix Section B describes these relative standard data sources in some detail. Table D.I in the appendix also provides detailed definitions of all variables used in the empirical analysis.

Table I reports summary statistics. The sample period is 2009–2021. Panel A reports that on average 4.3 thousand individuals live in a census tract. Note that the per capita mortgage lending is \$5.8 thousand while the small business lending is a fraction of that at \$254. This is an observation that helps ascertain the relative benefits of small business lending in areas with skilled labor compared to costs of more mortgage lending in areas with less skilled labor.

Panel B reports county-year level statistics. Most outcomes of interest as well as demographic and economic characteristics are available at a county-level geographical resolution. When we investigate county-level outcomes, we utilize a change in the fraction of tracts in a county that have been reclassified as LMI as the measure of administrative shock for the CRA policy. We refer to this measure as Δ *LMI Fraction*. The average county has a population of 102 thousand

[9] See U.S. Small Business Administration, "Forgiveness Platform Lender Submission Metrics, (embedded link) with data as of June 20, 2022.

persons, out of which an average of 13.8 thousand receive food stamps. Small businesses employ 7.7 thousand persons on average in a county.

Panel C reports summary statistics at the bank-year level. On average, about 16% of small business loans are smaller than $100 thousand. The data show that the average chargeoff rate on business loans is less than half of real estate loans. At the same time, the relative size of real estate (RE) and commercial and industrial (C&I) loans on the balance sheet of banks suggests that the median bank lends almost nine times more in mortgages compared to real estate. Thus, even though C&I loans lead to less chargeoffs, they are a smaller fraction of total lending.

I.B Identification concerns and strategy

Our paper seeks to identify the differential effects of government-directed bank lending policies conditional on skilled labor. Thus, the general specification for geography g and time t is as follows:

$$\begin{aligned} \text{Outcome}_{g,t} &= \gamma_t + \eta_g + \beta_1 \cdot \text{Policy Shock}_{g,t} + \beta_2 \cdot \text{Skilled Labor}_{g,t} \\ &\quad + \beta_3 \cdot \text{Policy Shock}_{g,t} \times \text{Skilled Labor}_{g,t} + \beta_4 \cdot X_{c,t-1} + \varepsilon_{g,t}, \end{aligned} \tag{1}$$

where the main coefficient of interest is β_3. Geographical unit is tract or county, depending on the resolution of data available. Similarly, time frequency is yearly or monthly.

We face two sources of potential selection bias that can confound the estimate of interest, related to the two variables in the interaction term. First, areas with high skilled labor are inherently different from other areas. Second, areas treated with government-directed lending policy are different across many other dimensions from areas that are not targeted for lending. We discuss these concerns below.

I.B.1 Selection bias regarding skilled labor

Regarding the first threat to identification, note that after controlling for tract or county fixed effects depending on the specification, relevant characteristics are not statistically different between areas that differ on skilled labor. Our approach is similar to that in Greenstone, Mas, and Nguyen (2020); the authors investigate small business lending across geographies and over the business cycle.

Panel A of Table II reports the available demographic and economic characteristics at the tract level. For tract-level analyses, we always employ a sub-sample that has a median income in the 75–85 percentile range compared to the parent MSA. Nevertheless, Panel A reports the differences in available demographic and economic characteristics with tract fixed effects. We note that in presence of tract fixed effects, differences are statistically insignificant conditional on skilled labor.

For county level analyses, as expected, Panel B reports that there are differences in characteristics before fixed effects. But after fixed effects, the remaining variation in county population, median household income, bank competition, and bank deposits is statistically insignificant across counties that differ based on skilled labor.

Continuing with the first concern, our primitive of skilled labor is based on theoretical and empirical insights in development and growth research streams (Becker, 1964; Uzawa, 1965; Lucas, 1988, 1990). Nevertheless, a reader may believe that it is not skilled labor, but rather population or income of the geographical unit is driving the differential response by skilled labor that we estimate. More populated areas, for example, may attract more skilled labor—even though our measure, fraction of college graduates, already has population in the denominator. Similarly, a concern could be that higher income areas have more skilled workers—even though our CRA treatment is in areas that are relatively lower income compared to their MSA.

In other words, β_3 suffers from an omitted variable bias. To alleviate this concern, we run our analyses by flexibly controlling for income and population of a geography using income and population quintiles interacted with program treatment. The argument is that if geographies in different tiers of population and income respond different to government-directed lending, then these quintile interactions will absorb those differences. Our results remain robust to this test.

I.B.2 Selection bias regarding targeted geographies

The second identification challenge that we face is that access to credit is endogenous to the borrowers' economic conditions (demand-driven effects). We need exogenous shocks in credit supply to separate demand-driven effects from supply-side effects.

In the case of the first policy of CRA, we utilize the reclassification of target census tracts as low and moderate income (LMI) as the shock. This difference-in-differences approach has been utilized in the literature (see, for example, Bhutta, 2011; Ding, Lee, and Bostic, 2020). Target areas for the Community Reinvestment act, i.e., LMI tracts, change over time because an LMI census tract is one where the median family income is less than 80-percent of the "parent area" median family income. The parent area is the metropolitan statistical area (MSAs) for tracts located in cities and the state non-MSA area for tracts located outside metros. As census updates incomes of the MSA and tracts, the Office of Management and Budget changes the classification of census tracts. Table D.II in the Appendix provides details regarding the reclassification of census tracts in our sample. In our sample period, most changes occur in 2012 and 2017.

Even though we cannot completely eliminate selection concerns regarding intrinsic differences between treated and control tracts, we take steps to mitigate concerns to the extent of our ability. In the tract-level results, we focus on the tracts in a sub-sample that either become eligible for CRA lending or are within 75–85 percentile of their parent area in terms of income without becoming eligible. We also show the results for 50-120 percentile income range to establish generality. Always, specifications include area and year fixed effects to address unobserved heterogeneity across space and over time.

Researchers have demonstrated that if some tracts get treated much earlier than others, the resulting heterogeneity of treatment effects across time can lead to biased treatment estimates (Goodman-Bacon, 2021; Borusyak, Jaravel, and Spiess, 2021; Roth et al., 2022). Our data provide a way to sidestep these concerns: Almost all tracts that gain CRA eligibility do so in two years, 2012 and 2017 (see Table D.II). Therefore, to reduce heterogeneity of treatment effects across time, we use a three-year window before and after a track gains eligibility to estimate our effects. The control group consists of tracts that have similar income to the treated tracts but did not gain program eligibility. Our approach thus seeks to address estimation bias concerns by reducing comparison between treated observations in 2017 with already treated observations from 2012.

Finally, for both county and tract-level results, we follow Begley and Purnanandam (2021) and use a matched sample approach as well. In the case of counties, the empirical design exploits within state variation in county-year observations with and without a change in LMI in a year. The approach thus attempts to control for variation in outcomes that can arise due to unobserved state-level differences due to state laws and regulation, economic conditions, and demographics. Further, the matching on a set of county-level characteristics attempts to address outcome differences due to these observable characteristics. We also take a similar approach for matching tracts, where we restrict the matched tract to the same county, and match on income and number of households.

II Government-directed capital: Policies and Effects

This section presents our main results. We first show that government policy driven capital flows differently to targeted areas conditional on the availability of skilled labor in the areas. We then explore how such bank lending affects welfare outlays and housing prices.

II.A CRA and lending

We start by corroborating the findings in the literature that bank lending is affected by CRA. Our difference-in-differences specification is at the census-tract-level and follows Bhutta (2011) and Ding, Lee, and Bostic (2020), among others. Literature has shown that when a tract becomes CRA eligible, it receives more small business and mortgage lending.

Figure D.3 in the Appendix confirms these findings. There is no pre-trend in small business lending and mortgage lending in the tracts that gain CRA eligibility. Once the tracts gain eligibility they receive more mortgage and small business lending.

Moving the discussion forward, Figure 1 reports the effect of CRA on annual lending conditional on skilled labor. The specification used for the figures is below:

$$\begin{aligned} \log\ l_{c,t} \;=\; & \sum_{t=-3}^{2} \beta_{1,t} \cdot \mathbb{1}(t)\mathbb{1}(LMI_c) + \beta_2 \cdot h_{c,t} + \sum_{t=-3}^{2} \beta_{3,t} \cdot \mathbb{1}(t) \cdot \mathbb{1}(LMI_c) \times h_{c,t} \\ & + \beta_4 \cdot X_{c,t-1} + \gamma_t + \eta_c + \varepsilon_{c,t}, \end{aligned} \tag{2}$$

where the outcome variable $\log l_{c,t}$ represents small business or mortgage lending to census tract c in time t. The variable of interest is $\mathbb{1}(LMI_c)$ which equals 1 for tracts that gain LMI status during our observation period (i.e. treated tracts) and is 0 for controls tracts. We focus on a 3 year before/after eligibility window, $t \in \{-3,-2,-1,0,1,2\}$. h is skilled labor and measures the fraction of college graduates in the population. We include tract c and year fixed effects as well as available tract-level characteristics $X_{c,t}$. Variable definitions are in the Appendix. The sample period is 2009–2019, i.e., after the financial crisis and before the COVID pandemic.

The coefficients of interest are $\beta_{3,t} \cdot \mathbb{1}(t)$. The time indicator allows the impact of LMI status to vary by year. These series of coefficients thus help identify whether CRA eligibility induced banks to lend differentially to tracts based on skilled labor availability, i.e., $\beta_{3,t} \geq 0 \mid t \in \{0,1,2\}$. Further, the coefficients allow us to check if there was a pre-trend, i.e., difference in lending patterns before eligibility. In this case as well, we estimate the value of $\beta_{3,t} \mid t \in \{-3,-2,-1\}$.

Figure 1 (a) reports that there is significantly more CRA-driven small business lending after a tract gains LMI status if it has more skilled labor. The additional lending is persistent. The additional lending for small business lending in recently eligible tracts does not seem to relate to existing positive trends in the tracts before eligibility.

Figure 1 (b) shows that the opposite picture emerges for mortgage lending. Banks seem to lend relative more in mortgages to tracts with less skilled labor. The figure thus validates our research design by displaying the relevance of skilled labor in determining CRA-driven lending. The figure also shows the absence of pre-trends, which is a necessary condition for our research design.

To tabulate our results, we employ a specification similar to above where we estimate the average differential in CRA-driven lending conditional on skilled labor in an area:

$$\begin{aligned} \log\, l_{c,t} \quad = \quad & \beta_1 \cdot [\mathbb{1}(Post) \times \mathbb{1}(LMI_c)] + \beta_2 \cdot h_{c,t} + \beta_3 \cdot [\mathbb{1}(Post) \times \mathbb{1}(LMI_c) \times h_{c,t}] \\ & + \beta_4 \cdot X_{c,t-1} + \gamma_t + \eta_c + \varepsilon_{c,t}, \end{aligned} \tag{3}$$

where the outcome variable $\log l_{c,t}$ represents small business lending to census tract c in time t based on change in LMI eligibility captured by $\mathbb{1}(Post) \times \mathbb{1}(LMI_c)$. The independent variable LMI_c is 1 for census tracts that gain eligibility. The variable $\mathbb{1}(Post)$ is 1 for three periods when such reclassifications take place, and 0 for three periods before the change. As discussed in Section I.B, our approach of limiting the estimation window to three years before and after treatment helps address some of the recent concerns regarding the difference-in-differences estimation strategy (Goodman-Bacon, 2021; Roth et al., 2022).

An important concern is selection bias: policy target tracts and remaining census tracts are different across many dimensions, including but not limited to skilled labor. These differences can lead to biased causal inferences. To alleviate this selection bias concern, we restrict the control tracts to those tracts that have relative median family incomes between 75% and 85% of the MSA median family income. Note that a treatment tract is classified as LMI when it falls below 80%

of the MSA median family income. Thus, in terms of median income, the treatment and control tracts are similar. We always include tract fixed effects to address time-invariant differences.

Further, a concern is that lending patterns are driven by population variation across counties: larger counties get more capital and the level effects of higher (lower) capital lead to smaller (larger) changes in response to LMI. Therefore, we utilize per capita lending levels as the outcome variables.

Table III reports the results of our tract-year level analysis. In the table, we use change in LMI, i.e., ΔLMI to denote $\mathbb{1}(Post) \times \mathbb{1}(LMI_c)$.[10] Column (1) shows that indeed, small business lending increases by an average of 0.58 pp. when the tract becomes classified as an LMI tract. Additional capital is not directed only to small business loans. Column (2) shows that mortgage lending also increases by 2.88 pp. in these reclassified tracts. While a large set of controls are not available at the census-tract level, columns (1) and (2) include available relevant controls such as median family income, population as well as lagged lending in the tract. The results remain similar without these controls as well.

Column (3) shows the importance of the presence of skilled labor to absorb small business loans. When census tracts become eligible for CRA-driven lending through LMI reclassification, small business loans flow more towards tracts with higher skilled labor: the tract with 10 pp. more college graduates receives 0.298% more small business loans per capita at the mean after becoming CRA eligible. This result is in comparison to another tract that also becomes CRA eligible but has an average fraction of college graduates in its population. This result is intuitive: an important ingredient in absorbing additional credit is skilled labor in the target area. The baseline result of column (1) becomes insignificant in column (3). This insignificance also suggests that skilled labor is an important determinant of the cross-sectional differences in small business lending due to CRA.

[10] In presence of tract and year fixed effects, only the interaction term is relevant.

When skilled labor is not available to the same extent, and yet banks are directed to lend, how do they proceed? Column (4) provides the answer. Areas with *less* college graduates receive relatively less small business loans and relatively *more* mortgage loans. When a tract is reclassified to receive CRA-eligible loans, an area with 10 pp. lower college graduates receives 2.64% more mortgage loans at the mean.

Comparing the results in column (3) and (4), we note that mortgages are about nine times more responsive than small business lending to skilled labor. Thus, it is not the case that there is dollar for dollar substitution between small business lending and the residential mortgages. Indeed, banks have a variety of investment opportunities including loans to larger firms, commercial real estate lending, investing in mortgage backed securities, among others.[11] Further, banks do not have to lend within the same geographical region. They allocate capital and transmit shocks across a larger geographical footprint (see, for example, Loutskina and Strahan, 2015). Hence, within geography substitution between different types of loans is not practised by banks. Our results suggest that compared to their respective mean levels, as skilled labor rises, small business lending rises and mortgage lending falls. Column (5) and (6) show that a discrete measure of skilled labor (above/below median) also delivers similar results.

A concern could be that our results depend somehow on the limited control sample where tracts are restricted to those where relative median family incomes are between 75% and 85% of the MSA median family income. Hence, in columns (7) and (8), we expand the sample set to include tracts that have a relative median household incomes between 50% and 120% of the MSA median household income. The observations increase almost six times. The results regarding the effect of skilled labor remain quantitatively similar in this expanded set of tracts.[12]

[11] See Chakraborty, Goldstein, and MacKinlay (2018) as an example where banks trade off mortgage lending with commercial and industrial lending to large firms.

[12] Our focus in the analyses above is on tracts that gain CRA eligibility. CRA does not prohibit banks from lending to a tract that loses eligibility. Thus, lending to recently ineligible areas is a bank's decision based on lending opportunities in that area. Nevertheless, in the Appendix, we investigate the effects of losing CRA eligibility on bank lending (Table D.VI). As expected, since CRA is not a binding constraint when tracts lose eligibility, the results do not show that banks always respond to CRA eligibility loss.

The differential allocation of capital conditional on skilled labor documented above has significant real effects. We discuss these effects in the next two subsections.

II.B Effects: Reduction in welfare demand

While there are many approaches to estimate the real effects of government-directed capital programs, this section focuses on Supplemental Nutrition Assistance Program (SNAP) utilization. Other than Medicaid, SNAP is the largest welfare programs in the U.S. that targets lower income population.[13] In 2019, before COVID, 35.7 Million individuals participated in the program, at a total cost of \$60 Billion.[14] If directed credit benefits the lower income population facing hardship, we should expect a reduction in SNAP utilization.

We start as before with a figure that reports the differential effect on SNAP recipients of CRA based on the availability of skilled labor. As for lending, Figure D.4 (a) in the Appendix reports the baseline effect of CRA on SNAP recipients. Further, there is an additional reduction if skilled labor is higher (Figure 2 (a)). The figures suggest that there are no significant pre-trends before an area becomes CRA eligible. Afterwards, there is a significant and persistent effect. Note that data availability for SNAP recipients is at the county level. Hence, the observation unit is county-year.

Table IV tabulates our findings using the following specification which is similar to Eq. 3:

$$\begin{aligned} \log\, l_{c,t} \quad &= \quad \beta_1 \cdot \Delta\text{LMI Fraction}_{c,t} + \beta_2 \cdot h_{c,t} + \beta_3 \cdot \Delta\text{LMI Fraction}_{c,t} \times h_{c,t} \\ &\quad + \beta_4 \cdot X_{c,t-1} + \gamma_t + \eta_c + \varepsilon_{c,t}, \end{aligned} \tag{4}$$

The only difference is that we use Δ *LMI Fraction* in the above county-level specification compared to an indicator variable for LMI eligibility in a tract-level specification. The county-level

[13]Tanner (2012) provides a comparison of welfare program sizes in 2012. Shaefer, Naranjo, and Harris (2019) notes that excluding means-tested healthcare programs reduces welfare outlays by about half for a total of \$393 billion in 2018.

[14]See U.S. Department of Agriculture SNAP Data Tables (link embedded).

independent variable $\Delta\, LMI\ Fraction$ measures the difference in the fraction of census tracts that are CRA-eligible in a county in a period t compared to the previous period. As before, we use a three-year window before and after a change to estimate the effect.

Column (1) shows that 10 pp. increase in the fraction of LMI tracts reduces SNAP recipients by 10 bps on average. Regarding magnitudes of the effects, a back of the envelope calculation suggests that for each dollar of CRA lending, SNAP outlays decline by about 3.55 cents.[15] Note that SNAP outlays are approximately 16.5% of total means tested welfare outlays in recent years.

A county with more skilled labor should benefit more from CRA-driven lending, as borrowers there deploy the capital in more productive projects. The interaction term estimate of column (2) confirms this intuition: the effect of CRA-driven lending through additional LMI is stronger in counties with more college-educated population. If the fraction of CRA-eligible tracts increases by 10 pp., then the resulting credit flow reduces SNAP usage by 0.17% more in a county that has 10% more college graduates. This result is compared to the similar county that has an average fraction of college graduates but also receives 10% additional CRA-driven credit due to change in eligibility. The interaction term of column (3) shows that counties with above median skilled labor benefit more from CRA-driven lending.

When it comes to economic welfare through directed lending, demographic characteristics of the affected population beyond skilled labor also matter. For example, single parents and their children have been identified as a population group that faces particular persistent disadvantage (Heckman and Krueger, 2005). Column (4) shows that counties with a larger fraction of single parent households benefit less from CRA-driven capital. Presumably, even if opportunities are generated through improved financing, single parents cannot take up the opportunities as easily as they have less time to invest in skill building.

[15]The calculation is (Total SNAP benefits in 2017 \$63,711 million$\times$estimated reduction in outlay 0.0102)/((Mortgage per capita \$5,832$\times$estimated mortgage effect of 0.0288+SBL per capita \$254$\times$estimated SBL effect of 0.0058)$\times$325 million population in 2017$\times$33.2% LMI tracts in the country) =0.0355. See ProximityOne (embedded link) as a reference to the fraction of LMI tracts in the U.S. Mortgage lending sensitivity to CRA and Small business lending sensitivity to CRA are from the first two columns of Table III.

Columns (5)–(8) repeat the analysis in columns (1)–(4) for a matched sample. The matching procedure is described in detail in the Appendix C. As before, results suggest that when areas becomes eligible for CRA lending, communities with higher skills reduce SNAP dependency more compared to similar income communities with lower skills.

Overall, the results in this section suggest that along with capital flow, policymakers should also design policies to improve labor skills of the targeted geographies. Higher education and training will generate superior real outcomes from CRA-driven capital allocation.

II.C Effects: Housing prices

This section investigates the effect of CRA-driven lending on housing prices conditional on the presence of skilled labor. We have shown so far that when a government directs bank credit supply, and there is not enough skilled labor in an area, then there is relatively less business lending and less improvement in the condition of the lower income population. We have also shown before the first part of an important corollary: when there is less business lending, banks lend relatively more in mortgages. In this section, we confirm a rather expected outcome: relatively more mortgage lending in areas with less skilled labor lead to relatively higher house prices.

Before we test the effects of government-directed credit supply conditional on skilled labor, we establish baseline effects documented in the literature regarding mortgage lending and housing prices (see, for example, Bhutta, 2011; Saadi, 2020). Figure D.4 (b) in the Appendix reports the baseline effects of CRA on house prices. The first two columns of Table V investigate the baseline relation between CRA lending and house prices. The sample in column (1) consists of census tracts that are within 50%–120% of the median household income of the MSA.[16]

[16]While our time period differs, this result is in line with the findings in the literature that CRA eligibility increases housing prices along with mortgage lending. As noted earlier, our sample period is for the years 2009–2019 which is after the financial crisis and before COVID, with most eligibility changes occurring in the years 2012 and 2017 (see Table D.II for details).

In column (2), we turn to on our main question of this section regarding the impact of government directed bank lending on house price growth in presence of skilled labor. Figure 2(b) shows that after the financial crisis induced downturn ended, tracts with less college graduates that became CRA-eligible for new lending experienced a greater increase in housing prices. The comparison group is tracts with more college graduates that are also low and moderate income and became CRA eligible.

Column (2)–(4) use our baseline sample of census tracts with 75%–85% household income compared to the MSA. Column (2) shows that tracts with lower skilled labor experience higher increase in housing prices after they become eligible for CRA-driven lending. Note that in addition to the sample restriction based on income, all columns include tract fixed effects to address concerns regarding cross-tract differences.

Further, house prices can be correlated across a larger region than tracts. Hence, in column (3) we include county-year fixed effects to soak away increase in house prices explained by time varying county-level conditions. The interaction term of column (3) shows that when two tracts with 10 pp. difference in college graduates become eligible, housing prices increase by an average of 77.5 bps more per year in the area with less college graduates. This effect is not second order given the baseline effect in column (1)–(3) of gaining LMI eligibility. Column (4) utilizes a discrete measure of skilled labor. It also reports that census tracts with above median skilled labor experience less house price inflation conditional on CRA-driven lending.

How does this allocation of mortgage lending conditional on skilled labor affect housing prices? Comparing the conservative estimate in column (2) of Table V with the interaction term estimate in column (6) of Table III, we obtain a credit elasticity of housing price of 0.22 (0.0588/0.2644). In other words, a one percent increase in mortgage lending in presence of CRA conditional on skilled labor leads to a 0.22% average increase in house prices in the census tract. Census tracts with 10 pp. lower skilled labor than the mean will receive 2.64% more mortgage backed lending (from Table III) and house prices will rise 0.58% more in such areas (elasticity $0.22 \times 2.64\%$ more mortgage lending).

A standard concern in these regressions is selection bias: even though we have focused on tracts which are within a tight band of income compared to the MSA, the absolute income of the MSAs being compared are different. Note that tract and county-year fixed effects absorb most of the time-invariant heterogeneity in columns (3) and (4). Table D.V in the Appendix shows that differences in covariates are limited in presence of tract and county fixed effects. Nevertheless, we match treated and control tracts by median family income to address concerns regarding differences in absolute levels of income. We also match by number of households in tract to allow for variation in the type of households that reside across tracts. Further, treated and control tracts are required to be within the same county. Details of the matching procedure are in Appendix C. Table D.IV reports summary statistics on treated and matched counties.

Columns (5)–(7) repeat the analysis in the previous columns using the matched sample. The results remain similar. In sum, CRA leads to higher housing prices, and more so in areas with less skilled labor. Higher house prices have mixed effect on the population: While rising housing prices benefit existing homeowners, prospective homeowners and renters may find housing less affordable. In addition, many lower income households are not homeowners. Thus, income-based credit supply may reduce housing affordability in some cases.

III Additional Results and Robustness Tests

In this section, we provide tests that help ameliorate concerns that the our results above are due to differential response by income and population rather than skilled labor (Section III.A). We also conduct additional robustness in Section III.D to ensure that tracts that are outliers in terms of relative proportion of mortgage lending or small business lending are not providing our results. Finally, we investigate how lending patterns vary by skilled labor at the bank level.

III.A Differential response by income and population

A concern is that skilled labor is not the main factor that explains our results so far: It could be that population or income of the target geographical unit is driving the differential response. As an example, counties with more population could be receiving more *per capita* loans from banks, and have higher house price inflation. The concern would suggest that what we estimate as differential response to skilled labor is essentially due to omitted variable bias due to the omission of population or income interaction terms.

To alleviate this concern, we run our analyses by flexibly controlling for income and population of a geography using income and population quintiles interacted with program treatment. The argument is that if geographies in different tiers of population and income respond differently to government-directed lending, then these quintile interactions will absorb those differences. Our quintile interactions also allow for non-linear differential responses due to, say, a threshold after which house prices respond more to population or income levels.

Table VI reports the results after including both income and population quintile interactions. Columns (1) and (2) find that the results regarding differential lending to small businesses and mortgages by skilled labor due to CRA are similar to those obtained in Table III. The same is the case for differential response in house prices by skilled labor when tracts gain eligibility: Column (3) finds similar results to those in Table V.

Column (4) in Table VI shows that the results in Table IV are also robust to the inclusion of the population and income quintile interactions. The estimated coefficient of ΔLMI Fraction $\times$ Skilled Labor remains similar in magnitude to the results in Table IV. The result is statistically significant at 10% level in this case.

III.B Paycheck protection program

While the CRA is a longstanding program targeted at LMI communities, the U.S. also experienced a larger recent government-directed lending program: the Paycheck Protection Program. Naturally, the program, the circumstances of implementation, and the target population are very different from the Community Reinvestment Act. However, we conduct an analysis that parallels—to the extent possible—the exercise in Section II.

In the case of CRA, identification was obtained from the change in eligibility of a tract. For PPP, we utilize per capita county-level PPP loans made across the country during the COVID crisis (see Figure D.2). In this case we utilize the variation in the amounts of capital directed through the PPP program.

As before, we test whether business lending due to PPP had differential effects conditional on availability of skilled labor. We continue with SNAP recipients change as the outcome of interest. The analysis uses data from the year 2020, which is the year of peak COVID crisis.

Table VII reports the estimated coefficients of the following equation:

$$\Delta \log(\text{SNAP recipients}) = \beta_1 \cdot \log PPP_c + \beta_2 \cdot h_c + \beta_3 \cdot \log PPP_c \times h_c + \beta_4 \cdot X_c + \eta_{MSA} + \varepsilon_c, \quad (5)$$

where the outcome variable $\Delta \log(\text{SNAP recipients})$ represents the change in the number of SNAP recipients from January 2020 to January 2021 in county c. Amount of PPP loans to the county is represented by PPP_c. h represents our measure of skilled labor. We utilize relevant county-level demographic controls X_c and MSA fixed effects.

Column (1) shows that when a county receives more PPP loans then SNAP outlays grow slower in that county during COVID. We include MSA fixed effects to soak away some of the time-invariant heterogeneity. Column (2) shows that the benefits of lending in terms of reduction of SNAP outlays and associated hardship are stronger in counties with higher skilled labor. The interaction term suggests that counties with more college graduates experiences higher reduction in SNAP utilization. This result is in line with our key result in the paper: government-directed lending is more effective when capital matches with skilled labor.

Results remain similar when we utilize a discrete measure of skilled labor in column (3). Counties with above median skilled labor experience lower SNAP recipient growth in presence of PPP loans.

Similar to Table IV, we note that skilled labor is not the only determinant of the efficacy of government-directed lending. If there are more single parents in a county, then there is a smaller impact of PPP lending on SNAP utilization. we conclude this based on the estimated coefficient in the first row of column (4) as well as the interaction term.

Our results remain robust in columns (5)–(8) when we employ a matching technique to reduce the cross-sectional heterogeneity across counties. For this analysis, we define treated counties as those that are in the top tercile of per capita PPP loans. The control counties are those that are in the bottom tercile of per capita PPP loans. We match based on median family income and unemployment rate. We also require that the treated and control counties both belong to the same state.

III.C Skilled labor and lending by bank size

A large literature discusses the ability of banks to utilize soft information (Petersen and Rajan, 1994; Berger et al., 2005; Liberti and Petersen, 2018). Researchers have also noted the changing lending patterns of banks by size in recent years, due to recent regulations (see Chen, Hanson, and Stein, 2017; DAcunto and Rossi, 2021; Reher, 2021, among others). In this section, we investigate how banks' lending patterns and losses respond to government directed lending requirements. Specifically, we investigate how skilled labor affects bank lending patterns and losses when banks are required to lend to target areas. Our hypothesis is that small banks may be more responsive to the presence of skilled labor in an area as the quality of workers is a potential component of soft information.

Table VIII conducts a bank-year level analysis that differentiates banks by size. Banks below \$10 billion worth of deposits are classified as small. Based on the deposit footprint of the bank, we calculate the exposure of each bank holding company to skilled labor and CRA regulation at the tract level. The coefficient of interest is thus that of the triple interaction term Small Bank × Fraction Skilled Labor Above Median × Fraction CRA Eligible.

Column (1) of Table VIII suggests that small banks with a larger CRA eligible footprint are more willing to provide smaller sized mortgages if they also have access to borrowers with more skilled labor. The results are however, not statistically significant in our aggregated bank-year panel.

When we consider small business lending, results are stronger. Column (2) regresses the fraction of loans that are small—i.e., less than \$100 thousand in origination amount—on bank size and footprint. The column shows that smaller banks in presence of government direction, offer more small loans in areas with higher skilled labor. This result resonates with the finding in the literature regarding the importance of small banks in small business lending (Berger et al., 2005; Srivastav and Vallascas, 2021). Column (3) compares the applicant income of borrowers of large and small banks, and finds some evidence—even though statistically insignificant—that smaller banks cater to relatively lower income borrowers, ceteris paribus.

Next, we investigate how credit losses differ by bank size. The estimated triple interaction coefficients in columns (4) and (5) suggest that smaller banks have lower mortgage and small business loan losses when they are required to lend due to CRA requirements and when these small banks have access to more skilled labor in their deposit footprint.

In sum, the evidence points to the ability of small banks to take skilled labor into account to make relatively safer loans to smaller borrowers. Our results tie in with the larger literature on the ability of banks to utilize soft information.

III.D Additional robustness tests

Table IX conducts two additional robustness tests. First, we check if our results are driven by geographical outliers. A concern is that there are residential census tracts that are mostly mortgage lending. Banks in these locations do not choose the type of loans. Rather, attractive housing tracts are driving the results in terms of higher house price inflation, and banks in these location are not switching away from (potentially non-existent) small business lending opportunities.

To ensure that our results are not due to such census tracts, we take a ratio of small business lending to total lending in terms of mortgages and small business at the tract-level. We exclude the tracts that are either in the first or the tenth decile of this fraction. This approach ensures that we are avoiding tracts that mostly receive mortgage loans or small business loans. Then, we rerun our small business lending, mortgages, and ultimately housing price analyses in columns (1)–(5). The results continue to suggest that banks allocate capital conditional on skilled labor, and house prices rise faster in tracts with less skilled labor.

Second, columns (6) and (7) also confirm that, as expected, rents also rise along with higher house prices in our main sample. For this exercise, we obtain Fair Market Rents data from Housing and Urban Development (see Table D.I). The rising rents point towards the reduction in housing affordability for non homeowners. Often, these renters are also lower income households.

IV Conclusion

Our paper provides evidence that government-directed income-based allocation of bank credit has led to improvement in economic conditions of the target population. Such lending has also led to house price increase. We show that the outcome depends on the skilled labor of the target area. With higher skilled labor, additional credit increases business activity and reduces future government welfare expenses. In contrast, if skilled labor is less present in an area, then government-directed lending leads to house price increase.

In his seminal work, Lucas (1988, 1990) points out that differences in skilled labor between countries can help explain the lack of capital flow towards less developed countries despite higher potential return on capital. Our work suggests that the insights of Lucas (1988) and others in the context of development of countries are important for within country allocation of capital. Skilled labor availability in an area determines the effectiveness of government-directed lending.

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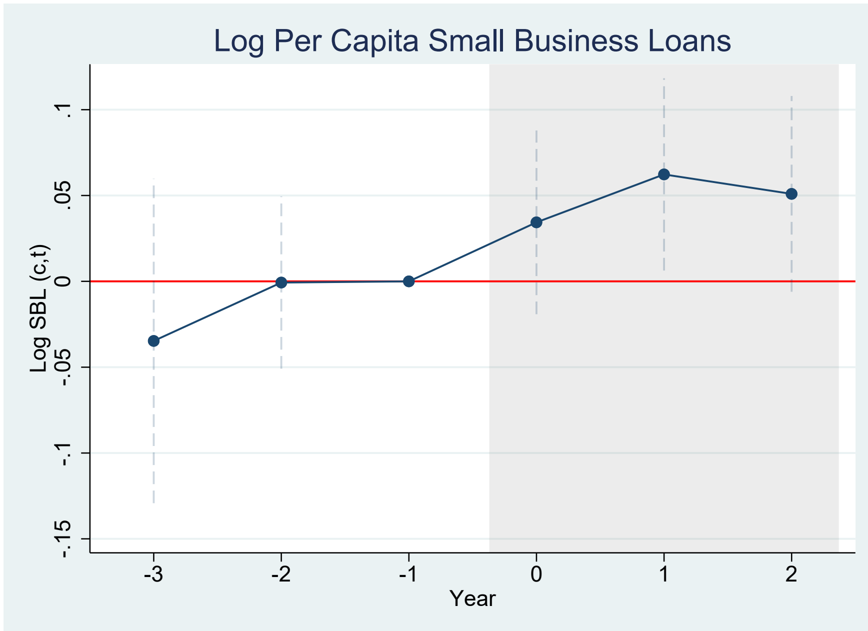
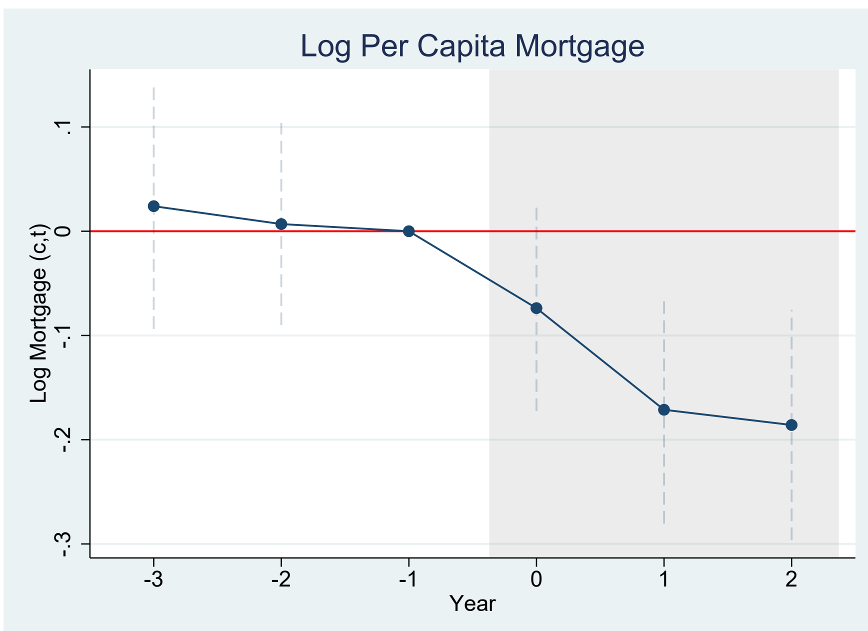
Figure 1: Effect of CRA on Bank Lending Conditional on Skilled Labor

This figure plots the point estimates (β_3) of Eq. 2. The outcome variable in panel (a) is per-capita small business loans. The outcome variable in panel (b) is mortgage lending. The shaded area represents the sample period after which the tracts become CRA-eligible.



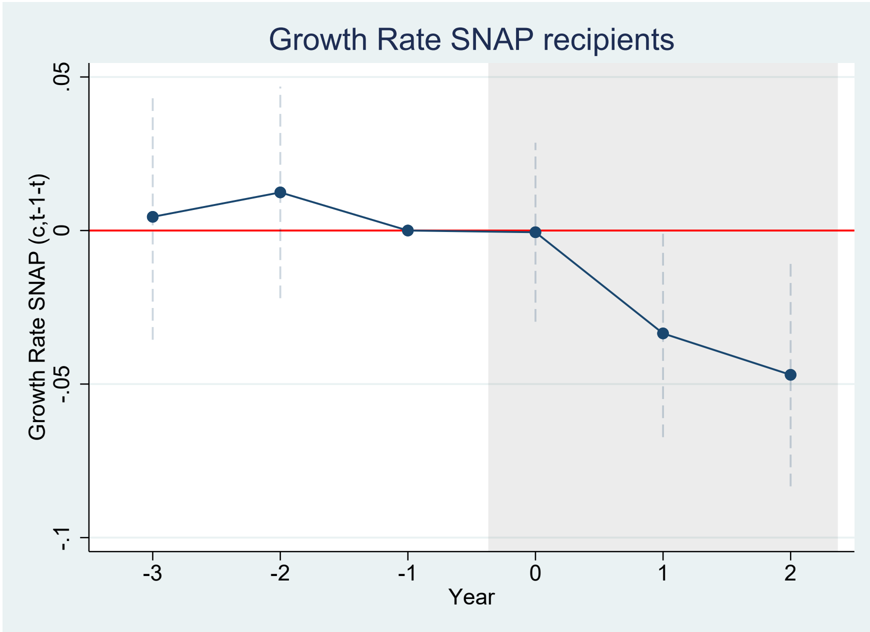
(a)



(b)

Figure 2: Effect of CRA on SNAP Recipients and Housing Prices Conditional on Skilled Labor

This figure plots the point estimates (β_3) of Eq. 2. The outcome variable in panel (a) is growth rate of SNAP recipients. The outcome variable in panel (b) is log housing price index. The shaded area represents the sample period after which the tracts become CRA-eligible.



(a)

(b)

Table I: Summary Statistics

This table reports summary statistics. The top panel reports census tract-year level statistics. The middle-panel provides county-year level statistics. The bottom panel reports bank-year level statistics. The sample period is from 2009–2021. Data sources and variable definitions are discussed in Appendix B and Table D.I.

	Mean	**Std. Dev**	**P50**	**P25**	**P75**	**N**
			Census Tract-Year			
Skilled Labor (Fraction College Graduates)	0.2846	0.1852	0.2337	0.1420	0.3910	734,483
Population	4,269	1,915	4,028	2,926	5,326	734,483
Median Housing Value ($)	232,207	189,043	169,300	108,500	291,200	673,914
Median Family Income ($)	63,343	31,623	56,803	42,034	77,169	734,483
Per Capita Mortgage ($)	5,833	6,579	3,625	1,585	7,509	734,483
Per Capita Small Business Loans ($)	255	311	152	62	321	734,483
Relative Family Income (%)	101.75	41.97	97.08	75.26	120.49	734,483
Households	1,586	685	1,507	1,102	1,982	734,483
Housing Price Index HPI (1985 = 100)	236.36	143.08	198.75	153.38	268.02	536,214
Growth Rate of Housing Price	0.0305	0.0752	0.0308	-0.0129	0.0741	471,199
			County-Year Level			
LMI fraction	0.2035	0.2330	0.1538	0	0.3333	34,172
Skilled Labor (Fraction College Graduates)	0.2023	0.0881	0.1806	0.1400	0.2398	34,172
Δ LMI Fraction	0.0066	0.1298	0	0	0	27,308
Population	102,195	325,791	26,140	11,327	68,302	34,172
SNAP Recipients	13,822	45,859	3,926	1,520	9,743	34,171
Herfindahl Index	0.2369	0.2171	0.1717	0.0892	0.3048	34,172
Unemployment Rate	0.0653	0.0299	0.0590	0.0420	0.0840	34,172
County Deposits ($ billion)	3.2	23.4	0.4	0.2	1.0	34,172
Median Household Income ($)	46,370	12,228	44,319	38,132	51,845	27,990
Per Capita PPP ($)	1824.95	948.12	1649.07	1164.81	2246.93	27,396
County HPI (1985 = 100)	250.34	152.02	201.22	156.82	294.04	21,491
SNAP Recipient Growth	-0.0161	0.0681	-0.0216	-0.0575	0.0146	31,064
Fraction Single Parent Households	0.3200	0.0898	0.3153	0.2613	0.3708	31,061
Small Establishments	247	779	50	20	157	29,282
Employment in Small Establishments	7,668	27,602	1,342	537	4,103	29,227
			Bank-Year			
Average Mortgage Size ('000s)	406.84	647.80	239.79	169.81	390.19	5,064
Fraction Small Business Loans Less Than 100K	0.1628	0.1026	0.1443	0.0943	0.2087	5,064
Applicant Income ('000s)	191.70	178.91	145.28	112.68	210.82	5,060
RE Charge-offs as a Fraction of Total Outstanding	0.0085	0.0150	0.0027	0.0003	0.0094	4,935
C&I Charge-offs as a Fraction of Total Outstanding	0.0034	0.0069	0.0006	0.0000	0.0036	5,057
Total Assets ($ billion)	17.94	126.00	1.74	0.98	4.05	5,064
Total Equity ($ billion)	1.97	13.10	0.18	0.10	0.45	5,064
Short-term Funding as a Fraction of Assets	0.1160	0.0797	0.1007	0.0541	0.1623	5,064
C&I Loans as a Fraction of Tier 1 Capital	0.9774	0.7269	0.8054	0.4590	1.3287	5,064
RE Loans as a Fraction of Tier I Capital	5.0689	1.7868	4.9824	3.9328	6.0976	5,064
Cost of Interest Bearing Funds (%)	0.8850	0.6423	0.6900	0.4100	1.2081	5,064
Mortgage Applicant/s Income ('000)	191.70	178.91	145.28	112.68	210.82	5,060

Table II: Differences in covariate means conditional on skilled labor

This table reports the differences in the means of covariates between areas with above median skilled labor and areas with below median skilled labor. Panels A and B report the results for tract level and county level, respectively. The first two columns report the raw differences in means and the associated standard error. Column 3 reports the differences in means within the respective geographic area by controlling for geographic area fixed effects (i.e. Within difference). The associated standard errors are clustered at the respective geographic area-level and are reported in Column 4. Data sources and variable definitions are discussed in Appendix B and Table D.I.

Variable Name	Raw difference	Std. error	Within difference	Std. error
Tract-Level				
Log Population	-0.0090***	(0.0034)	0.0013	(0.0021)
Log Median Household Income	0.2041***	(0.0019)	0.0013	(0.0026)
Log Male Population	-0.0180***	(0.0034)	0.0033	(0.0023)
Log Minority Population	0.1985***	(0.0078)	0.0075	(0.0048)
County-Level				
Log County Population	0.9559***	(0.0148)	-0.0009	(0.0012)
Log Median Family Income	0.1024**	(0.0015)	0.0014	(0.0025)
Unemployment Rate	-0.0183***	(0.0003)	0.0025***	(0.0006)
Herfindahl Index	-0.0946***	(0.0023)	0.0003	(0.0018)
Log County Deposits	1.2509***	(0.0152)	0.0023	(0.0052)

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

Table III: Effect of CRA eligibility on Small Business and Mortgage Lending

This table estimates the effect of Community Reinvestment Act (CRA) and its interaction with skilled labor on small business and mortgage lending. The dependent variables are logarithm of per capita small business loans (Small Business) and logarithm of per capita mortgage loans (Mortgage). The main explanatory variable is ΔLMI, which takes on a value of 1 for three years when a tract becomes newly CRA eligible, i.e., the tract's relative household income falls below 80% of the MSA median household income. The variable takes a value of 0 for the previous three years before gaining eligibility. The tract-level measure of skilled labor is the fraction of college graduates among the population aged 25 and above. In columns (1)–(6), the sample consists of tracts that have relative median household incomes between 75% and 85% of the MSA median household income. In columns (7)–(8), the tracts have relative median household incomes between 50% and 120% of the MSA median household income. Data sources and variable definitions are discussed in Appendix B and Table D.I. Observations are at the tract-year level. Continuous variables are winsorized at 99%. Standard errors are clustered by census tract and are reported in parentheses.

	75-85 pctile income						50-120 pctile income	
	Small Business (1)	Mortgage (2)	Small Business (3)	Mortgage (4)	Small Business (5)	Mortgage (6)	Small Business (7)	Mortgage (8)
ΔLMI	0.0058**	0.0288***	<0.0000	0.0812***	0.0039	0.0423***	-0.0010	0.0763***
	(0.0025)	(0.0098)	(0.0035)	(0.0136)	(0.0026)	(0.0101)	(0.0024)	(0.0102)
Skilled Labor			0.0914***	0.1234			0.0523***	-0.0241
			(0.0264)	(0.0816)			(0.0081)	(0.0301)
ΔLMI × Skilled Labor			0.0298**	-0.2644***			0.0277**	-0.02770***
			(0.0121)	(0.0499)			(0.0111)	(0.0456)
Skilled Labor Above Median					0.0032	0.0159		
					(0.0026)	(0.0100)		
ΔLMI × Skilled Labor Above Median					0.0066**	-0.0485***		
					(0.0029)	(0.0108)		
Lagged Log SBL	-0.0792***		-0.0800***		-0.0795***		0.0479***	
	(0.0079)		(0.0079)		(0.0079)		(0.0036)	
Lagged Log Mortgage		-0.0247***		-0.0249***		-0.0249***		0.1536***
		(0.0091)		(0.0091)		(0.0091)		(0.0048)
Lagged Log Median Household Income	-0.0090	-0.0993***	-0.0076	-0.1068***	-0.0083	-0.1041***	-0.1726***	0.0159***
	(0.0072)	(0.0277)	(0.0071)	(0.0276)	(0.0072)	(0.0277)	(0.0112)	(0.0027)
Lagged Log Population	-0.0701***	-0.3941***	-0.0720***	-0.4105***	-0.0712***	-0.4124***	0.0689***	-0.3981***
	(0.0141)	(0.0394)	(0.0141)	(0.0402)	(0.0142)	(0.0403)	(0.0042)	(0.0162)
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,524	62,524	62,524	62,524	62,524	62,524	359,899	359,899
Adjusted R^2	0.7634	0.8759	0.7636	0.8760	0.7634	0.8759	0.7306	0.8833

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

Table IV: Effect of CRA lending on food-stamp participation

This table estimates the effect of the Community Reinvestment Act (CRA) and its interaction with skilled labor on food-stamp participation. The main explanatory variable in columns (1)–(4) is ΔLMI Fraction, which denotes the change in the fraction of low-medium income tracts in a county year. Skilled labor measures the fraction of college graduates in the population aged 25 and above. Columns (5)–(8) present the same results using a matched county sample. Details of the matching procedure is described in Appendix C. Data sources and variable definitions are discussed in Appendix B and Table D.I. Continuous variables are winsorized at 99%. Standard errors are clustered county and are reported in parentheses. Observations are weighted by the county population.

	SNAP Growth							
	CRA				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ LMI Fraction	-0.0102**	0.0221*	-0.0046	-0.0540***	-0.0143***	0.0192	-0.0067	-0.0478**
	(0.0051)	(0.0153)	(0.0054)	(0.0219)				
Skilled Labor		-0.0673				-0.0859		
		(0.1117)				(0.1294)		
Δ LMI Fraction × Skilled Labor		-0.1747**				-0.1825**		
		(0.0770)				(0.0877)		
Skilled Labor Above Median			0.0017				-0.0002	
			(0.0022)				(0.0043)	
Δ LMI Fraction × Skilled Labor Above Median			-0.0156*				-0.0193*	
			(0.0094)				(0.0103)	
Fraction Single Parent Household				0.0182				-0.0168
				(0.0202)				(0.0241)
Δ LMI Fraction × Fraction Single Parent Household				0.1289**				0.0993*
				(0.0528)				(0.0592)
Lagged Log Population	-0.0336	-0.0315	-0.0327	-0.0345	0.0576	0.0592	0.0576	0.0555
	(0.0309)	(0.0305)	(0.0306)	(0.0309)	(0.0602)	(0.0601)	(0.0601)	(0.0601)
Lagged Log Median Household Income	0.0401**	0.0435**	0.0397**	0.0410**	0.0364*	0.0415**	0.0384*	0.0374*
	(0.0193)	(0.0194)	(0.0193)	(0.0193)	(0.0214)	(0.0210)	(0.0212)	(0.0213)
Lagged Unemployment Rate	-0.0029***	-0.0029***	-0.0029***	-0.0029***	-0.0047***	-0.0048***	-0.0048***	-0.0048***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Lagged Herfindahl Index	-0.0425	-0.0421	-0.0425	-0.0411	-0.0721***	-0.0731***	-0.0713**	-0.0709**
	(0.0286)	(0.0282)	(0.0286)	(0.0284)	(0.0278)	(0.0277)	(0.0277)	(0.0277)
Lagged Log Deposits	0.0293***	0.0292***	0.0293***	0.0287***	0.0188**	0.0195**	0.0186**	0.0184**
	(0.0078)	(0.0076)	(0.0078)	(0.0078)	(0.0093)	(0.0091)	(0.0092)	(0.0094)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,175	23,175	23,175	23,175	15,187	15,187	15,187	15,187
Adjusted R^2	0.6438	0.6442	0.6439	0.6441	0.6073	0.6078	0.6074	0.6074

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

Table V: Effect of CRA lending on Housing Price Growth

This table reports the effect of the Community Reinvestment Act (CRA) on housing price growth conditional on skilled labor. The dependent variable is the natural logarithm of the housing price index. The main explanatory variable ΔLMI takes on a value of 1 for 3 years when a tract becomes newly CRA eligible, i.e., the tract's relative family income falls below 80% of the MSA median family income. Skilled labor is the fraction of college graduates among the population aged 25 and above. Control tracts in column (1) have relative family incomes between 50%-120% of the MSA median household income, while in columns (2)–(4) there is a tighter relative income band of 75% to 85%. Columns (5)–(7) reproduce results using a matched sample. Details of the matching procedure are in Appendix C.

	Log HPI						
	CRA				Matched Sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔLMI	0.0025***	0.0063*	0.0150***	0.0030	0.0018**	0.0128*	-0.0004
	(0.0006)	(0.0033)	(0.0037)	(0.0025)	(0.0008)	(0.0068)	(0.0063)
Skilled Labor		0.0120	0.0171			0.0220	
		(0.0167)	(0.0148)			(0.0209)	
ΔLMI $\times$ Skilled Labor		-0.0588***	-0.0775***			-0.0888***	
		(0.0093)	(0.0122)			(0.0136)	
Skilled Labor Above Median				0.0023			0.0048**
				(0.0016)			(0.0024)
ΔLMI $\times$ Skilled Labor Above Median				-0.0130***			-0.0148***
				(0.0021)			(0.0025)
Lagged Log HPI	0.7288***	0.5565***	0.0226**	0.0233**	0.2488***	0.0521***	0.0540***
	(0.0023)	(0.0077)	(0.0106)	(0.0106)	(0.0054)	(0.0133)	(0.0133)
Lagged Log Population	0.0278***	0.0542***	0.0092	0.0092	-0.0106***	0.0298**	0.0299**
	(0.0030)	(0.0101)	(0.0089)	(0.0088)	(0.0024)	(0.0117)	(0.0117)
Lagged Log Median Family Income	-0.0272***	-0.0083	0.0070	0.0082*	-0.0013	0.0079	0.0103
	(0.0021)	(0.0053)	(0.0049)	(0.0049)	(0.0020)	(0.0082)	(0.0082)
Year FE	Yes	Yes	No	No	No	No	No
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	261,190	38,421	38,421	38,421	209,580	19,992	19,992
Adjusted R^2	0.9815	0.9813	0.9894	0.9894	0.9900	0.9892	0.9891

* p<0.10, ** p<0.05, *** p<0.01

Table VI: Controlling for differential responses due to income and population heterogeneity

This table reports the effects of CRA based on skilled labor availability, controlling for interactions between CRA and quintiles of income and population. Data sources and variable definitions are discussed in Appendix B and Table D.I.

	Tract-level CRA			County-level CRA	
	Table III		Table V		Table IV
	Small Business	Mortgage	House Price		Food Stamps
	(1)	(2)	(3)		(4)
Δ LMI	0.0051	0.0530**	0.0276***	ΔLMI Fraction	0.0122
	(0.0053)	(0.0206)	(0.0059)		(0.0182)
Skilled Labor	0.0902***	0.1189	0.0171	Skilled Labor	-0.0395
	(0.0264)	(0.0818)	(0.0149)		(0.1246)
Δ LMI × Skilled Labor	0.0326**	-0.2554***	-0.0769***	ΔLMI Fraction × Skilled Labor	-0.2033*
	(0.0136)	(0.0559)	(0.0124)		(0.1214)
Lagged Log Small Business Loans	-0.0806***				
	(0.0079)				
Lagged Log Mortgage		-0.0259***			
		(0.0090)			
Lagged Log HPI			0.0219**		
			(0.0106)		
Lagged Log Pop.	-0.0691***	-0.4008***	0.0088	Lagged Log Pop.	-0.0586
	(0.0142)	(0.0401)	(0.0089)		(0.0569)
Lagged Log Median Household Income	-0.0066	-0.1149***	0.0096*	Lagged Log Median Household Income	0.0506**
	(0.0072)	(0.0282)	(0.0049)		(0.0241)
				Lagged Unemp. Rate	-0.0021***
					(0.0008)
				Lagged Herfindahl Index	-0.0479
					(0.0313)
				Lagged Log Deposits	0.0373***
					(0.0089)
Year FE	Yes	Yes	No	County FE	Yes
Tract FE	Yes	Yes	Yes	MSA-Year	Yes
County Year FE			Yes		
Δ LMI × Income Quintile	Yes	Yes	Yes	Δ LMI Fraction × Income Quintile	Yes
Δ LMI × Pop. Quintile	Yes	Yes	Yes	Δ LMI Fraction × Pop. Quintile	Yes
Observations	62,524	62,524	38,421		20,801
Adjusted R^2	0.7637	0.8762	0.9894		0.6446

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

Table VII: Effect of PPP on Supplemental Nutrition Assistance Program

This table reports the effect of the federal Paycheck Protection Program (PPP) on the growth rate of food-stamp recipients (between January 2020 and January 2021) based on skilled labor availability. The main explanatory variable is log per-capita PPP funding in the first draw PPP and its interaction with the county-level skilled labor measure. Columns (5)–(8) conduct the same analysis using a matched county sample. The treated sample (high PPP funding counties) and remaining control counties are matched based on relative income levels and unemployment rates and are required to be in the same state. Data sources and variable definitions are discussed in Appendix B and Table D.I. Continuous variables are winsorized at 99%. Standard errors are clustered by county, and are reported in parenthesis. County observations are weighted by the 2019 county population.

	SNAP Growth							
	PPP				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Per Capita PPP First Draw	-0.0775**	0.0167	0.0019	-0.2265***	-0.0709*	0.0571	0.0214	-0.2507***
	(0.0332)	(0.0402)	(0.0233)	(0.0800)	(0.0374)	(0.0450)	(0.0267)	(0.0899)
Skilled Labor		1.9763			2.9248**			
		(1.2508)			(1.3327)			
Per Capita PPP First Draw × Skilled Labor		-0.3250**			-0.4478***			
		(0.1629)			(0.1704)			
Skilled Labor Above Median			0.8079***				0.8966***	
			(0.2489)				(0.2633)	
Per Capita PPP First Draw × Skilled Labor Above Median			-0.1221***				-0.1350***	
			(0.0360)				(0.0386)	
Fraction Single Parent Households				-3.3251**				-4.1798***
				(1.3817)				(1.5768)
Per Capita PPP First Draw × Fraction Single Parent Households				0.4899**				0.5996**
				(0.2056)				(0.2337)
Lagged Log Population	-0.0024	-0.0158	-0.0049	-0.0023	-0.0022	-0.0193	-0.0048	0.0027
	(0.0288)	(0.0283)	(0.0284)	(0.0283)	(0.0323)	(0.0328)	(0.0321)	(0.0323)
Lagged Log Median Household Income	-0.0383	0.0946	-0.0142	0.0398	-0.0765	0.0449	-0.0555	-0.0196
	(0.0719)	(0.0748)	(0.0734)	(0.1033)	(0.0815)	(0.0829)	(0.0826)	(0.1160)
Lagged Unemployment Rate	-0.0192	-0.0154	-0.0184	-0.0200*	-0.0114	-0.0091	-0.0134	-0.0128
	(0.0118)	(0.0112)	(0.0116)	(0.0118)	(0.0153)	(0.0144)	(0.0154)	(0.0148)
Lagged Herfindahl Index	0.0058	0.0363	0.0283	0.0167	0.0155	0.0487	0.0353	0.0324
	(0.0659)	(0.0681)	(0.0661)	(0.0655)	(0.0740)	(0.0757)	(0.0734)	(0.0738)
Lagged Log Deposits	0.0236	0.0448**	0.0330	0.0182	0.0231	0.0458*	0.0326	0.0138
	(0.0232)	(0.0228)	(0.0235)	(0.0224)	(0.0256)	(0.0255)	(0.0260)	(0.0252)
MSA-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,567	1,567	1,567	1,567	1,190	1,190	1,190	1,190
Adjusted R^2	0.3425	0.3589	0.3510	0.3501	0.3861	0.4058	0.3946	0.3955

* p<0.10, ** p<0.05, *** p<0.01

Table VIII: Lending by bank size

This table reports the effect of CRA based on skilled labor availability on bank-level mortgage lending and Commercial and Industrial (C&I) loans. Dependent variables are (i) average mortgage size, (ii) fraction of small business loans with origination amount less than $100,000, (iii) average income of approved mortgage applicant, (iv) mortgage charge-offs (as a fraction to total outstanding), and (v) C&I charge-offs (as a fraction to total outstanding). All specifications control for lagged bank-year level controls including log assets, log equity, short term non-core funding as a fraction of total assets, total real estate loans as a fraction of tier-1 capital, total C&I loans as a fraction of tier-1 capital, and cost of all interest-bearing funds(%). Observations are the bank-year level. Data sources and variable definitions are discussed in Appendix B and Table D.I. All continuous variables are winsorized at 99%. Standard errors are in parentheses and are clustered at the bank level.

	Mortgage Size (1)	Fraction of Small Business Loans (2)	Applicant Income (3)	Mortgage Charge-off (4)	C&I Charge-off (5)
Fraction Skilled Labor Above Median	0.2458	0.1753*	0.0363	-0.0241	-0.0054
	(0.5253)	(0.0926)	(0.4228)	(0.0148)	(0.0082)
Fraction CRA Eligible	-0.7199	0.3845***	-0.6330	-0.0686***	-0.0359***
	(0.8619)	(0.1179)	(0.4223)	(0.0224)	(0.0060)
Fraction Skilled Labor Above Median × Fraction CRA Eligible	3.4456	-3.0522**	6.0256	0.8289**	0.2234***
	(9.8392)	(1.3544)	(6.0844)	(0.3953)	(0.0622)
Small Bank	0.0817	0.0271***	0.0351	0.0018	-0.0010
	(0.0860)	(0.0104)	(0.0712)	(0.0023)	(0.0011)
Small Bank × Skilled Labor Above Median	-0.1914	-0.2041**	0.0558	0.0250	0.0092
	(0.5414)	(0.0951)	(0.4399)	(0.0155)	(0.0085)
Small Bank × Fraction CRA Eligible	0.3434	-0.3903***	0.6264	0.0700***	0.0372***
	(0.8790)	(0.1189)	(0.4321)	(0.0226)	(0.0068)
Small Bank × Skilled Labor Above Median ×	-2.7090	3.0431**	-5.7181	-0.8267**	-0.2246***
Fraction CRA Eligible	(9.8849)	(1.3566)	(6.1171)	(0.3957)	(0.0633)
Lagged Log Mortgage Size	0.1931***				
	(0.0419)				
Lagged Fraction Small Business Loans less than $100K		0.4150***			
		(0.0560)			
Lagged Log Applicant Income			0.0505		
			(0.0355)		
Lagged Real Estate Chargeoffs				0.4260***	
				(0.0420)	
Lagged Commercial & Industrial Chargeoffs					0.2090***
					(0.0445)
Lagged Log Assets	-0.0113	0.0208	-0.2676***	0.0009	0.0030
	(0.1360)	(0.0135)	(0.0886)	(0.0039)	(0.0022)
Lagged Log Equity	0.0795	-0.0161	0.1846***	0.0025	0.0001
	(0.1032)	(0.0115)	(0.0704)	(0.0031)	(0.0018)
Lagged Short-term Non-core Funding	-0.0387	0.0281	0.0192	0.0088	0.0060
as a Fraction of Total Assets	(0.2308)	(0.0286)	(0.1556)	(0.0059)	(0.0041)
Lagged Total Real Estate Loans	-0.0061	-0.0045**	0.0403***	0.0016***	0.0011***
as a Fraction of Tier-1 Capital	(0.0181)	(0.0022)	(0.0132)	(0.0006)	(0.0003)
Lagged Total C&I Loans	0.0213	0.0159***	-0.0345	-0.0009	-0.0017**
as a Fraction of Tier-1 Capital	(0.0602)	(0.0051)	(0.0488)	(0.0012)	(0.0007)
Lagged Cost of All Interest-Bearing Funds	0.0063	0.0067	0.0424	-0.0020	-0.0002
	(0.0541)	(0.0059)	(0.0394)	(0.0014)	(0.0008)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2,809	2,809	2,806	2,809	2,809
Adjusted R^2	0.7944	0.8055	0.7212	0.6252	0.4811

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

Table IX: Additional Robustness: Geographical Outliers and Rent

This table reports the effect of Community Reinvestment Act (CRA), the federal Paycheck Protection Program (PPP), and their interactions with skilled labor on small business loans, mortgage lending, housing prices, and rent growth by excluding potential geographical outliers in our sample. The potential geographic outliers are the areas where the ratio of small business loans to total lending in terms of mortgages and small business is in the first and tenth decile. Our analysis sample is restricted to census tracts that have median family incomes between 75% and 85% of the MSAs median family income. Rents are measured by fair market rents obtained from HUD. Data sources and variable definitions are discussed in Appendix B and Table D.I. Continuous variables are winsorized at 99%. Standard errors are clustered by corresponding geographic unit and are reported in parentheses. Observations are weighted by 2019 population in the corresponding geographic area.

	Tract-level CRA								County-level PPP
	Small Business (1)	Mortgage (2)	Small Business (3)	Mortgage (4)	Housing Price (5)		Rent (6)		Rent (7)
ΔLMI	0.0071***	0.0232***	0.0012	0.0733***	0.0158***	ΔLMI Fraction	0.0405**	Per Capita PPP First Draw	0.0088
	(0.0027)	(0.0085)	(0.0037)	(0.0116)	(0.0037)		(0.0188)		(0.0067)
Skilled Labor			0.0947***	0.0679	0.0237	Skilled Labor	-0.0585**	Skilled Labor	0.4146**
			(0.0248)	(0.0738)	(0.0153)		(0.0226)		(0.1843)
ΔLMI × Skilled Labor			0.0291**	-0.2449***	-0.0794***	ΔLMI Fraction × Skilled Labor	-0.2226**	Per Capita PPP First Draw × Skilled Labor	-0.0558**
			(0.0134)	(0.0415)	(0.0127)		(0.1121)		(0.0276)
Lagged Log Small Business Loans	-0.0827***		-0.0833***						
	(0.0083)		(0.0083)						
Lagged Log Mortgage		-0.0174**		-0.0181**					
		(0.0072)		(0.0072)					
Lagged Log HPI					0.0293***				
					(0.0108)				
Lagged Log Median Household Income	-0.0051	-0.1052***	-0.0039	-0.1132***	0.0067	Lagged Log Median Household Income	-0.0242**	Lagged Log Median Household Income	-0.0188
	(0.0071)	(0.0204)	(0.0070)	(0.0205)	(0.0051)		(0.0122)		(0.0201)
Lagged Log Population	-0.0614***	-0.3660***	-0.0630***	-0.3612***	0.0066	Lagged Log Population	0.0238***	Lagged Log Population	-0.0062
	(0.0123)	(0.0378)	(0.0123)	(0.0376)	(0.0089)		(0.0085)		(0.0056)
						Lagged Unemp. Rate	-0.0007	Lagged Unemp. Rate	0.0006
							(0.0008)		(0.0041)
						Lagged Herfindahl Index	0.0326	Lagged Herfindahl Index	-0.0067
							(0.0219)		(0.0127)
						Lagged Log Deposits	0.0015	Lagged Log Deposits	0.0052
							(0.0044)		(0.0038)
Tract FE	Yes	Yes	Yes	Yes	Yes				
Year FE	Yes	Yes	Yes	Yes	No				
County Year FE	No	No	No	No	Yes				
						County FE	Yes		
						MSA-Year	Yes		
								MSA FE	Yes
Observations	52,706	52,706	52,706	52,706	35,406	Observations	19,626	Observations	2,114
Adjusted R^2	0.7591	0.8345	0.7593	0.8348	0.989	Adjusted R^2	0.6319	Adjusted R^2	0.5417

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

Appendix: For review and online publication only

A Positive Externalities of Skilled Labor

In this paper, previous sections empirically demonstrate that the effect of government-directed lending depends crucially on skilled labor, i.e., human capital in the area. The reason of this dependence are the same as the insights from Lucas (1988, 1990) in the case of economic development of nations. In this section, we provide a stylized model that borrows the setup of Lucas (1988) and incorporates government-directed lending. The model, under transparent simplifying assumptions, shows the proportional relationship between skilled labor and investment in productive assets (business lending).

We assume a representative consumer-entrepreneur with productive physical capital K and productivity A. The entrepreneur benefits from the average skilled labor h in the area that provides a positive externality (seminal work includes Lucas, 1988; Mankiw, Romer, and Weil, 1992, among others). In this standard setup, we introduce government-directed lending of $g \cdot K$.

While the policymakers hope that all the directed capital is invested in production, the entrepreneur maximizes his utility by dividing this capital into two parts. He consumes fraction f of the capital $g \cdot K$, and invests the rest $(1-f)g \cdot K$ along with his previously invested private capital K. To keep the model close to the trade-off in data, consumption in this case takes the form of investment in housing. Housing provides a consumption utility stream. Thus, the optimization problem of the consumer-entrepreneur is:

$$V^*(K,h,\theta,\underline{c},g) = \max_f \underbrace{u(\underline{c}+fgK)}_{\text{consumption}} + \theta \underbrace{A\Big(K(1+(1-f)g)\Big)^\alpha h^\gamma}_{\text{production}}, \tag{6}$$

where α and γ represent the returns to scale on capital and skilled labor, respectively. θ is the “price" to value the increment in physical capital, similar to Lucas (1988). In this stylized model with a representative consumer-entrepreneur, we abstract away from the amount of labor in the production function.

Under the assumption of log utility, the first order condition for f, that maximizes the consumer-entrepreneur's value:

$$\frac{gK}{\underline{c}+fgK}-\alpha\theta Ah^{\gamma}gK\Big(K(1+(1-f)g)\Big)^{\alpha-1}=0 \tag{7}$$

Thus, we obtain a relation between fraction f for consumption and skilled labor h that provides the production externalities:

$$\frac{1}{\underline{c}+fgK}=\alpha\theta Ah^{\gamma}\Big(K(1+(1-f)g)\Big)^{\alpha-1} \tag{8}$$

In the special case, where return on capital approaches linearity ($\lim\alpha\to 1$), we obtain:

$$f=\frac{1}{G}\left(\frac{1}{\theta Ah^{\gamma}}-\underline{c}\right), \tag{9}$$

where we denote $G\equiv g\cdot K$ to shorten the notation of government-directed lending. If the government-directed lending is large enough, i.e., $G\gg\underline{c}$, then $\lim_{G\gg c}\frac{\underline{c}}{G}\to 0$, allowing us to log-linearize the relation between fraction f and skilled labor h:

$$\log f=\log\frac{1}{AG\theta}-\gamma\log h \tag{10}$$

As skilled labor increases in an area, a relatively smaller fraction f of government-directed lending G is allocated towards mortgages and housing (consumption) in that area. This result matches our empirical findings in Section II.

To estimate f from data, we use the CRA program, where we have tract-level data on small business lending and mortgage lending. We proxy f with census tract level percentage change in mortgage lending in a period t when a tract gains CRA eligibility, scaled by percentage change in mortgage lending and percentage change in small business lending:

$$f_{CRA} = \frac{\Delta m/m_{t-1}}{\Delta m/m_{t-1} + \Delta s/s_{t-1}}. \tag{11}$$

Thus, identification of externality parameter γ is obtained from tract-level allocation of government-directed lending to mortgages and small business lending.

We can estimate Eq. 11 to obtain the positive externalities of skilled labor, i.e., human capital in U.S. census tracts. The stylized model fits well with data. Figure D.5 plots the almost (log) linear estimated relation between skilled labor and f_{CRA}. Table D.VII estimates the value of skilled labor externality parameter γ.

The estimated coefficient of the interaction term suggests that the value of γ in periods when a tract gains eligibility is 2.48%. The point estimate of 2.65% for log skilled labor in the first row suggests that the cross-sectional estimate is also similar. The estimate of the interaction term remains similar in magnitude after adding available controls in column (2). A three year window around CRA eligibility change in columns (3) and (4) also yields similar magnitudes. Column (4) estimates that the elasticity of productivity with respect to the skilled labor at the tract level is 0.022.

A vast literature investigates human capital externalities using a variety of techniques. Compared to this literature, our estimates are obtained from a new approach: by observing the allocation of government-directed lending into production and immediate consumption. Before us, researchers have compared wages across geographies and output across plants to obtain a measure of human capital externalities (e.g., Rauch, 1993; Acemoglu and Angrist, 2000; Moretti, 2004;

Ciccone and Peri, 2006; Guo, Nicolas, and Seshadri, 2018).[17] Our approach complements these approaches and finds a statistically positive output elasticity with respect to skilled labor.

B Data Sources and Additional Information

Tract-level loan data

We obtain small-business lending data from the CRA disclosures provided by the Federal Financial Institutions Examination Council (FFIEC) and mortgage data from the Home Mortgage Disclosure Act (HMDA) flat files provided by the Consumer Finance Protection Bureau (CFPB). Banks covered by CRA report loans at the census tract level for each income group level every year. We use the CRA aggregate table "A1-1" for our analysis, which contains information on small business loan origination aggregated at a census tract level. For mortgages, we use the Loan Application Record (LAR) data which provided mortgage application information and applicant demographics by bank at a census tracts level.

CRA reporting banks report totals of loan amounts and number of loans separately for four different categories. These categories are loans where the origination amount is less than $100,000, between $100,000 and $250,000, and between $250,000 and $1 million. Also, reported separately are loans to small businesses having gross annual revenues less than $1 million. In our empirical analysis we use this final definition of small business loans, as we focus on small businesses (Greenstone, Mas, and Nguyen, 2020). For mortgages, we use data for approved mortgage applications for the purpose of owner occupied 1-4 single family residential purchases.

[17] Acemoglu and Angrist (2000) use variation in child labor laws and compulsory attendance laws over time and across states to obtain returns to education of approximately 1% that are not significantly different from zero. Ciccone and Peri (2006) investigate U.S. cities and states from 1970–1990 and find no evidence of average-schooling externalities. Moretti (2004) utilizes plant-level data for estimating human capital externalities and finds that a 1-percent increase in the city share of college graduates is associated with a 0.5-0.6 percentage-point increase in output. Guo, Nicolas, and Seshadri (2018) estimate that the elasticity of a firm's productivity with respect to average human capital of an economy is 0.12.

From the "A1-1" table, we focus on granular data at census tract-year level. We drop observations where the census tract income group is unknown, or the census tract itself is not known. Similarly, for mortgages we drop observations where either the primary purpose of the mortgage application is for refinancing, or the property is not owner-occupied, or the mortgage application is application is denied.

Education

We use the American Community Survey (ACS) to obtain information on tract and county-year level educational attainment level by county/tract demographics indicators. Specifically, we use the S1501-Educational Attainment tables provided as apart of ACS 5 year estimates subject table.

Housing Data Sources

For housing price index, at an annual level, we use the Federal Housing Finance Agency's (FHFA) Housing Price Index (HPI). The FHFA HPI is a broad measure of the movement of single-family house prices. The FHFA HPI is a weighted, repeat-sales index. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975.

For monthly housing prices post April 2020, we use data from Zillow. Zillow Home Value Index (ZHVI) is a smoothed, seasonally adjusted measure of the typical home value and market changes across a given region and housing type. It reflects the typical value for homes in the 35th to 65th percentile range.

PPP loans and Food Stamps

Data for PPP loans are provided at a loan level by the Small Business Administration (SBA). We aggregate this data to the county level. Data on county income and Supplemental Nutrition Assistance Program (SNAP) are obtained from the U.S. Census Bureaus Small Area Income and Poverty Estimates (SAIPE) program. The datasource provides single-year estimates of income and poverty for all U.S. states and counties. SNAP data for January 2021 are obtained from Bi-Annual (January and July) State Project Area/County Level Participation and Issuance Data provided by the U.S. Department of agriculture (USDA) food and nutrition service. Besides S1501 - Educational Attainment, we also use the ACS tables: S1101 - Household and Families, DP04-Selected housing characteristics, B25077 - Median housing value, in our analysis.

Bank data

To obtain financial information regarding depository institutions, we utilize Reports of Condition and Income (Call Reports) and Uniform Bank Performance Reports (UBPRs). We exclude mortgage specialty and credit card specialty banks as well as banks that are not chartered as commercial banks. The data allow us to obtain bank-level financial characteristics such as total assets of a bank, total equity, cost of deposits, fraction of assets that are core deposits, etc.

We obtain banks' deposit data at the county-level from the Summary of Deposits (SOD) provided by the Federal Deposit Insurance Corporation (FDIC). SOD is the annual survey of branch office deposits as of June 30 for all FDIC-insured institutions, including insured U.S. branches of foreign banks. The data allow us to obtain deposit growth for each bank at the county-level as well as the market share of each bank in a county based on deposits.

C Matching Procedure

For the census tract level results, we match the treated census tracts with the control census tracts based on median family income and the number of households using multivariate distance kernel matching technique. Treated tracts are defined as those census tracts that became newly CRA-eligible during our sample period (2009–2019). Control tracts are defined as those census tracts that never switched their CRA eligibility status during our sample period. All control tracts are restricted to have their relative median family income between 75% to 85% of the MSA median family income. Further, we require the control and treated census tracts to be within the same county. Our approach is similar to one used in Begley and Purnanandam (2021) where zip codes within the same MSA are matched on demographic characteristics.

We use the Epanechnikov kernel function and weigh the matches on Mahalanobis Distance. The bandwidth used is 1.5 times the 90% quantile of the non-zero distances in pair matching with replacement (Huber, Lechner, and Steinmayr, 2015). For the sub-sample having a median family income between 75%-85% of the MSA family income, this procedure results in 26,636 treated tracts and 20,117 control tracts. Table D.III presents the summary statistics for the treated and control samples. As can be inferred, the treated and the control tracts are virtually identical in their demographic and economic characteristics.

At the county level, we have much richer demographic and economic data. For our county-level results, we match counties on median family income, unemployment rate, the concentration of banking markets, total county deposits, MSA median income, and population growth rate. We define treated counties are those that experienced a change in the fraction of LMI tracts, while control counties are those that did not experience any change in the fraction of LMI tracts. We also require that the treated and untreated counties be in the same state. Table D.IV presents the summary statistics of the 7,338 treated counties and 13,522 matched control counties. As with the census tracts, the county matching also results in demographically similar treated and control counties.

For the treatment and control samples, for all the variables we use in the regressions, we test for differences in means with and without the presence of geography and time fixed effects. Table D.V reports the results. The matching procedure, at a tract level, renders the raw differences among the covariates statistically indifferent from zero. At a county level, we see that for some co-variates, raw differences in means remain statistically significant. However, in the presence of fixed effects, which we always employ in our regressions the within difference among covariates becomes statistically indifferent from zero.

D Additional Tables and Figures

Table D.I: Definition and Sources of Main Variables

Data sources are the Community Reinvestment Act (CRA) Database from Federal Financial Institutions Examination Council (FFIEC), the Summary of Deposits (SOD), Uniform Bank Performance Report (UBPR), the American Community Survey (ACS), the Local Area Unemployment Statistics (LAUS) program provided by U.S. Bureau of Labor Statistics (BLS), Zillow, Federal Housing Finance Agency (FHFA), U.S. Small Business Administration (SBA), Small Area Income and Poverty Estimates (SAIPE), and County Business Patterns (CBP).

Panel A: Tract-Year and County-Year level variables		
Variable name	Description	Source
Small Business Loans (SBL)	From the Table "A1-1" of CRA aggregate flat files, defined as Commercial and Industrial Loans (C&I Loans) secured by non-farm non-residential properties extended to businesses with annual revenues less than $1 million and having principal origination amounts less than $1 million.	FFIEC
Mortgage Loans	From the Loan Application record files aggregate flat files, defined as mortgages extended for purchases of conventional owner-occupied 1-4 single family homes.	FFIEC
Annual Housing Price Index	Housing price index constructed from FHFA's all-transactions sample, which includes conventional mortgages of single-family purchases and refinances that are acquired or guaranteed by Fannie Mae or Freddie Mac, not seasonally adjusted.	FHFA
Monthly Housing Price Index	Constructed using Zillow Home Value Index (ZHVI): A smoothed, seasonally adjusted measure of the typical home value and market changes across a given region and housing type. It reflects the typical value for single family homes in the 35th to 65th percentile range.	Zillow
Total Population	Total population of a census tract updated as per the latest decennial Census or American Community Survey.	ACS
Median Household Income	Median income in a tract based on data collected in the American Community Survey (ACS) and the Puerto Rico Community Survey (PRCS) conducted annually by the U.S. Census Bureau.	ACS
LMI	Low to moderate income (LMI) census tracts are tracts where the median family income is 80% or less of the parent area's median family income. The parent area is the metropolitan statistical area (MSAs) for tracts located in cities and the state non-MSA area for tracts outside cities. LMI tracts are eligible for CRA lending.	FFIEC
LMI Fraction	Fraction of LMI census tracts in a county.	FFIEC

Panel A (contd.): County-Year level variables		
Variable name	Description	Source
ΔLMI	An indicator variable of a change in LMI classification and becoming CRA eligible. It takes value of 1 for three periods when the tract becomes classified as an LMI tract and 0 for three periods before the change.	FFIEC
Skilled Labor	The fraction 25 years or older population that has a bachelor degree or higher from table S1501 of the Census.	ACS
County Deposits	Branch office deposits as of June 30 for all FDIC-insured institutions, including insured U.S. branches of foreign banks aggregated to county-year level.	SOD
Unemp. Rate	All persons who had no employment during the reference week, were available for work, except for temporary illness, and had made specific efforts to find employment some time during the 4 week-period ending with the reference week. Persons who were waiting to be recalled to a job from which they had been laid off need not have been looking for work to be classified as unemployed as percent of the civilian labor force.	LAUS
SNAP	Population that received of the Supplemental Nutrition Assistance Program (SNAP) benefits in a county.	SAIPE
Herfindahl Index	Sum of squared deposit shares of a banks in county in a given year.	SOD
Single-Parent Households	From ACS table S1101 defined as Single-Parent Households with Children as a Percentage of Households with Children.	ACS
PPP-first Draw	Current approval amount of forgivable Paycheck Protection Program Loans received in a county in the first phase, that is, from April to August 2020.	SBA
Average Fair Market Rent	Average value of rents for efficiency, 1, 2, 3, and 4 bedroom apartments in a county-year.	HUD
Small Establishments	A fixed physical location or permanent structure where some form of business activity is conducted and employing between 20–49 employees	CBP

Table continued.

Panel B: Bank-Year Variables		
Variable name	Description	Source
RE Loans	*ubpre884* -Construction, land development and other land loans, closed-end loans secured by 1-4 family residential properties (first liens, junior liens, and revolving open-end loans), loans secured by farmland, loans secured by multifamily residential properties, and loans secured by non-farm non-residential properties divided by Tier 1 Capital plus Allowance.	UBPR
C&I Loans	*ubpre887* - For banks filing Call Report form 031, commercial and industrial loans in domestic and foreign offices divided by Tier 1 Capital plus Allowance. For banks filing Call Report form 041, commercial and industrial loans divided by Tier 1 Capital plus Allowance.	UBPR
RE charge-offs	*ubpre401& ubpre402* - The year-to-date net loss (change offs less recoveries from Call Report Schedule RI-B) for single family/home equity loans divided by average 1-4 family residential mortgages/Home equity loans.	UBPR
C&I charge-offs	*ubpre405* - Weighted average of Annualized % of the year-to-date net loss (change offs less recoveries from Call Report Schedule RI-B) for commercial and industrial loans divided by average commercial and industrial loans from Call Report Schedule RC-K and Non-Farm Non-Residential Mortgages divided by the average of nonfarm nonresidential mortgages from Call Report Schedule RC-C.	UBPR
Cost of Deposits	*ubpre116* - Interest on all interest-bearing deposits in domestic offices, interest-bearing foreign office deposits, demand notes (note balances) issued to the U.S. Treasury, other borrowed money, subordinated notes and debentures, and expense on federal funds purchased and securities sold under agreements to repurchase, interest expense on mortgage and capitalized leases divided by the average of the liabilities or funds that generated those expenses.	UBPR
Core Deposits	*ubpre592* - Short term non core funding divided by total assets. Short term non core funding March 31, 2011 forward equals the sum of time deposits of more than $250,000 with a remaining maturity of one year or less + brokered deposits issued in denominations of $250,000 and less with a remaining maturity or one year or less + other borrowed money with a remaining maturity one year or less + Time deposits with a remaining maturity of one year or less in foreign offices + securities sold under agreements to repurchase and federal funds purchased.	UBPR
Total Equity	*ubpr3210* - Total bank equity capital from Call Report Schedule RC.	UBPR
Total Assets	*ubpr2170* - Total Assets from Call Report Schedule RC.	UBPR

Table D.II: LMI Census Tracts over time

This table provides detailed information regarding the change in LMI census tracts in the U.S. from the year 2008–2019.

Year	# of Tracts	LMI Tracts	Reason for Change
2008	68,065	19,061	The following update announced by the Office of Management and Budget (OMB) on November 20, 2007 is included in the 2008 FFIEC Census File: Sarasota-Bradenton-Venice, FL Metropolitan Statistical Area (code 42260) was changed to Bradenton-Sarasota-Venice, FL Metropolitan Statistical Area (code 14600).
2009	68,065	19,056	Three new Metropolitan Statistical Areas (previously classified as Micropolitan Statistical Areas) were announced (A) Cape Girardeau-Jackson, MO-IL Metropolitan Statistical Area (code 16020) (B) Manhattan, KS Metropolitan Statistical Area (code 31740) (C) Mankato-North Mankato, MN Metropolitan Statistical Area (code 31860)
2010	68,066	19,056	The following update announced by the Office of Management and Budget (OMB) on December 1, 2009 is included in the 2010 FFIEC Census File: 1. Bradenton-Sarasota-Venice, FL Metropolitan Statistical Area (code 14600) was changed to North Port-Bradenton-Sarasota, FL Metropolitan Statistical Area (code 35840). Fort Walton Beach-Crestview-Destin, FL Metropolitan Statistical Area (code 23020) was changed to Crestview-Fort Walton Beach-Destin, FL Metropolitan Statistical Area (code 18880). Weirton-Steubenville, WV-OH Metropolitan Statistical Area (code 48260) was changed to Steubenville-Weirton, OH-WV Metropolitan Statistical Area (code 44600). 2. One county was deleted and two new counties were added to the 2010 Census File: Skagway-Hoonah-Angoon Census Area, AK (02-232) was deleted and split to create two new counties: Skagway Municipality, AK (02-230) and Hoonah-Angoon Census Area, AK (02-105)
2011	68,067	19,056	1. One county was deleted and two new counties were added to the 2011 Census Files: Wrangell-Petersburg Census Area, AK (02-280) was deleted and split to create two new counties: Wrangell City and Borough, AK (02-275) and Petersburg Census Area (02-195) 2. One county was deleted and new county was added to the 2011 Census File: Prince of Wales-Outer Ketchikan Census Area, AK (02-201) was deleted and created new county: Prince of Wales-Hyder Census Area, AK (02-198) included the remainder of new Wrangell City and Borough (02-275).
2012	75,665	22,953	Census tract information and demographics are from the 2010 Census, replacing the 2000 census information from previous years
2013	75,881	23,162	Due to the possibility of the inclusion of small areas of land and potentially some population, the underwater tracts (tract => 990000 and tract not equal to 999999) have been reinstated in the 2013 FFIEC Census file
2014	75,881	23,072	On February 28, 2013 OMB released the revised delineations of Metropolitan Statistical Areas. The revised MSA/MD delineations apply to HMDA and CRA data collected on or after January 1, 2014 and therefore were incorporated in the 2014 FFIEC Census file.
2015	75,880	23,071	-
2016	75,880	23,071	-

Table D.II Continued

Year	# of Tracts	LMI Tracts	Reason for Change
2017	75,883	24,215	Starting with 2017, the FFIEC Census File uses the 2011-2015 American Community Survey (ACS) for its demographic fields. This contrasts to previous years when the FFIEC Census used 2006-2010 ACS for the majority of its demographic fields, with selected 2010 Census Summary
2018	75,883	24,215	-
2019	75,883	24,079	On September 14, 2018 OMB released an update to MSA/MD delineations that are incorporated in the 2019 FFIEC Census file. Due to the implementation of the new OMB delineations, the FFIEC has recalculated the MSA/MD Median Family and Household Incomes in the cases were a MSA/MD boundary change has occurred and the data are not available from Census.

Table D.III: Summary Statistics - Matched Sample - Tract-Year

This table reports summary statistics of the matched sample. Treated tracts are defined as those census tracts that became newly CRA-eligible during our sample period (2009–2019). Control tracts are defined as those census tracts that never switched their CRA eligibility status during our sample period. The top panel reports census tract-year level statistics for treated tracts. The bottom-panel provides same statistics for matched control tracts. The sample period is from 2009–2021. Data sources and variable definitions are discussed in Appendix B and Table D.I.

	Mean	**Std. Dev**	**P50**	**P25**	**P75**	**N**
			Treated Tracts			
Population	4,488	1,655	4,319	3,277	5,513	26,634
Skilled Labor	0.204	0.104	0.183	0.130	0.255	26,634
Median Housing Value	174,531	109,572	141,100	103,400	207,200	24,980
Per Capita Mortgage ($)	3781.78	4902.50	2718.67	1593.48	4644.05	26,634
Per Capita Small Business Loans ($)	217.59	295.00	126.07	55.60	270.16	26,634
Relative Family Income (%)	81.07	13.24	80.04	73.24	88.10	26,634
Median Family Income ($)	51,671	12,351	49,882	43,262	58,270	26,634
Households	1,693	607	1,638	1,242	2,091	26,634
Housing Price Index (1985 = 100)	209.67	124.60	180.01	140.02	237.69	26,634
			Control Tracts			
Population	4,494	1,649	4,328	3,287	5,509	20,117
Skilled Labor	0.206	0.105	0.183	0.132	0.258	20,117
Median Housing Value	174,244	110,158	139,600	102,100	207,600	18,089
Per Capita Mortgage ($)	3731.42	4989.91	2754.62	1674.16	4665.21	20,117
Per Capita Small Business Loans ($)	220.03	332.33	123.82	51.83	266.46	20,117
Relative Family Income (%)	83.16	15.53	82.89	72.56	92.48	20,117
Median Family Income ($)	51,495	12,336	49,949	42,685	58,024	20,117
Households	1,694	596	1,641	1,249	2,086	20,117
Housing Price Index (1985 = 100)	203.96	113.55	176.96	138.13	230.74	20,117

Table D.IV: Summary Statistics - Matched Sample - County-Year

This table reports summary statistics of the matched county-year sample. Treated county observations are those that experienced a change in the fraction of LMI tracts. Control counties did not experience any change in the fraction of LMI tracts. The sample period is from 2009-2021. Data sources and variable definitions are discussed in Appendix B and Table D.I.

	Mean	**Std. Dev**	**P50**	**P25**	**P75**	**N**
			Treated Counties			
Population	181,483	485,623	50,040	23,072	147,313	7,338
Skilled Labor	0.214	0.092	0.191	0.145	0.265	7,338
LMI Fraction	0.273	0.190	0.250	0.143	0.379	7,338
Δ LMI Fraction	0.022	0.191	0.026	-0.071	0.125	7,338
SNAP Recipients	26,101	73,573	7,772	3,636	18,907	7,338
SNAP Growth	-0.0295	0.0474	-0.0326	-0.0605	-0.0010	7,338
Fraction Single-Parent Household	0.3495	0.0544	0.3480	0.3145	0.3810	7,334
Herfindahl Index	0.1609	0.1496	0.1181	0.0589	0.2130	7,338
Housing Price Index (1985 = 100)	290.7	191.3	230.4	171.4	350.7	7,328
Median Family Income	47,573	12,597	45,162	39,312	52,808	6,010
Unemployment Rate	0.0649	0.0259	0.0600	0.0440	0.0820	7,338
County Deposits ($ billion)	5.02	20.71	0.74	0.33	2.12	7,338
			Control Counties			
Population	81,023	221,613	25,444	12,552	58,506	13,522
Skilled Labor	0.200	0.085	0.179	0.141	0.236	13,522
LMI Fraction	0.155	0.207	0.059	0.000	0.250	13,522
Δ LMI Fraction	–	–	–	–	–	13,522
SNAP Recipients	10,924	30,315	3,666	1,515	8,947	13,522
SNAP Growth	-0.0104	0.0746	-0.0194	-0.0599	0.0308	13,522
Fraction Single-Parent Household	0.3498	0.0617	0.3455	0.3115	0.3820	13,490
Herfindahl Index	0.2081	0.1646	0.1672	0.0933	0.2736	13,522
Housing Price Index (1985 = 100)	237.9	141.8	195.3	155.3	268.4	13,486
Median Family Income	47,365	11,598	45,718	39,588	52,592	12,678
Unemployment Rate	0.0670	0.0288	0.0620	0.0450	0.0840	13,522
County Deposits ($ billion)	2.08	11.36	0.42	0.22	0.91	13,522

Table D.V: Test of Difference in Means

This table reports the raw difference and within difference among variables used in our regressions between the treated and control samples. Data sources and variable definitions are discussed in Appendix B and Table D.I.

Variable	**Type**	**Raw Difference**	**T-Statistic**	**Significance**	**Within-Difference**	**T-Statistic**	**Significance**
			Tract-Year				
Skilled Labor	Explanatory	-0.003	-2.65	***	-0.003	-3.48	***
Population	Covariate	31.51	1.46		-9.98	-1.01	
Median Family Income	Covariate	104.13	0.56		-311	-3.88	***
Per Capita SBL	Outcome	0.805	0.25		-1.09	-0.47	
Per Capita Mortgage	Outcome	76.59	1.84	*	62.37	1.91	*
Log Housing Price Index	Outcome	0.032	5.93	***	-0.005	-1.59	
			County-Year				
Skilled Labor	Explanatory	0.062	10.47	***	-0.0007	-0.68	
Population	Covariate	297,157	18.52	***	888	1.41	
Unemployment Rate	Covariate	-0.00872	-6.2	***	-0.00022	-0.9	
Median Family Income	Covariate	924.41	0.86		137.54	0.93	
SNAP Recipient Growth	Outcome	-0.0052	-1.63		-0.006	-2.13	**
Log Deposits	Covariate	1.554	24.7	***	0.0019	0.4	
Herfindahl Index	Covariate	-0.0304	-7.73	***	0.0022	2.57	**

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

Table D.VI: Effect of Losing CRA Eligibility Status on Annual Lending

This table estimates the effect of the losing Community Reinvestment Act (CRA) eligibility status on annual small business and mortgage lending, conditional on skilled labor. The dependent variable in odd-numbered columns is the natural logarithm of per capita small business lending, while in the even-numbered columns, it is the natural logarithm of per capita mortgage lending. Our main explanatory variables are ΔLMI, which takes on a value of 1 for 3 years when a tract loses its CRA eligibility (i.e., the tract's relative family income is above 80% of the MSA median family income) and skilled labor (i.e., the fraction of college graduates among the population aged 25 and older). Control tracts are those tracts that do not change their CRA eligibility status and have relative family income between 75% to 85% - pv - relative to MSA

	CRA Eligible Tracts							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔLMI	0.0045	-0.0011	0.0087***	-0.0000	0.0116***	0.0407***	0.0081***	0.0014
	(0.0031)	(0.0109)	(0.0029)	(0.0110)	(0.0042)	(0.0152)	(0.0030)	(0.0119)
Skilled Labor					0.0973***	0.3068***		
					(0.0299)	(0.1064)		
ΔLMI × Skilled Labor					-0.0131	-0.1686***		
					(0.0151)	(0.0465)		
Skilled Labor Above Median							0.0046	0.0288**
							(0.0032)	(0.0121)
Skilled Labor Above Median × ΔLMI							0.0013	-0.0042
							(0.0040)	(0.0144)
Lagged Log SBL	-0.0388***		-0.0599***		-0.0602***		-0.0600***	
	(0.0142)		(0.0088)		(0.0088)		(0.0088)	
Lagged Log Mortgage		-0.0090		-0.0247**		-0.0247**		-0.0249**
		(0.0112)		(0.0106)		(0.0106)		(0.0106)
Lagged Log Median Family Income			-0.0129	0.0210	-0.0122	0.0388	-0.0131	0.0226
			(0.0090)	(0.0251)	(0.0090)	(0.0254)	(0.0090)	(0.0252)
Lagged Log Population			-0.1555***	-0.4578***	-0.1558***	-0.4515***	-0.1557***	-0.4575***
			(0.0309)	(0.0580)	(0.0309)	(0.0586)	(0.0309)	(0.0580)
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,536	46,536	46,536	46,536	46,536	46,536	46,536	46,536
Adjusted R^2	0.7886	0.8832	0.7915	0.8842	0.7916	0.8843	0.7915	0.8842

* p<0.10, ** p<0.05, *** p<0.01

Table D.VII: Estimation of Human Capital Externality

This table estimates the value of γ by estimating the slope coefficient of the Eq. 10. The dependent variable is f_{CRA}, as defined in Eq. 11. The independent variable *Skilled labor* is the fraction of college graduates in the tract.

	(1)	(2)	(3)	(4)
Log skilled labor	-0.0265*	-0.0294**	-0.0227	-0.0214
	(0.0151)	(0.0147)	(0.0154)	(0.0155)
Newly CRA eligible	-0.0429*	-0.0431*		
	(0.0235)	(0.0237)		
Newly CRA eligible × Log skilled labor	-0.0248**	-0.0243*		
	(0.0125)	(0.0126)		
ΔLMI			-0.0490***	-0.0410***
			(0.0144)	(0.0137)
ΔLMI × Log skilled labor			-0.0238***	-0.0218***
			(0.0085)	(0.0083)
Lagged Log Median Household Income		0.0356**		0.0473**
		(0.0168)		(0.0191)
Lagged Log Population		0.0696*		0.0741**
		(0.0364)		(0.0363)
Tract FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Observations	104,264	104,264	104,264	104,264
Adjusted R^2	0.0136	0.0137	0.0147	0.0149

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

Figure D.1: Community Reinvestment Act

The Community Reinvestment Act (1977) encourages banks to lend to low (purple), moderate (light purple), and distressed/under-served middle (blue) income census tracts. The targeted areas are updated over time based on eligibility criteria. The areas shown above are in the year 2018. Source: PolicyMap.

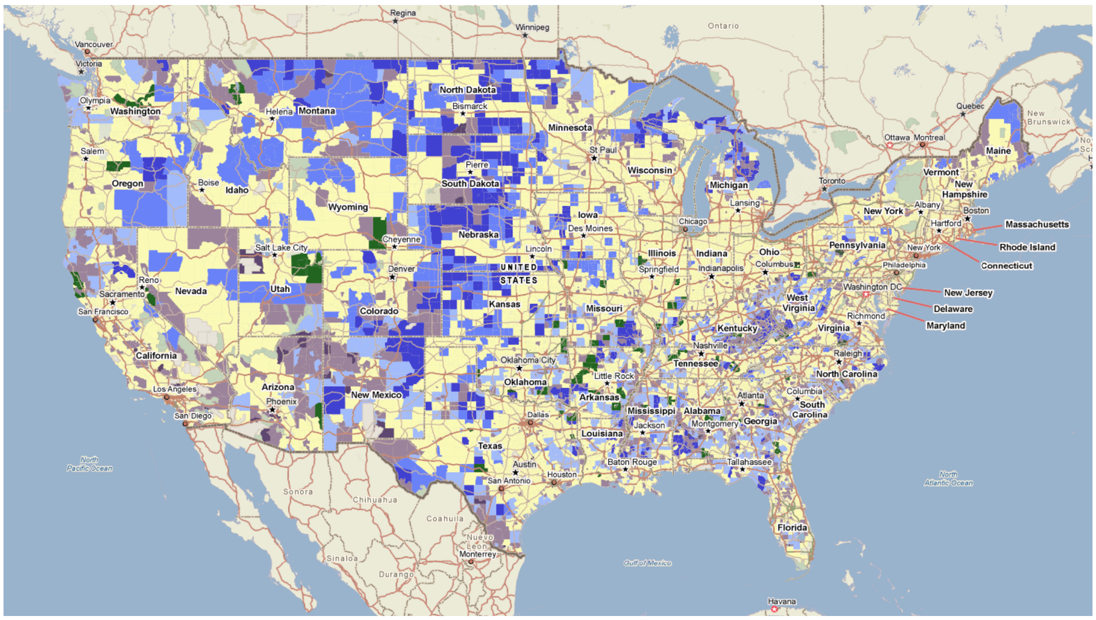


Figure D.2: Paycheck Protection Program

This figure plots the initial approval amount of Paycheck Protection Program forgivable loans (in $ billions). PPP was administered in two phases and three tranches, Phase I (2020) received $350 billion from the the Coronavirus Aid, Relief, and Economic Security Act of 2020 (CARES), additional $320 billion from the Paycheck Protection Program and Health Care Enhancement Act, while the Phase II (2021) was funded ($285 billion) via the Consolidated Appropriations Act of 2021.

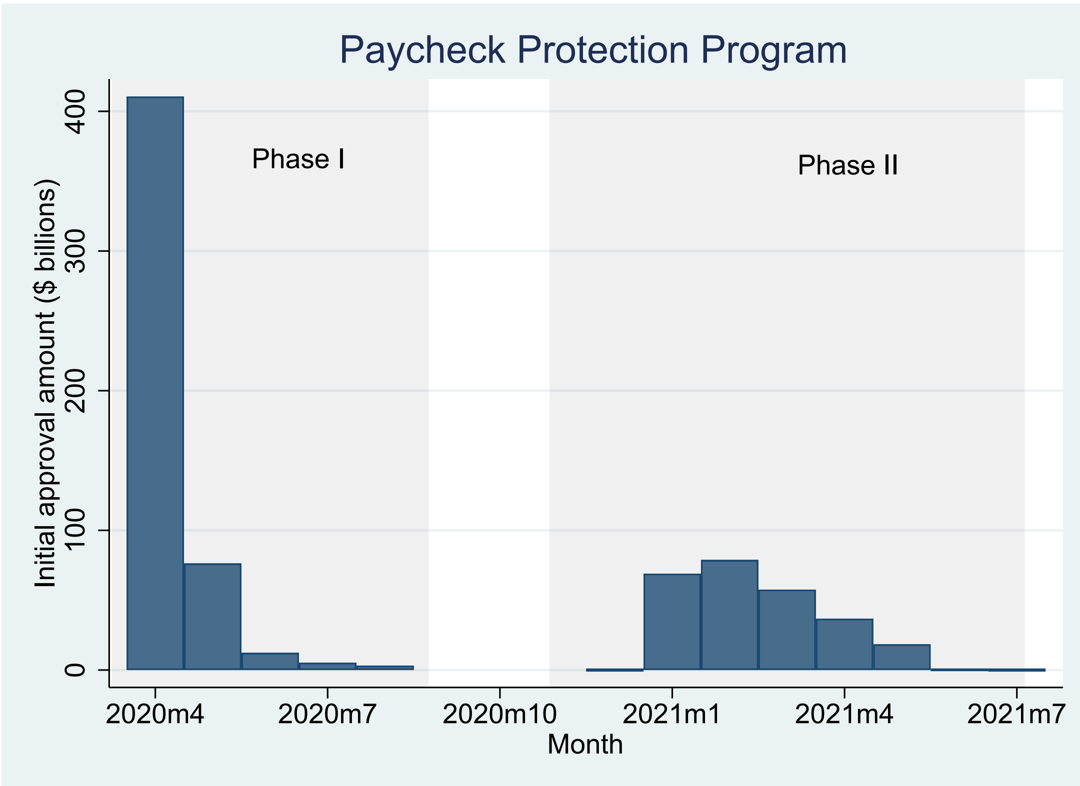
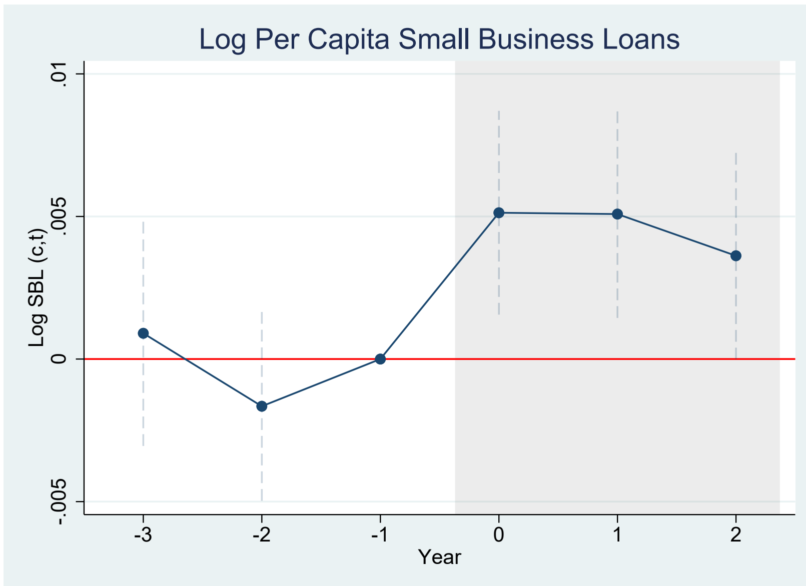
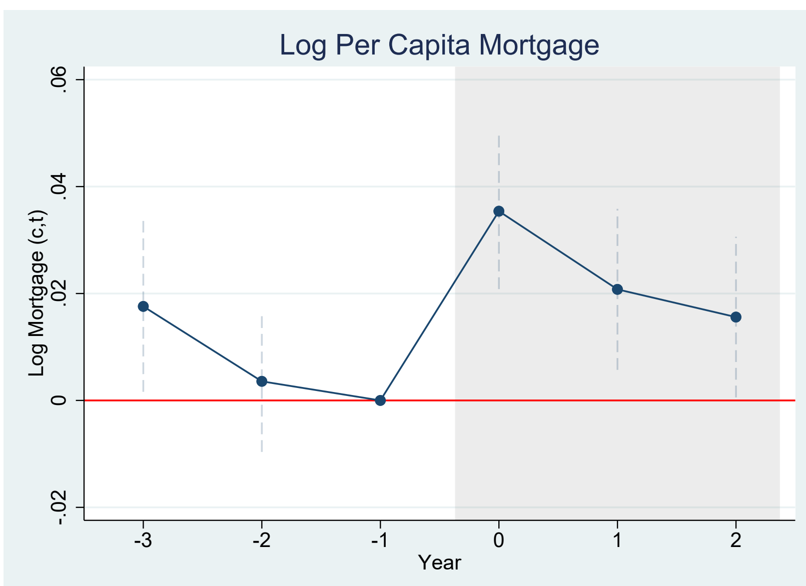


Figure D.3: Effect of CRA on Bank Lending

This figure plots the point estimates (β_1) of Eq. 2. The outcome variable in panel (a) is per-capita small business loans. The outcome variable in panel (b) is mortgage lending. The shaded area represents the sample period after which the tracts become CRA-eligible.



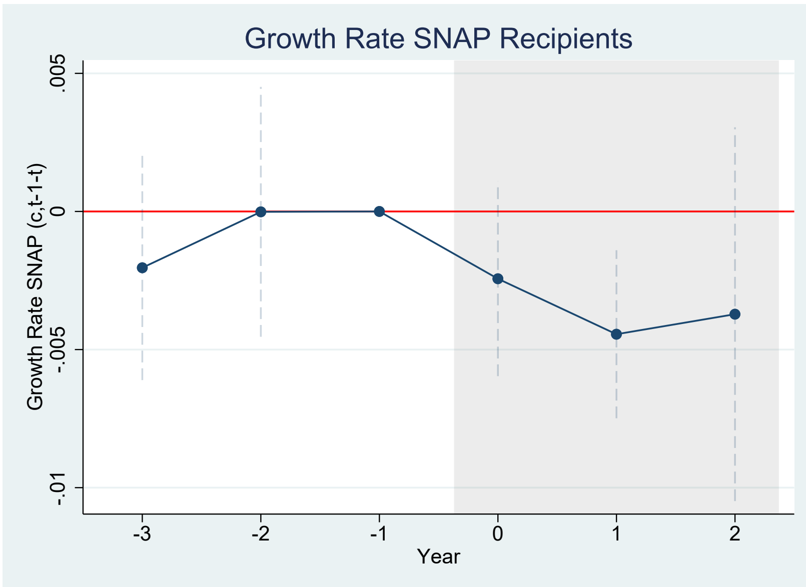
(a)



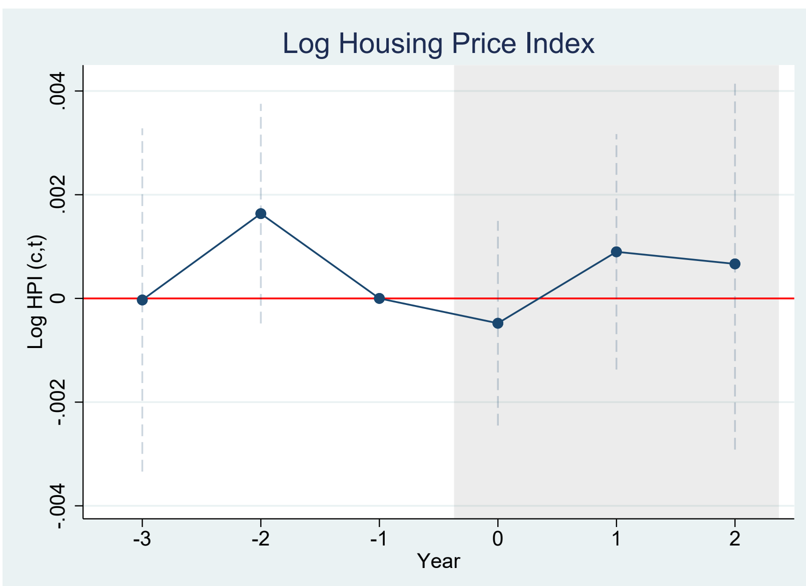
(b)

Figure D.4: Effect of CRA on SNAP Recipients and Housing Prices

This figure plots the point estimates (β_1) of Eq. 2. The outcome variable in panel (a) is growth rate of SNAP recipients. The outcome variable in panel (b) is log housing price index. The shaded area represents the sample period after which the tracts become CRA-eligible.



(a)



(b)

Figure D.5: Estimated Value of Skilled Labor Externality

This figure plots the relation in Eq. 10 non-parametrically. The dependent variable is f_{CRA} as defined in Eq. 11. The slope provides the estimate for skilled labor externality at different levels of skilled labor, i.e., human capital across the U.S. in the last decade. Skilled labor is the fraction of college graduates in the tract.