# Credit Supply Shocks and Fertility: Long-Term Consequences*

Bokyung Kim[†] Minseog Kim[‡] Narae Park[§]

January 2024

Click here for the latest version

**Abstract**

The Great Recession marked a beginning of a historic downward trend for fertility rates in the US. However, little is known about the role of credit supply shocks in explaining these declines. This study investigates whether and to what extent negative credit supply shocks decrease fertility rates. We construct county-level credit supply shocks using variation in year-to-year changes in loans for small businesses and home mortgages. Using these exogenous shocks derived from Bartik (1991)'s shift-share measure, we find that negative credit supply shocks decrease fertility rates both in the short and long run. Counties experienced an average-sized credit reduction in 2009 have had a long-term decrease in fertility rates by 3.17% between 2009–2019. Our heterogeneity analysis reveals that Whites and those aged under 30 decrease their fertility the most in response to negative credit shocks. The findings of this study highlight that credit supply is a key factor influencing fertility choices and that negative credit supply shocks can have long-lasting adverse impacts on fertility rates.

**JEL classification:** J13, E32, G21, E24, R31

**Keywords:** Fertility, Credit Supply Shocks, Great Recession

*We thank Jun-Tae Park, Seik Kim, Jaeyeon Lee, Jun Hyung Kim, Misun Park, Chirok Han, Su Hwan Chung, and Jinyoung Kim. This research was supported by the BK21 FOUR (Fostering Outstanding Universities for Research) funded by the Ministry of Education (MOE) of Korea and the National Research Foundation (NRF) of Korea. Any errors are our own.

[†]Stanford University, SIEPR. Email: bokyung@stanford.edu.

[‡]Department of Economics, University of Texas at Austin. Email: minseog.kim@utexas.edu.

[§]Department of Economics, Korea University. Email: naraepark@korea.ac.kr.

# 1 Introduction

The United States has experienced a decline in its fertility rates (the number of births per 1,000 women aged 15-44). This downward trajectory reached a historic low in 2020. Since reaching its lowest point on record in 2020, there has been a modest rebound in fertility rates, making a departure from the continuous decline observed in the preceding years.

Examining the historical fertility trends since the 1980s depicted in Figure 2, we notice that this decline started with the Great Recession. This suggests a potential correlation between a decrease in fertility rates and the occurrence of the Great Recession. Morgan, Cumberworth and Wimer (2011) argue that the Great Recession directly impacted fertility by highlighting that states most severely affected by the recession also exhibited low fertility rates. Kearney, Levine and Pardue (2022) reveal that there has been an approximately 20% decrease in fertility since the recession, yet this decline has not been explained to the same extent through policy changes or other economic variables. They coin this phenomenon a "puzzle."

There are two perspectives on how an economic downturn affects fertility: one that suggests fertility is counter-cyclical (Butz and Ward, 1979), which argues that the bad labor market conditions decrease the opportunity cost of childbearing for women, leading to an increase in births. The alternative perspective, pro-cyclical fertility (Sobotka, Skirbekk and Philipov, 2011), has gained prominence in recent papers. For example, Storesletten, Telmer and Yaron (2004) suggest that households delay births when faced with economic uncertainty.

In this paper, we explore whether fertility is pro-cyclical. More specifically, we focus on the impact of negative credit supply shocks during the Great Recession. The role of credit markets on fertility is elucidated by Kearney et al. (2022). In the instance where credit markets are imperfect, individuals can be liquidity-constrained, potentially hindering them from making optimal choices in family planning. Kim, Chen and Lin (2023) illustrate an increase in fertility corresponding to the extent of bank development. This finding is linked to the alleviation of liquidity constraints, as discussed earlier, which tends to occur with the advancement of bank development. Cumming and Dettling (2023) demonstrate how the decrease in mortgage loan rates, induced by monetary policy during the Great Recession, affected fertility. The reduction in interest rates resulted in an increase in disposable income, ultimately leading to a rise in fertility rates.

We suggest two pathways through which credit supply shocks affect fertility: the income effect and the wealth effect (illustrated in Figure 1). Changes in individual income and wealth due to credit supply shocks may alter the relative "price" of children (Becker, 1960; Becker and Lewis, 1973), potentially impacting fertility rates.

If the quantity of children is "normal" goods, then a decrease in wages or job loss during a bust would result in a reduction in income (decreasing purchasing power). Consequently, individuals will have fewer children. Black, Kolesnikova, Sanders and Taylor (2013) illustrate exogenous shocks leading to an increase in the husband's wages results in higher fertility, while Schaller (2016) shows improvement in men's labor market conditions lead to increased fertility, providing empirical evidence of the income effect. Therefore, to investigate the impact of credit supply shocks on the income effect, we explore various labor market outcomes.

Similarly, changes in wealth can also have an impact on fertility. Assuming that children are normal goods, an increase in wealth could lead to an increase in the number of children (Lovenheim and Mumford, 2013; Dettling and Kearney, 2014). Conversely, during a bust, a decrease in the value of assets or housing could result in a fertility reduction (reverse or negative wealth effect). We study the effect of housing prices. If housing prices decrease in regions where negative credit supply shocks occur, individuals may perceive a reduction in their wealth, potentially leading to a decrease in fertility.

In this paper, we explain the declining fertility since the Great Recession using exogenous variation in county-level credit supply shocks. We test the two channels, the income and wealth effect, and then show the impact of credit shocks in the long run. Our research is closely aligned with the work of Diebold and Soriano-Harris (2023); Kim, Lee and Lee (2022); Yang (2023). Each of these studies has utilized exogenous credit expansion resulting from bank deregulation to investigate the effect of credit expansion on fertility. While Kim et al. (2022) focus on the effects of deregulation at the state level, Diebold and Soriano-Harris (2023); Yang (2023) investigate these effects on the county level outcomes (e.g., fertility rates in the county). Furthermore, similar to our approach, Kim et al. (2022) derive credit supply shocks at the state level through bank loan origination, integrating it with micro-level data to investigate individual fertility decisions.

Our study contributes to the literature studying the link between credit markets and fertility in three key ways. First, we address concerns about endogeneity by using county-level exogenous credit supply shocks, which offer a geographically more granular perspective and are based on a relatively more recent period compared to shocks used in previous studies. A key challenge in this literature is that omitted variables could simultaneously affect both credit markets and fertility (Diebold and Soriano-Harris, 2023; Kim et al., 2022; Yang, 2023). To address this concern, prior studies have used state-level exogenous variation in the timing of banking deregulation implemented between the 1960s and 1990s. In addition, using individual-level survey data, Kim et al. (2022) show that state-level negative credit supply shocks adversely impact individual fertility decisions. Expanding upon this framework, we study the causal effect of credit supply on fertility by constructing exogenous county-level shocks during the 2008 Great Recession and using county-level administrative data on fertility rates. The use of more granular shocks in our study allows us to capture variation even within each state, providing a finer understanding of the impact of credit markets on fertility.

Second, we focus on the effect of credit reduction, in contrast to the investigation of credit expansion resulting from bank deregulation studied in the literature (Diebold and Soriano-Harris, 2023; Kim et al., 2022; Yang, 2023). Credit expansion and reduction may have asymmetric effects on the transmission channels of shocks to fertility. As demonstrated by Gilchrist, Siemer and Zakrajšek (2018) and Greenstone, Mas and Nguyen (2020), credit supply shocks have no impact on economic outcomes during non-bust periods (normal periods in Greenstone et al. (2020) and boom periods in Gilchrist et al. (2018)). Due to this asymmetry, depending on the period, credit shocks may exert different effects on the two channels, the labor and housing markets, and consequently, their impact on fertility may vary greatly.

Finally, we use comprehensive loan data on small business and home mortgage loan lending. While both types of loans represent credit supply shocks at the county level, their impact on fertility can vary. In addition, we explore two channels—income and wealth effects—as mechanisms through which credit markets affect fertility (depicted in Figure 1). When we explore the wealth effect channel, a home mortgage loan is more suitable for measuring credit shocks in the housing market. Therefore, by considering both types of loans, we provide a more comprehensive understanding of the impact of credit markets on fertility.

This paper investigates the impact of credit supply shocks on fertility since the Great Recession. Using data from two distinct sources of loan origination, namely small business loans and home mortgage loans, we find that negative credit shocks, particularly the credit reduction in 2009, lead to a decline in fertility rates, and this impact persists in the long run. Counties experiencing an average-sized credit reduction in 2009 have a long-term decrease in fertility rates by 3.17%, accounting for approximately 20% of the overall fertility reduction from 2007 to 2019. In addition, our results indicate that the age of mothers increases in response to negative credit shocks in the short run. By shedding light on the intricate interplay between credit dynamics and demographic trends, our research contributes to explaining a fertility “puzzle” in the literature.

# 2 Data

## 2.1 Birth outcomes

The analysis is based on data obtained from the Centers for Disease Control and Prevention’s (CDC) National Center for Health Statistics through the National Vital Statistics System. The data were accessed from the Natality Records in the CDC WONDER Online Database. These records compile data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program.

We utilize these birth records from 2003 to 2019. Bailey, Currie and Schwandt (2022) demonstrate that the Covid-19 pandemic led to an unexpected increase in birth rates among US-born mothers, an occurrence commonly referred to as the "Covid-19 baby bump." This phenomenon marked a striking departure from the prevailing downward fertility trend. While the initial spike in birth rates during the pandemic raised hopes for a potential resurgence, the long-term implications remain uncertain. It is an open question whether this sustained increase will lead to a lasting recovery in fertility rates or if it signifies a fundamental shift in demographic trends.

Therefore, we have opted to restrict our analysis to date up to the year 2019. This time frame allows us to more effectively scrutinize the trends and dynamics that were in place prior to the notable Covid-19-related changes in fertility, and it provides a solid foundation for our investigation into the declining fertility trends in the United States.

The dataset includes a wide array of county-level birth indicators. These include birth rates, fertility rates, average age of mothers, birth weights, and gestational age. Birth rates are calculated by dividing the total number of births within a county by the total population of that county and then multiplying by 1,000, indicating the number of births per 1,000 people. On the other hand, fertility rates are derived by dividing the total number of births in a county by the female population aged 15-44 within the same county. The dataset also contains information about the average age of mothers at the time of giving birth. Additionally, it includes data on birth weights. Two measures of gestational age are provided by CDC Wonder - Last Menstrual Period (LMP) and Obstetric Estimate (OE). The National Center for Health Statistics (NCHS) is transitioning from using the date of the last normal menses (LMP) to the obstetric estimate of gestation at delivery (OE) (Martin, Osterman, Kirmeyer and Gregory, 2015), with LMP gestational age data available from 2003 and OE gestational age data publicly accessible since 2007 on CDC Wonder. Therefore, we analyze LMP gestational age only. The results for OE gestational age are in the Appendix for robustness check.

Due to privacy concerns, data points with counts below ten have been omitted from the provided dataset. Furthermore, certain counties have not disclosed their birth data, citing confidentiality apprehensions. Consequently, for counties with a total population of fewer than 100,000 residents, births are aggregated under the category of "Unidentified Counties." As a result, the CDC provided 572 counties from 2003 to 2006 and expanded to 629 counties from 2007 to 2019. Our sample is a balanced panel with 515 counties each year.

Figure 3 presents the trend of birth data from 2003 to 2019. Both birth and fertility rates have been declining since 2007. The age of mothers has consistently increased since 2007. Birth weights and gestational age follow similar trends, and these measures are be used as indicators of infant health in the Appendix.

Table 3 provides summary statistics. Birth outcomes are weighted based on the female population, while market outcomes are weighted based on the total population. The population variables used as weights are also from CDC Wonder. Population percentage is not weighted. The same weights are used for the main estimation. The average birth rate in 2007 was 14.04 births per 1,000 people, and the average fertility rate stood at 67.83 births per 1,000 females aged 15 to 44. Both declined approximately 2% in 2008 and 3% in 2009. The average age of mothers was 27.8 in 2007. It also increased both in 2007 and 2008.

## 2.2 Market outcomes

We analyze multiple market outcomes, starting with a focus on diverse labor market indicators such as the employment-to-population ratio, unemployment rates, per capita income, per capita earnings, and average earnings, aimed at examining the income effect. Additionally, to assess the wealth effect, we use the Housing Price Index (HPI) obtained from the Federal Housing Finance Agency (FHFA). Through the examination of these variables, we aim to investigate the impact of credit shocks on these market indicators, contributing to a better understanding of how credit shocks influence overall market status changes.

The employment-to-population is calculated by $Employed/CivilianPopulation$. The number of employed is from The United States Department of Agriculture (USDA). According to the definition provided by the U.S. Department of Economics, the civilian population consists of individuals aged 16 years and older residing in the 50 states and the District of Columbia, who are not inmates of institutions, and who are not currently serving on active duty in the Armed Forces. We were unable to obtain the county-level civilian population for our sample period. As a temporary estimate, we utilize the population aged 16 and above. We plan to supplement this with the specific county-level variable in the future. We examine the county's employment through the employment-to-population rates and unemployment rates. Also, we investigate their income using income and earnings variables.

The HPI by the FHFA is a measure to track changes in the prices of single-family homes. It covers all 50 states and incorporates tens of millions of home sales and appraisals. We use their annual count-level index from 2003-2019.[1] The HPI with the base year 2000 is used in our analysis.

Table 3 confirms that all economic variables do not necessarily react in the same direction and rate following the recession. Employment measures experienced immediate fluctuations, with the employment-to-population ratio decreasing and the unemployment rates increasing. Particularly, there was a significant surge in unemployment. This pattern persisted in 2009. However, income variables such as per capita income, per capita, and average earnings saw a slight increase in 2008 compared to 2007, followed by a decline in 2009. However, the average income remained nearly unchanged. The HPI has the same trends in employment measures, which decreased in both 2008 and 2009, with the decline in 2009 being more substantial than in 2008.

## 2.3 Data related to credit shock

### 2.3.1 Small business lending from the Community Reinvestment Act (CRA)

The Community Reinvestment Act (CRA) is a U.S. federal law that encourages financial institutions to meet the credit needs of the communities in which they operate, particularly low- and moderate-income neighborhoods. While the CRA does not directly provide small business loans, it plays a significant role in influencing how financial institutions address the credit needs of small businesses in underserved communities.

We utilize CRA flat files sourced from the Federal Financial Institutions Examination Council

[1] Available at: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx

(FFIEC). The transmittal sheet file contains essential information such as the respondent's name, address, city, state, and RSSD ID. Meanwhile, the disclosure file contains bank-level data pertaining to small business loans, with each entry representing a bank-by-county loan origination.

Within this dataset, the key variables of interest are the following: the count of small business loans originated, the total loan amount of small business loans originated, the count of loans originated for small businesses with gross annual revenues $\leq$ $\$1$ million, and the total loan amount for loans originated to small businesses falling within the same revenue bracket.

To facilitate our analysis, we merge the transmittal sheet file and the disclosure file using the respondent ID as the unique identifier. In our primary analysis, we employ the change in the total loan amount of small business loans originated at the bank-by-county level as the dependent variable.

### 2.3.2 Home mortgage loan lending from the Home Mortgage Disclosure Act (HMDA)

The Home Mortgage Disclosure Act (HMDA) provides comprehensive data on home mortgage loans in the United States, offering a wealth of information about lending practices. HMDA provides an insight of various aspects of mortgage lending. Firstly, it includes demographic details such as the race, ethnicity, gender, and income of mortgage applicants and borrowers. This demographic information is vital for assessing lending patterns and identifying potential disparities in mortgage lending practices.

Moreover, HMDA provides comprehensive insights into loan characteristics. It includes information about the type of mortgage, such as conventional, FHA, or VA loans, the purpose of the loan (e.g., home purchase, refinancing), and the loan amount. This wealth of data facilitates a nuanced analysis of market trends and the types of loans being issued.

Property information is another key dimension covered by HMDA. The data includes details about the location and characteristics of the properties associated with the mortgages, distinguishing between single-family homes and multifamily properties.

Lender information is crucial for evaluating lending practices across different financial institutions. HMDA data contains details about the lending institutions, including their names and locations, providing a comprehensive overview of the mortgage lending landscape.

From this information, we construct the county-level credit supply shocks. More specifically, HMDA maintains two flat files: the LAR file and the TS file. The LAR file primarily contains data related to the characteristics of each mortgage lending originated by individual banks. Therefore, the entries in this file consist of loan-by-bank data. On the other hand, the TS file records lender-level information, such as the bank's location and RSSD identifier for each bank.

As highlighted in García (2020), because the data is reported at the subsidiary level, we establish connections between subsidiaries and their parent companies using the crosswalk maintained by Robert Avery (Avery, Brevoort and Canner, 2007). This enables us to aggregate the mortgage loan amounts to the bank-county level for our analysis. Additionally, for our analysis, we focus on loans with the purpose of either 1) home purchase or 2) home improvement, and we include properties classified as one to four-family dwellings.

### 2.4 Other controls

The dataset used in our analysis comprises county-level labor market variables, including crucial elements such as the employed and unemployed population and unemployment rates. The USDA integrates data from the U.S. Department of Labor, Bureau of Labor Statistics, Local Area Unemployment Statistics (LAUS), U.S. Department of Commerce, Bureau of the Census, and Small Area Income and Poverty Estimates (SAIPE) Program. They provide pivotal metrics, which can be accessible at https://www.ers.usda.gov/data-products/county-level-data-sets/.

Additionally, county-level population data is drawn from the Surveillance, Epidemiology, and End Results (SEER) program, available at https://seer.cancer.gov/popdata/. We use a single-age population from 1990-2020. The control variables extracted from these sources for the analysis are female percentages and the percentages of the Black and Hispanic populations.

The combined datasets span the period from 2003 to 2019. Table 1 summarizes the data sources used in the analysis.

## 3 Empirical Strategy

### 3.1 Empirical models

Our empirical model takes the form:

$$\begin{aligned} y_{k,s,t} = &\sum_{\substack{j=2003 \\ j\neq 2007}}^{2019} \theta_j^{2008} Shock_{k,2008} * I[year = j] + \sum_{\substack{j=2003 \\ j\neq 2007}}^{2019} \theta_j^{2009} Shock_{k,2009} * I[year = j] \\ &+ \beta X_{k,s,t} + \alpha_{s,t} + \epsilon_{k,s,t} \end{aligned} \tag{1}$$

where $y_{k,s,t}$ is a birth outcome in county k and state s at year t. $Shock_{k,2008}$ is the credit supply shock in county k for 2008. $\theta_j^{2008}$ denotes the year j effect of the 2008 credit supply shock, with $\sum_{j=2008}^{2019} \theta_j^{2008}$ representing the cumulative impacts of the 2008 credit supply shocks on the birth outcomes. Similarly, $Shock_{k,2009}$ is the 2009 credit supply shock in county k, and $\theta_j^{2009}$ is the year j effect of the 2009 credit supply shock. The cumulative influences of the 2009 credit supply shock on birth outcomes is given by $\sum_{j=2009}^{2019} \theta_j^{2009}$. We control various demographic and economic factors, $X_{k,s,t}$, including the female, black, people aged 15 to 49, and Hispanic percentages in county k in year t. The weighted least square Equation 3.1 uses the female population as a weight for birth and the total population for market outcomes. Standard errors are clustered at a state level.

We analyze the impact of two types of credit supply shocks, $Shock_{2008}$ and $Shock_{2009}$. According to the National Bureau of Economic Research (NBER), the Great Recession began in December 2007. Therefore, most births that occurred in 2008 (considering the time lag between conception and birth) happened before people started feeling the effects of the recession (Morgan et al., 2011). The impacts of the 2008 credit supply shock, calculated from the growth of loans between 2007 and 2008, may differ from $Shock_{2009}$, when people fully experience the shock from the recession. However, the labor market and the housing market can respond more quickly and directly to shocks than births. Hence, we adopt the two shocks and analyze their effects separately.

First, we study the effect of the reduction in credit supply following the Great Recession on market variables. When we explore this effect, we employ the growth rate of the variable as the dependent variable: $ln(y_{k,s,t}) - ln(y_{k,s,t-1})$. While j starts from 2003 for birth outcomes, given the first difference of log is used in this analysis, the start year for the growth rate estimation is 2004. If our coefficient of interest, $\theta$, is negative, it indicates that the reduction in credit supply leads to a decrease in the growth rate of the variable. And then, we explore how credit supply shocks affect birth decisions. The log of the variable is used as a dependent variable ($ln(y)_{k,s,t}$), implying that a one standard deviation reduction in credit supply shocks results in an approximately 100*$\theta$% change in the dependent variable.

Section 3.2 explains how to construct the county-level credit supply shocks, $Shock_{k,2008}$ and $Shock_{k,2009}$.

## 3.2 County-level shift in credit supply

### 3.2.1 Decompose the bank-level credit supply shocks from the lending growth rate

We aim to obtain the credit supply shock in county k in year t, $\tilde{S}_{k,t}$ by employing the loan growth rate decomposition approach of Greenstone, Mas and Nguyen (2020).

$$\Delta lnL_{j,k,t} = S_{j,t} + D_{k,t} + \epsilon_{j,k,t} \tag{2}$$

Greenstone et al. (2020) decompose the variation in the growth of loan origination into the supply and the demand. $\Delta lnL_{j,k,t}$ represents the growth of the dollar amount of loan origination for bank j in county k and year t. The period-specific bank fixed effects, denoted as $S_{j,t}$ in Equation 2, address differences in lending within counties across banks. The period-specific county-fixed effects, $D_{k,t}$, capture variations in lending demand between counties.

This regression equation 2 is estimated by weighted least-squares. We used a county share $c_{j,k,t} = \frac{L_{j,k,t}}{\sum_{k \in \mathfrak{K}_{j,t}} L_{j,k,t}}$ as a weight in the regression. $\mathfrak{K}_{j,t}$ represents a set of counties where bank j has originated loans during year t. Another weight is a bank share, $b_{j,k,t} = \frac{L_{j,k,t}}{\sum_{j \in \mathfrak{B}_{k,t}} L_{j,k,t}}$. Here, $\mathfrak{B}_{k,t}$ denotes banks in county k in year t. Our estimation findings remain consistent when applying alternative weights, such as bank market shares and the geometric average ($\sqrt{bc}$) of the bank and county share weights.

### 3.2.2 Constructing the county-level credit supply shocks from the bank-level credit supply shocks

The estimated bank fixed effects, $\hat{S}_{j,t}$, only identify relative shifts in the supply of credit across banks. We want the credit supply shock in the county, $\tilde{S}_{k,t}$:

$$\tilde{S}_{k,t} = \sum_{j \in \mathfrak{B}_{k,t-1}} b_{j,k,t-1} * \hat{S}_{j,t} \tag{3}$$

Here, $\tilde{S}_{j,t}$ denotes the standardized estimated bank fixed effect. $b_{j,k,t-1}$ represents the bank market share of the lending of bank j in county k in year t-1.

$\tilde{S}_{k,t}$ is the credit supply shock in county k in year t. Therefore, in Equation 2, $Shock_{k,2008}$ corresponds to $\tilde{S}_{k,2008}$, and $Shock_{k,2009}$ corresponds to $\tilde{S}_{k,2009}$.

All the credit shocks are standardized using their mean and standard deviation. Figure 4 depicts the predicted lending shock constructed from small businesses and home mortgages in 2008. This figure shows the regional variations in the credit supply shocks. It reveals that states in the west and east faced more severe credit supply shocks than the central region. Furthermore, it underscores variations even within the same state. Notably, there is a divergence between credit supply shocks calculated through small business lending and mortgage loans.

Figure 5 is the U.S. map for the 2009 credit supply shocks. The credit supply shocks in 2008 and 2009 have a similar pattern, although they are not entirely identical. When examining the credit supply shocks derived from small business lending (CRA), the credit supply shock in the central region intensified in 2009. This pattern is consistent even when calculated using the home mortgage lending data (HMDA). The western region faced large negative credit supply shocks in 2008, but they were alleviated by 2009. In contrast, the southern region continued to experience strong negative credit supply shocks in 2009.

The distribution of the home mortgage credit shocks has a lower variance compared to credit supply shocks calculated through CRA. Furthermore, it is notable that states disclosing birth records, primarily those with larger populations, show a substantial presence of counties where credit shocks are negative.

Figure 7 visualizes fertility rates in 2009 at the county level. Due to limitations in public data, the figure depicts only 515 out of over 3000 counties. Similar to credit supply shocks, birth variables have substantial regional variation. The counties with low fertility rates are marked with dark red, paralleling the intensity of negative credit supply shocks. The heat map of fertility rates exhibits a similar pattern, particularly resembling the map of the 2009 shocks from HMDA. We leverage the regional variation in credit supply shocks to examine how these shocks impact birth outcomes.

Gilchrist et al. (2018) further purge any local demand effects from the county-level measures of credit supply shocks. Our future goal is to construct these credit supply shocks.

#### 3.2.3 The effect of credit supply shocks on loan origination

In the previous section, we have constructed county-level credit supply shocks and now explore their impact on the amount of loan originations. We use the same baseline equation, with the dependent variable being the log of the loan origination amount.

$$
\begin{aligned}
ln(l_{k,s,t}) = &\sum_{j=2008}^{2010} \theta_j^{2008} Shock_{k,2008} * I[year = j] + \sum_{j=2009}^{2010} \theta_j^{2009} Shock_{k,2009} * I[year = j] \\
&+ \beta X_{k,s,t} + \alpha_{s,t} + \epsilon_{k,s,t}
\end{aligned} \tag{4}
$$

Table 2 outlines the estimated effects of the predicted lending shock on loan originations. Columns (1) and (2) present estimates for small business loans, while Columns (3) and (4) focus on home mortgage loans. The estimated impact of the 2008 credit supply shocks in 2008 is -0.063. This implies that a one standard deviation reduction in credit supply in 2008 is associated with an approximately 6.3% decrease in total county-level small business loan originations. In terms of loan amounts, this corresponds to a reduction of approximately 4.27 million dollars. Greenstone et al. (2020) estimate the effect of the predicted lending shocks on loan origination, and their estimates align closely with ours.

# 4 Results

## 4.1 Fertility rates

Figure 8 illustrates the estimated effect of the credit supply shocks on fertility rates. The dots in the figure represent the impact of the credit supply shocks, denoted as $\theta$s in Equation 2. While the red region in the figure represents the estimates for the 2008 credit supply shocks, the blue region is for the 2009 credit supply shocks. The dashed blue line distinguishes between the pre- and post-shocks. Therefore, this line corresponds to 2008 and 2009, respectively, with the baseline set in 2007. The dependent variable is the log of fertility rates.

This paper examine how credit shocks during the Great Recession influence individuals' decisions regarding having children. As explained in Section 3, credit shocks are calculated from the loan origination growth rate so that it can have both positive and negative values. However, our primary focus lies in situations where there is a reduction in credit supply at the county level, especially after the Great Recession. In other words, we are interested in cases with negative credit shocks. To enhance interpretability, we use shocks with a negative sign. As illustrated in panel (a) of Figure 8, for instance, when the 2009 shock is negative (indicating a large reduction in small business loans by banks in the county compared to other counties in the same year), fertility rates decrease.

Both CRA and HMDA results indicate that the 2008 shocks do not have a statistically significant impact on fertility rates. In contrast, the negative credit supply shocks in 2009 are associated with decreased fertility rates and have a long-run effect on fertility rates. Credit shocks calculated through CRA have a larger impact on fertility rates than shocks derived from HMDA.

Column(1) in Table 4 reports the test results for the linear combination of our parameters of interest, denoted as $\sum_j \theta_j$. This represents the cumulative effects of the 2008 and 2009 credit supply shocks on fertility rates. The 2008 shocks from both CRA and HMDA are not statistically significant. One standard deviation decline in the credit supply from CRA in 2009 is linked to an approximate 18.4% decrease in fertility rates in the long run. Likewise, the HMDA estimate shows a 16.7% decline.

However, it is important to note that we standardize the shocks to have a mean of 0 and a standard deviation of 1. Therefore, a one standard deviation change represents a substantial deviation from the mean in the shock distribution (Figure 6). For example, the 2009 credit supply shock from CRA has a mean of -0.35. Consequently, for counties experiencing an average credit supply shock, the long-run fertility decrease would be about 6.44%. Similarly, for HMDA, the 2009 mean is -0.19, implying a 3.17% decrease in fertility rates in the long run.

Diebold and Soriano-Harris (2023); Kim et al. (2022) suggest that credit expansion leads to a short-term increase in fertility rates, whereas Yang (2023) finds that bank credit expansion results in a 7 percent decrease in annual county-level fertility rates.

Kearney et al. (2022) note that between 2007 and 2019, the fertility rate experienced a decline from 69.1 to 58.3, marking a 15.6% decrease. Our findings contribute to explaining a significant portion of this decline in fertility rates.

## 4.2 Other birth outcomes

We explore the impact of credit supply shocks on additional birth outcomes, specifically birth rates and the age of mothers. Birth rates represent the number of births per 1,000 people, while fertility rates indicate the number of births per 1,000 women aged 15-44. Consequently, the results for birth rates align with those for fertility rates, showing a decline in birth rates in response to negative credit supply shocks. However, unlike the findings for fertility rates, the 2008 CRA credit shock has statistically significant effects in the short run on birth rates. For both the 2008 and 2009 credit supply shocks from HMDA, the coefficients for both fertility rates and birth rates are positive, but they are not statistically significant.

Regarding the CRA 2009 shock, negative credit shocks increase the age of mothers in the short run, but they do not have a long run effect. In contrast, in the case of HMDA, the 2008 shock suggests a rise in the age of mothers after 2016, which leads to statistically significant cumulative effects.

We analyze the average age of mothers rather than the average age at first birth due to the data limitation. Therefore, while delays in having the first child could contribute to an increase in the average age, it is also possible for the average age to rise if mothers have additional births. However, according to Stone (2020), the decline in births after 2007 is primarily influenced by a decrease in initial childbearing and childlessness trends. While Diebold and Soriano-Harris (2023) analyze the age at first birth, and Yang (2023) examines the age at birth, both studies have the same conclusion that credit expansion increases the age at birth. Hence, we can infer that the increasing age of mothers in response to negative shocks is associated with delays in having their first child.

We also investigate infant health, considering birth weights and gestational age. The negative credit supply shock of 2009 from CRA leads to a short- and long-term reduction in birth weights. The estimated results from HMDA also indicate the same effect, but they are not significant at the 10 percent level. These findings are detailed in the Appendix.

## 4.3 Channel – income and wealth effect

The estimation results for six different market outcomes are presented in Figure 10 and Figure 11. The results from HMDA shocks are more precise than those from CRA, particularly that the 2009 shock has a statistically significant impact on those market variables. Gilchrist et al. (2018) also find a stronger association between home mortgage loan lending and labor market outcomes during the Great Recession compared to small business lending. They attributed this disparity to the features of CRA, which solely captures new credit lines. Furthermore, they acknowledged the possibility that external factors, beyond the control of banks, might influence CRA. Additionally, a notable distinction between these results and the findings related to birth outcomes lies in the temporal dynamics of the impact. While credit supply shocks exhibit a short-term influence on births that diminishes over time, the effects on fertility persist in the long term. When negative credit supply shocks occur, employment-to-population ratios and incomes decrease, while the unemployment rate increases. Housing prices experience a decline.

Schaller (2016) demonstrates that a one percentage point rise in unemployment is correlated with a 0.85 to 2.2 percent decline in the birth rate. Similarly, Diebold and Soriano-Harris (2023); Yang (2023) reveal that credit expansion leads to an increase in housing prices, subsequently contributing to a decrease in fertility rates. Furthermore, their findings indicate that this rise in housing prices is associated with an increase in the age of mothers at childbirth. The housing market conditions have a more substantial impact on fertility than labor market conditions (Dettling and Kearney, 2014; Diebold and Soriano-Harris, 2023; Kim et al., 2022; Yang, 2023).

According to Gilchrist et al. (2018); Greenstone et al. (2020), economic outcomes are not affected by credit supply shocks during non-bust periods. Previous studies examining the impact of credit markets on fertility focused on the period of bank deregulation. Yang (2023), for instance, indicates in their analysis time frame (1994-2005) that credit expansion had no impact on unemployment or wages. Yang (2023) also notes that the second wave of bank deregulation had a significant effect on house prices but not on the labor market, which is consistent with the findings of Gilchrist et al. (2018); Greenstone et al. (2020). In contrast, our results in Figure 11 show that both labor and housing markets are affected by credit supply shocks in the short run. This suggests that our mechanism linking credit shocks and fertility may differ. Our next step is to establish a connection between these two markets during the Great Recession and examine which pathway has a greater impact on people's decisions regarding childbirth.

## 4.4 Heterogeneous effects

Panel (a) in Figure 12 and Figure 13 depicts fertility trends from 2003 to 2019 categorized by race and age groups. Hispanics have higher fertility rates compared to Whites and Black or African Americans, but their rates have experienced the most pronounced decline. After the Great Recession, fertility rates for women aged 15-29 decreased, while rates for those over 30 slightly increased. This suggests that different demographic groups may have a heterogeneous response to credit shocks. Our analysis examines the heterogeneous effect of credit supply shocks on fertility by race and age.

Panel (b) in Figure 12 displays the estimated cumulative impact of the 2009 credit supply shock from HMDA on fertility categorized by race. The black dot represents the estimate for the cumulative effects of the 2009 credit shocks on fertility, documented as -0.167 in Table 4. It is observed that fertility rates for Blacks and Hispanics remain unaffected by credit supply shocks, whereas the 2009 credit supply shocks induce a reduction in fertility rates for Whites, and this impact persists in the long run.

Figure 13 illustrates the impact of credit supply shocks categorized by age groups. Notably, younger age groups are more significantly affected by credit supply shocks compared to their older counterparts. Fertility rates for individuals over the age of 35 remain unaffected by these shocks.

## 4.5 Robustness

The baseline model incorporates the 2008 and 2009 credit supply shocks, demonstrating that the 2009 shock reduces fertility, and their impact persists. We extend our analysis by estimating the model with additional year-specific credit supply shocks, and examine their effects on fertility. Figure 14 illustrates the estimated effect of credit supply shocks from HMDA on fertility, incorporating the 2007 and 2010 shocks along with the previously considered 2008 and 2009 shocks. The red areas depict the 2008 shocks' effect, while the blue areas represent the 2009 shocks. The green areas denote the newly added year shocks. Our findings remain robust with the inclusion of more shocks. The 2007 and 2010 shocks do not have statistically significant effects on fertility. Moreover, the inclusion of other year shocks in the model does not diminish the significance of the 2009 credit supply shocks, which continue to exert a substantial and enduring impact on reducing fertility.

When we construct credit supply shocks in Equation 2, we use the growth rate of the dollar amount of loan origination. Gilchrist et al. (2018) also consider changes in the extensive margins of lending, which means the number of loans. To ensure the robustness of our results, we account for both intensive and extensive margins of lending in our analysis. Figure 15 presents the results by different measures of loan. The shocks constructed from the growth rate of extensive margins have the same effect on fertility rates.

Gilchrist et al. (2018) use other weights as well. Figure 16 confirms that our results are robust to alternative weights for weighted least squares (Equation 2), such as bank shares, and the geometric mean of county and bank shares.

# 5 Discussion

We currently rely on publicly available birth records from CDC Wonder. As discussed in the previous section, due to data limitations, a substantial number of births in 2008 are not influenced by the credit supply shocks of that year since their pregnancies occurred in 2007. Therefore, for a more accurate examination of the impact, considering the conception date instead of the birth date, as demonstrated by Cumming and Dettling (2023), could be beneficial. Moreover, to investigate whether the age of mothers at the first childbirth is increasing, it is crucial to have information about birth order. Administrative data from the National Center for Health Statistics (NCHS), incorporating gestational age and birth order, has the potential to address this issue. Furthermore, it contributes to broadening geographic coverage, as public data refrain from offering statistics from small counties due to privacy concerns.[2]

We notice two distinct peaks in fertility rates from Figure 2, one in 1990 and another in 2007. Interestingly, both of these peaks coincided with periods of economic recession. In 1990, the fertility rate reached a high of 70.9 before declining in the aftermath of the recession. However, it rebounded from a low of 63.6 in 1997. In contrast, following the Great Recession, fertility rates have sustained their decline without having a distinct rebound pattern yet. The primary future aim is to unravel the channels contributing to the sustained decline in fertility rates in the United States and to discern whether there are similarities or disparities between the post-1990 recession fertility rebound and the contemporary scenario. By exploring these historical and current trends in fertility, we hope to gain valuable insights into the underlying drivers of fertility dynamics.

# 6 Conclusion

Over the last fifteen years, there has been a continuous decline in fertility rates in the United States, a trend that commenced during the Great Recession. We study this pro-cyclical move of fertility. A challenge in examining the relationship between fertility and economic variables lies in the potential influence of omitted variables that affect both. To address this endogeneity concern, we employ an exogenous shock measure—credit supply shocks at the county level—constructed using small business and home mortgage loan lending. This paper investigates the impact of credit supply shocks during the recession on various dimensions of fertility outcomes, encompassing fertility

[2] Our next step is to use restricted administrative data to enhance the precision of the analysis.

rates, birth rates, and the age of mothers at childbirth.

In this paper, we find that negative credit supply shocks reduce both fertility and birth rates. In particular, the 2009 credit supply shock has a substantial impact, lowering these outcomes both in the short and long run. Counties that experienced a 0.18 standard deviation decrease in credit in 2009, representing the average shock size in our birth sample, have experienced a cumulative 3.17 percent decrease in fertility rates by 2019. Moreover, the age of mothers at childbirth rises in response to negative credit supply shocks. Whites and people under 30 experience the most significant reduction in their fertility in response to negative credit shocks.

Our findings contribute to the ongoing discussion about declining fertility in the United States, shedding light on the role of credit supply that shapes fertility choices. Our study underscores that negative credit supply shocks not only impact the economy but also have enduring adverse effects on fertility rates. This sustained decline in fertility rates can, in turn, influence the economic situation. Therefore, an understanding of these dynamics becomes essential for both policymakers and researchers.

# References

**Avery, Robert, Kenneth Brevoort, and Glenn Canner**, "Opportunities and Issues in Using HMDA Data," *Journal of Real Estate Research*, January 2007, *29* (4), 351–380.

**Bailey, Martha J, Janet Currie, and Hannes Schwandt**, "The Covid-19 Baby Bump: The Unexpected Increase in US Fertility Rates in Response to the Pandemic," Technical Report, National Bureau of Economic Research 2022.

**Bartik, Timothy J**, *Who Benefits from State and Local Economic Development Policies?*, WE Upjohn Institute for Employment Research, 1991.

**Becker, Gary S**, "An Economic Analysis of Fertility," in "Demographic and Economic Change in Developed Countries," Columbia University Press, 1960, pp. 209–240.

_ **and H Gregg Lewis**, "On the Interaction Between the Quantity and Quality of Children," *Journal of Political Economy*, 1973, *81* (2, Part 2), S279–S288.

**Black, Dan A, Natalia Kolesnikova, Seth G Sanders, and Lowell J Taylor**, "Are Children "Normal"?," *The Review of Economics and Statistics*, 2013, *95* (1), 21–33.

**Butz, William P and Michael P Ward**, "Will US Fertility Remain Low? A New Economic Interpretation," *Population and Development Review*, 1979, pp. 663–688.

**Cumming, Fergus and Lisa Dettling**, "Monetary Policy and Birth Rates: The Effect of Mortgage Rate Pass-Through on Fertility," *The Review of Economic Studies*, 03 2023, p. rdad034.

**Dettling, Lisa J and Melissa S Kearney**, "House Prices and Birth Rates: The Impact of the Real Estate Market on the Decision to Have a Baby," *Journal of Public Economics*, 2014, *110*, 82–100.

**Diebold, Lukas and Julian Soriano-Harris**, "Financial Deregulation and Fertility Decisions: The Unintended Consequences of Banking Legislation," Available at SSRN 4544847 2023.

**García, Daniel**, "Employment in the Great Recession: How Important Were Household Credit Supply Shocks?," *Journal of Money, Credit and Banking*, 2020, *52* (1), 165–203.

**Gilchrist, Simon, Michael Siemer, and Egon Zakrajšek**, "The Real Effects of Credit Booms and Busts," Working Paper 2018.

**Greenstone, Michael, Alexandre Mas, and Hoai-Luu Nguyen**, "Do Credit Market Shocks Affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and "Normal" Economic Times," *American Economic Journal: Economic Policy*, 2020, *12* (1), 200–225.

**Kearney, Melissa S, Phillip B Levine, and Luke Pardue**, "The Puzzle of Falling US Birth Rates Since the Great Recession," *Journal of Economic Perspectives*, 2022, *36* (1), 151–176.

**Kim, Dong-Hyeon, Ting-Cih Chen, and Shu-Chin Lin**, "Fertility and Banking Development: New Panel Evidence," *International Journal of Finance & Economics*, 2023, *28* (4), 4220–4235.

**Kim, Jeong Ho John, Heebum Lee, and Sung Kwan Lee**, "Do Credit Supply Shocks Affect Fertility Choices?," *Journal of Behavioral and Experimental Finance*, 2022, *34*, 100633.

**Lovenheim, Michael F and Kevin J Mumford**, "Do Family Wealth Shocks Affect Fertility Choices? Evidence from the Housing Market," *Review of Economics and Statistics*, 2013, *95* (2), 464–475.

**Martin, Joyce A, MJ Osterman, Sharon E Kirmeyer, and EC Gregory**, "Measuring Gestational Age in Vital Statistics Data: Transitioning to the Obstetric Estimate," *National Vital Statistics Reports: From the Centers for Disease Control and Prevention, National Center for Health Statistics, National Vital Statistics System*, 2015, *64* (5), 1–20.

**Morgan, S Philip, Erin Cumberworth, and Christopher Wimer**, "The Great Recession's Influence on Fertility, Marriage, Divorce, and Cohabitation," *The Great Recession*, 2011, pp. 220–245.

**Schaller, Jessamyn**, "Booms, Busts, and Fertility: Testing the Becker Model Using Gender-Specific Labor Demand," *Journal of Human Resources*, 2016, *51* (1), 1–29.

**Sobotka, Tomáš, Vegard Skirbekk, and Dimiter Philipov**, "Economic Recession and Fertility in the Developed World," *Population and Development Review*, 2011, *37* (2), 267–306.

**Stone, Lyman**, "The Rise of Childless America," *Institute for Family Studies*, 2020, *4*.

**Storesletten, Kjetil, Chris I Telmer, and Amir Yaron**, "Cyclical Dynamics in Idiosyncratic Labor Market Risk," *Journal of Political Economy*, 2004, *112* (3), 695–717.

**Yang, Xi**, "More Credit, Fewer Babies? Bank Credit Expansion, House Price, and Fertility," Working Paper 2023.

# 7 Figures and Tables

Figure 1: The Transmission Mechanism of Negative Credit Shocks on Fertility

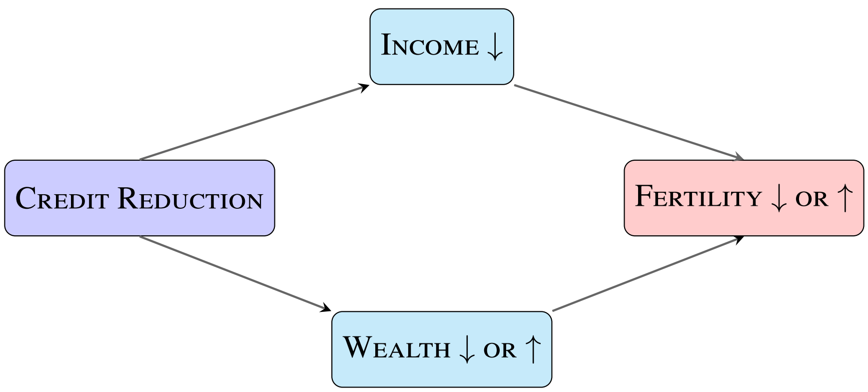
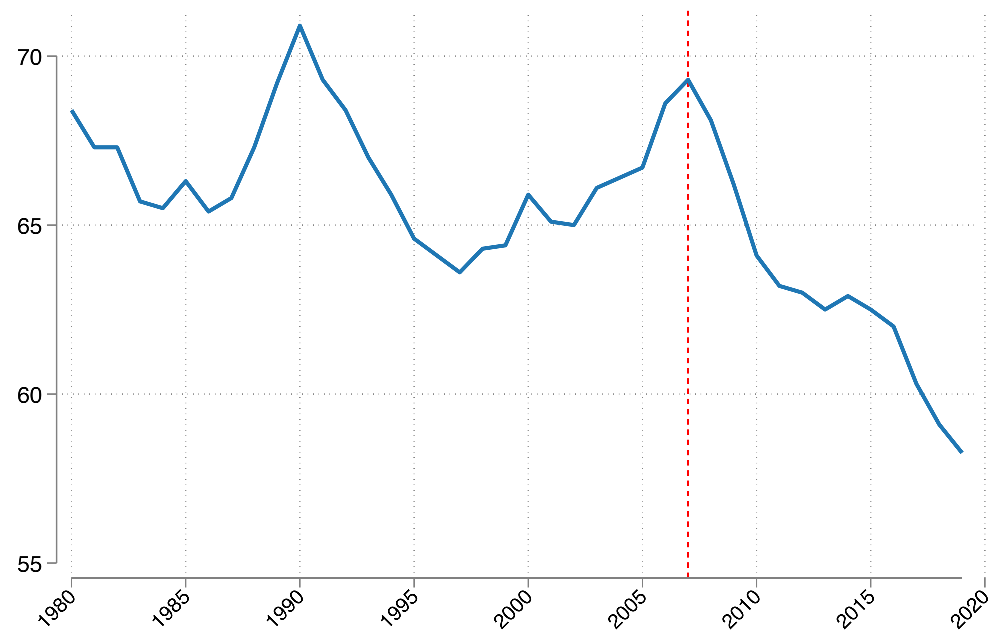


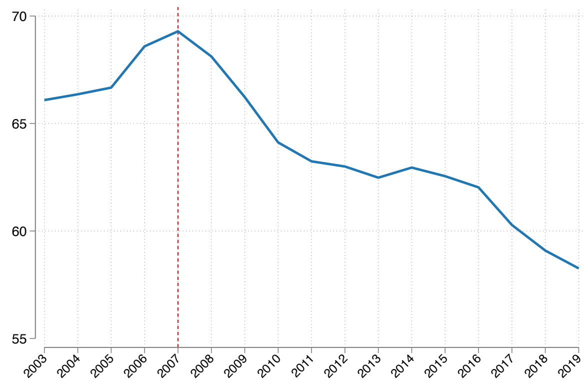
Figure 2: The Trend of Fertility Rates from 1980 to 2019



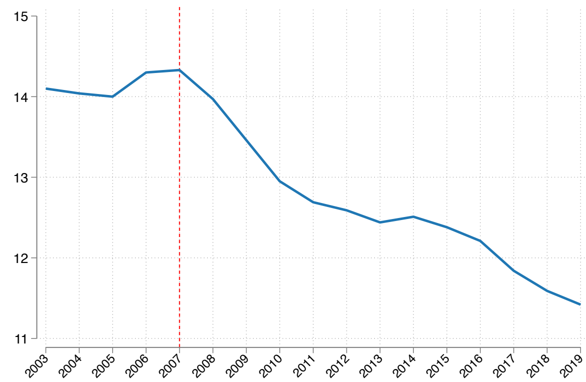

*Notes*: Fertility rates are the number of births per 1,000 women aged 15-44. Data are from National Center for Health Statistics. Health, United States, 2020-2021: Table Brth. Hyattsville, MD. Available from: https://www.cdc.gov/nchs/hus/contents2020-2021.htm#Table-Brth. The red dashed line indicates 2007.

Figure 3: Trends of Birth Data from 2003-2019

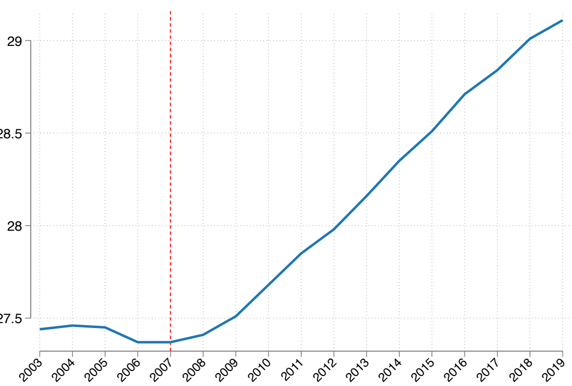
(a) Fertility Rates



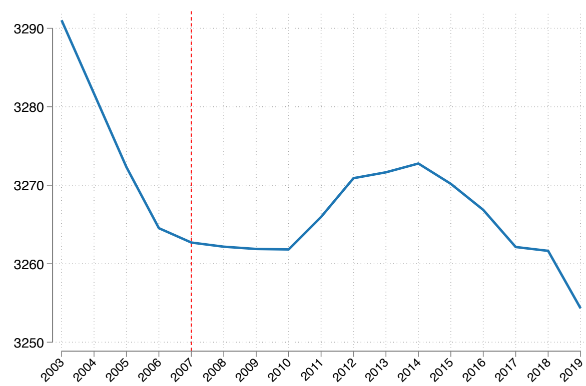

(b) Birth Rates



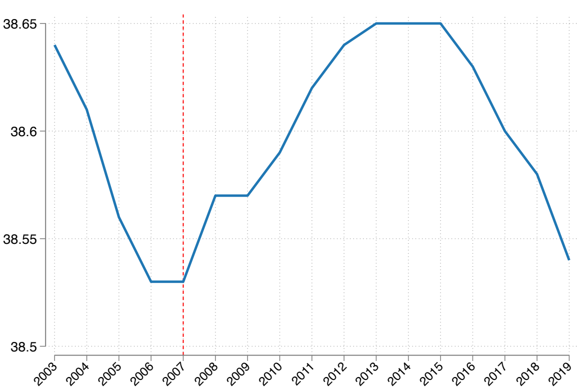

(c) Age of Mothers



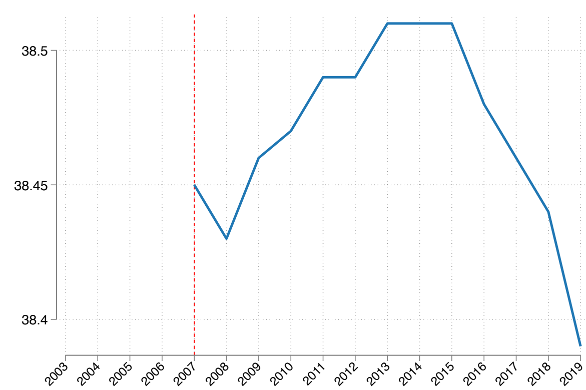

(d) Birth Weights




(e) LMP Gestational Age



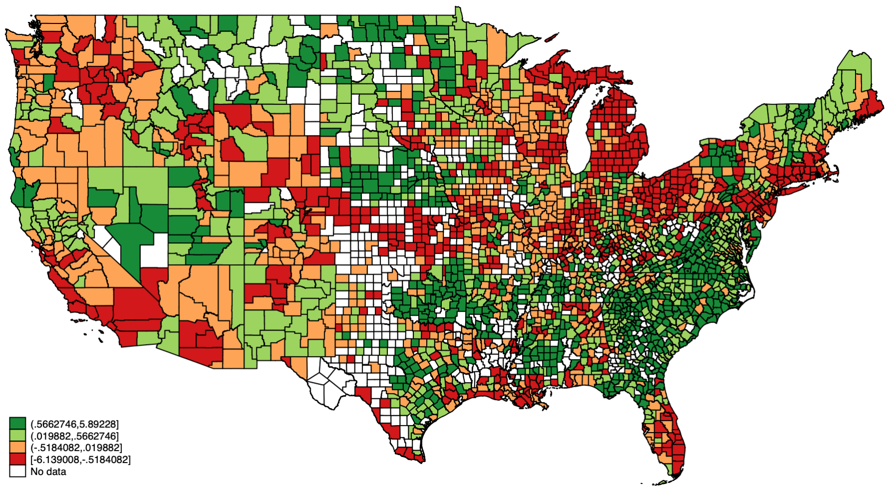

(f) OE Gestational Age



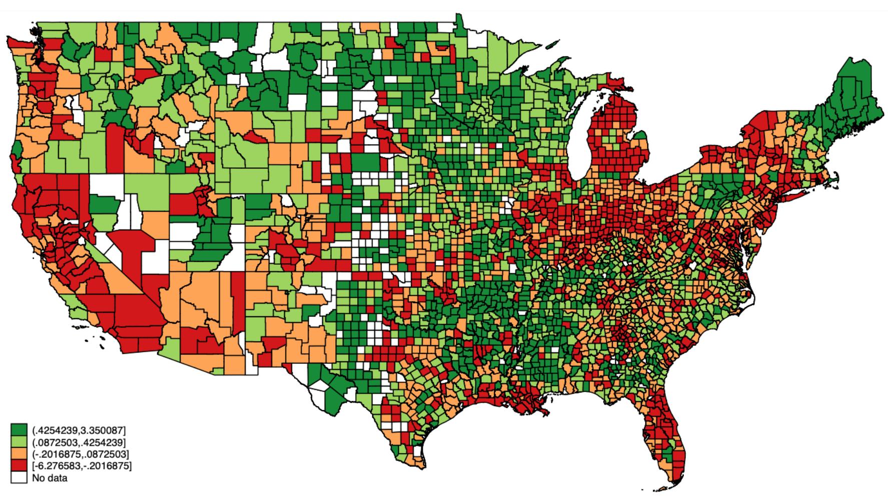

*Notes*: Data are from Natality Records 2003-2019 on CDC WONDER Online Database. Data for OE gestational age are available from 2007. Accessed at http://wonder.cdc.gov/natality-v2002.html.

Figure 4: Regional Variation in Credit Supply Shocks in 2008

(a) CRA



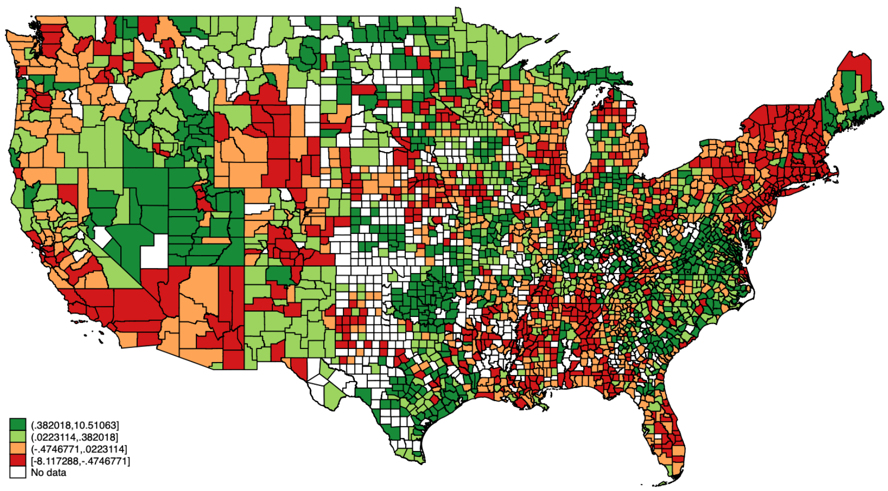

(b) HMDA




*Notes*: The credit supply shocks plotted are calculated from the dollar amount loan growth rate. County share is used as a weight.

Figure 5: Regional Variation in Credit Supply Shocks in 2009

(a) CRA




(b) HMDA

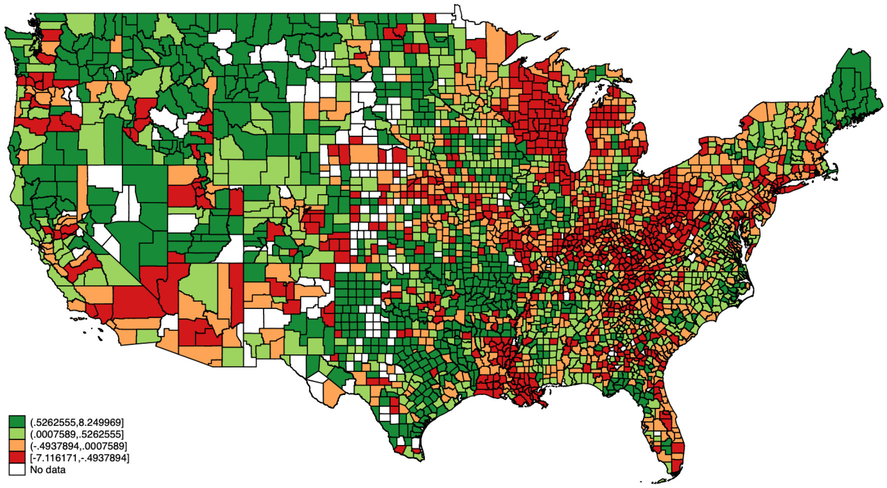
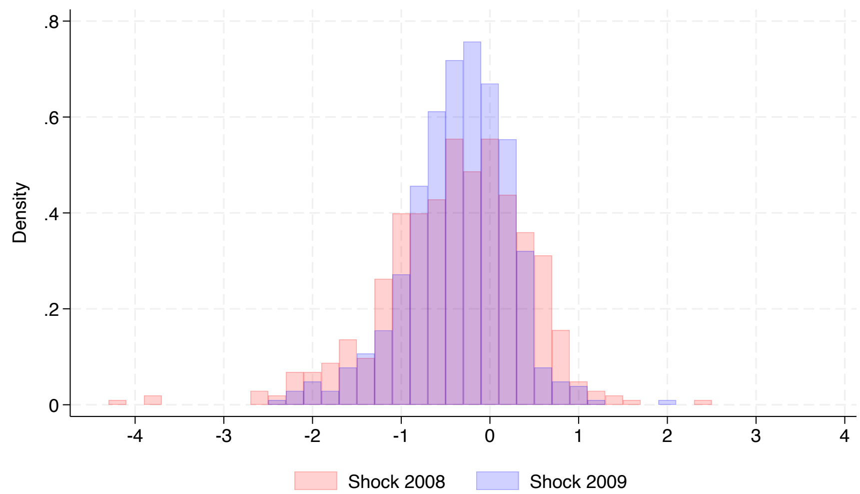


Figure 6: Distribution of Credit Supply Shocks

(a) CRA




(b) HMDA

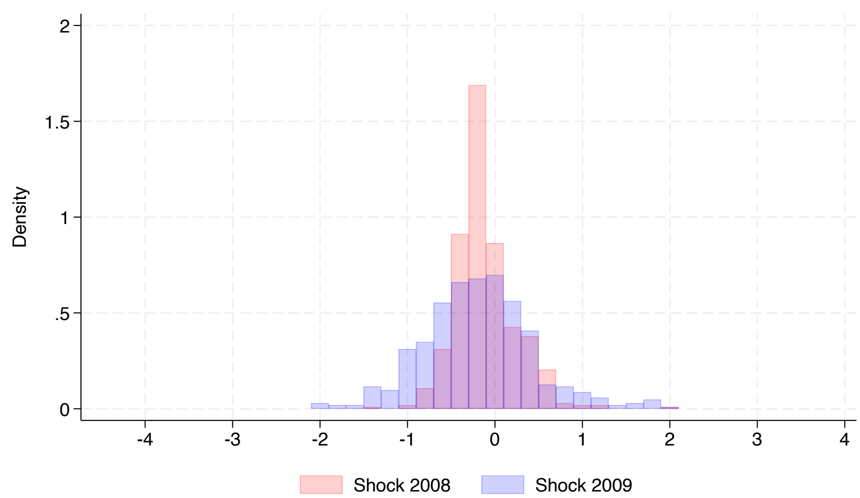
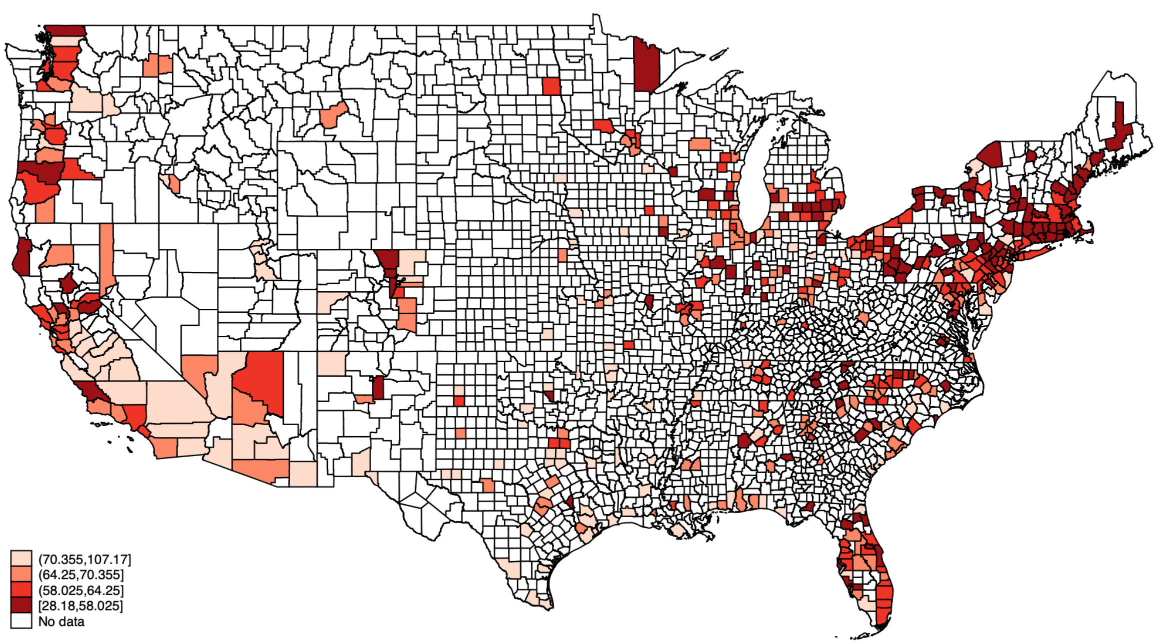


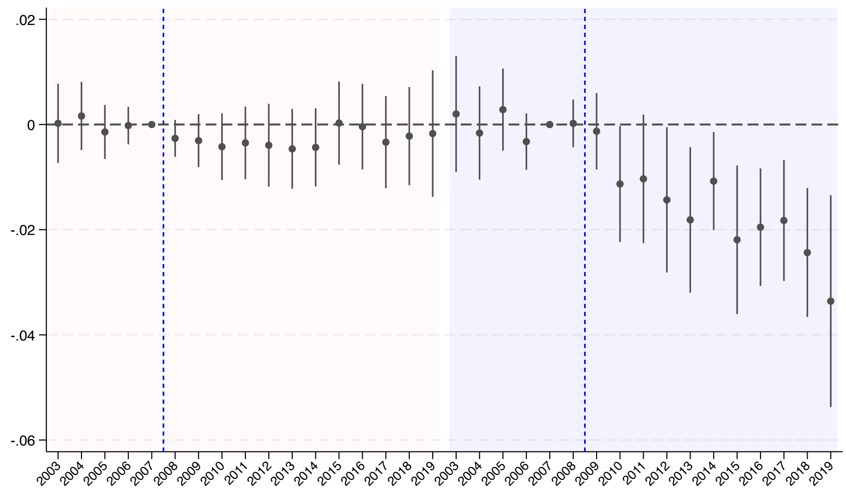
Figure 7: Regional Variation in Fertility in 2009



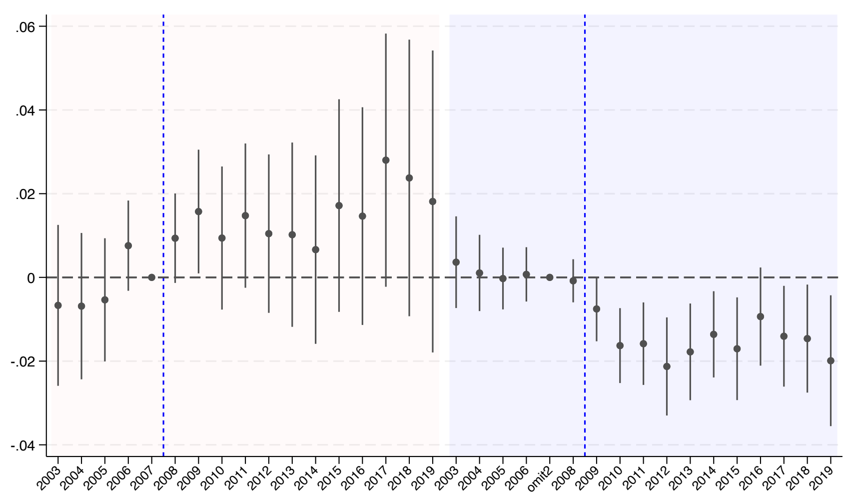

*Notes*: It plots fertility rates in 2009 using 515 counties.

Figure 8: The Effect of Credit Supply Shocks on Fertility Rates

(a) CRA




(b) HMDA

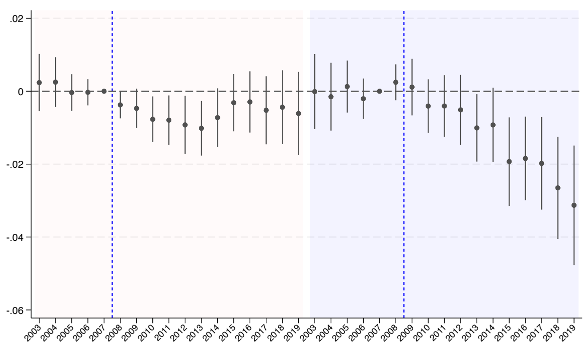



*Notes*: In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dashed blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of fertility rates.

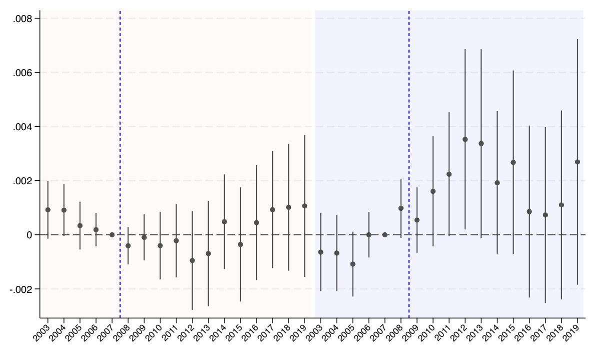
Figure 9: The Effect of Credit Supply Shocks on Other Birth Outcomes

**CRA**

(a) Birth Rates

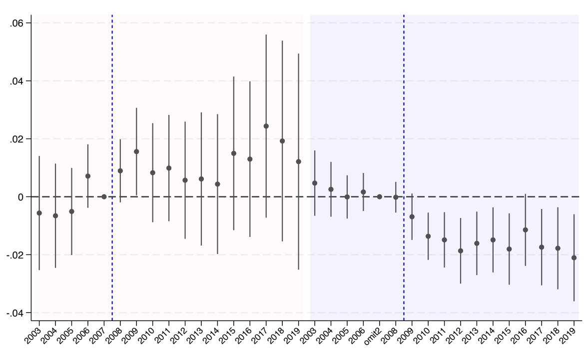


(b) Age of Mothers

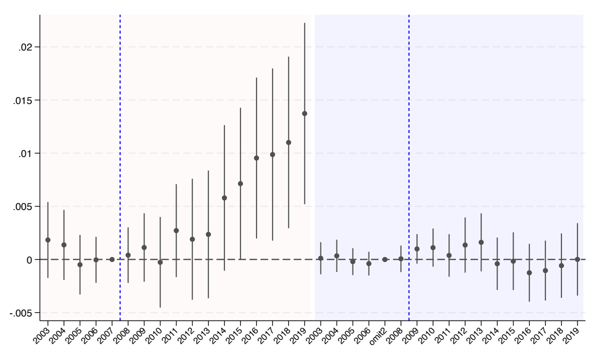


**HMDA**

(c) Birth Rates



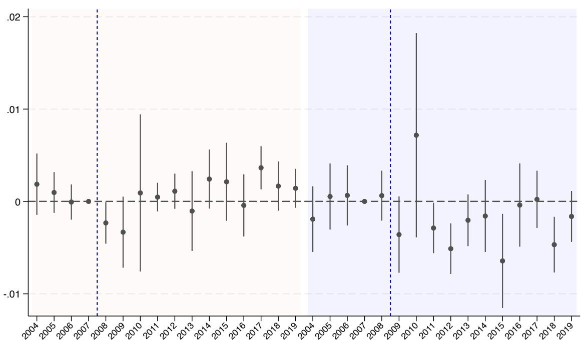
(d) Age of Mothers



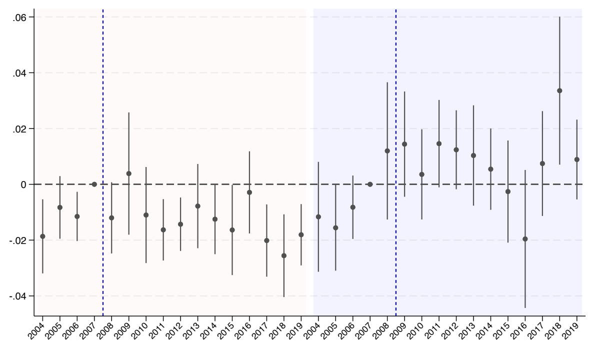
*Notes*: In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dashed blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of birth outcomes.

Figure 10: The Effect of Credit Supply Shocks from CRA on Market Variables

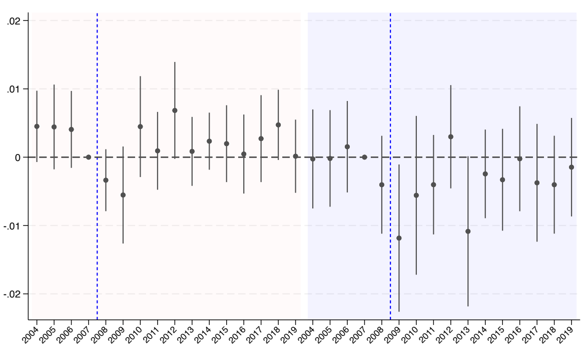
(a) Employment-to-Pop Ratio



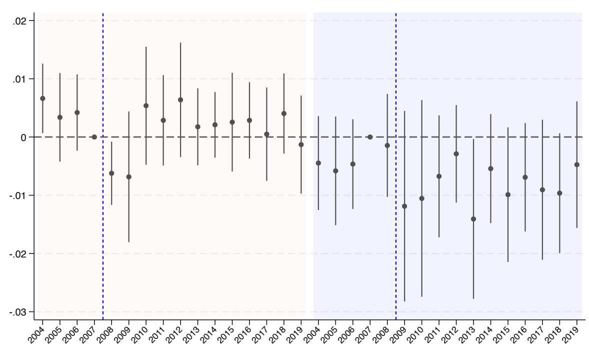

(b) Unemployment Rates



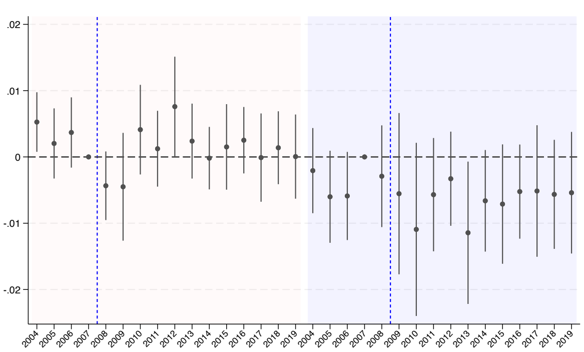

(c) Per Capita Income



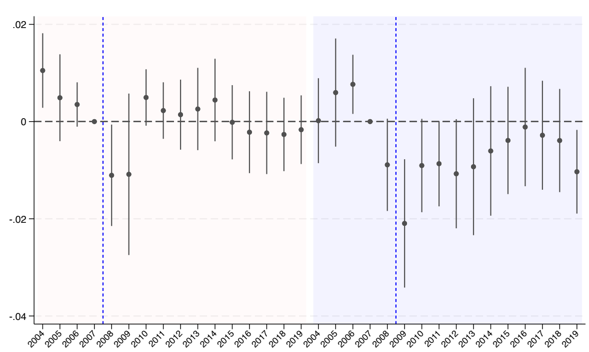

(d) Per Capita Earnings




(e) Average Earnings



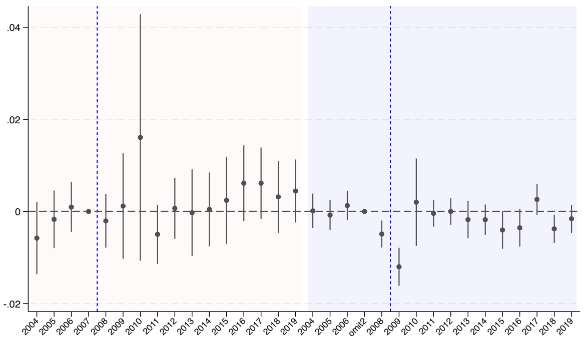

(f) HPI



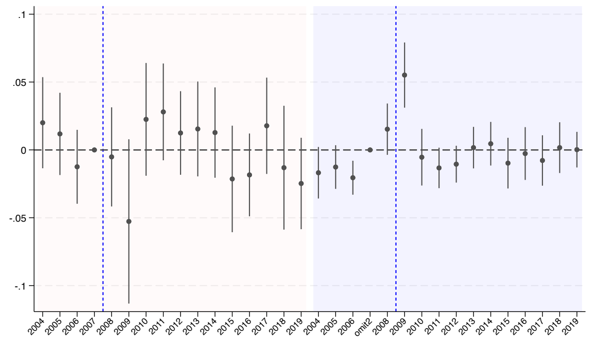

*Notes*: In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dashed blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of birth outcomes.

Figure 11: The Effect of Credit Supply Shocks from HMDA on Market Variables

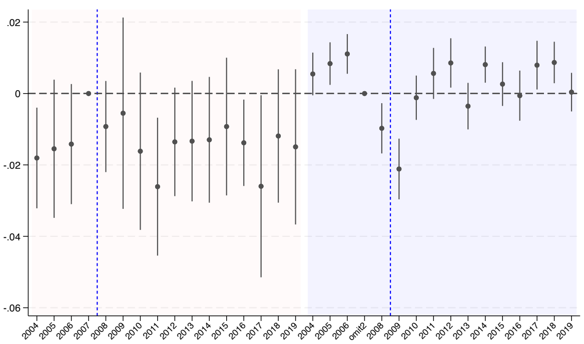
(a) Employment-to-Pop Ratio



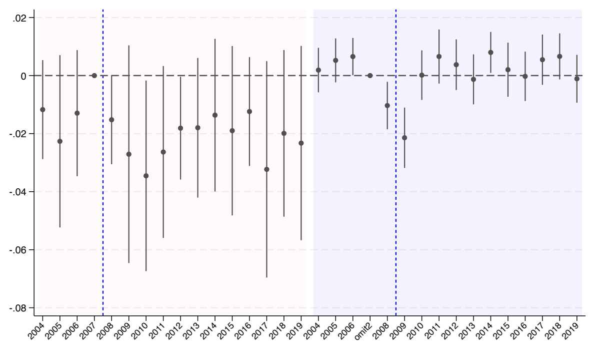
(b) Unemployment Rates



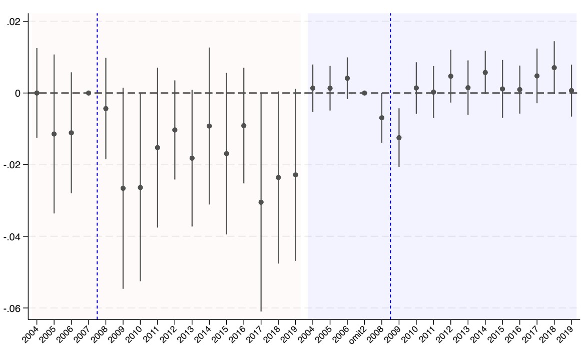
(c) Per Capita Income



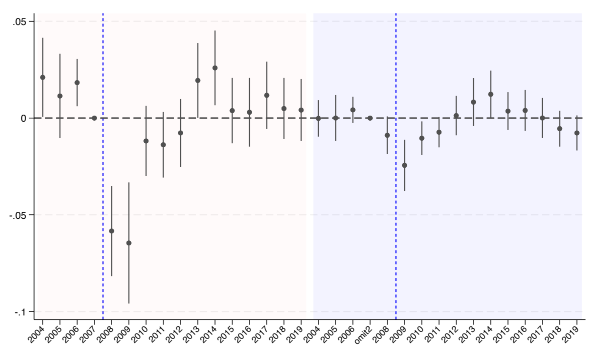
(d) Per Capita Earnings



(e) Average Earnings



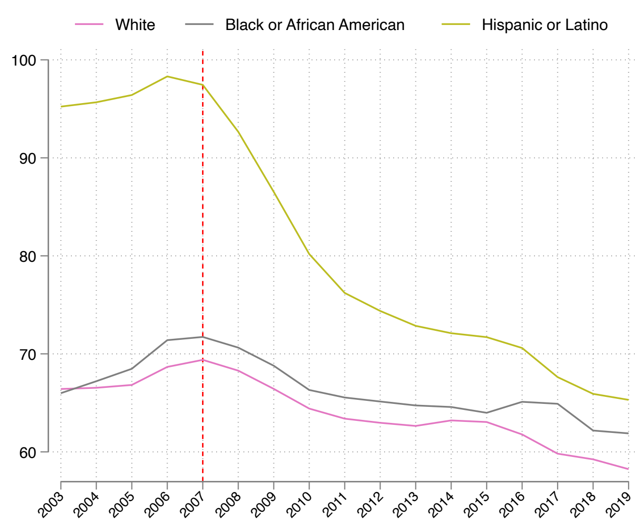
(f) HPI



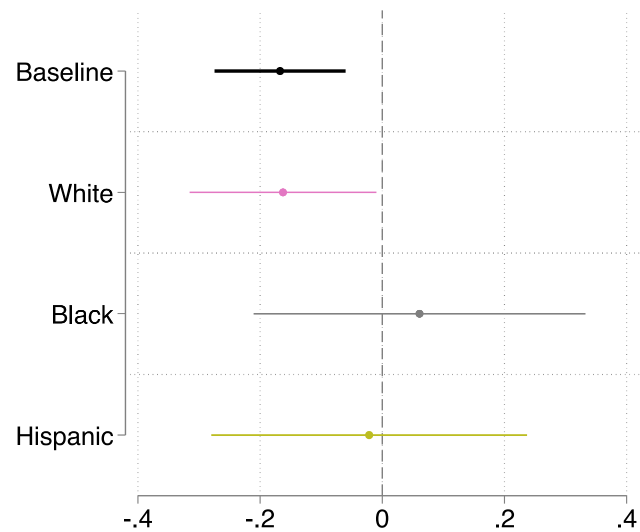
*Notes*: In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dashed blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of birth outcomes.

Figure 12: Heterogeneous Effect of Credit Supply Shocks by Race

(a) Fertility Rates by Race

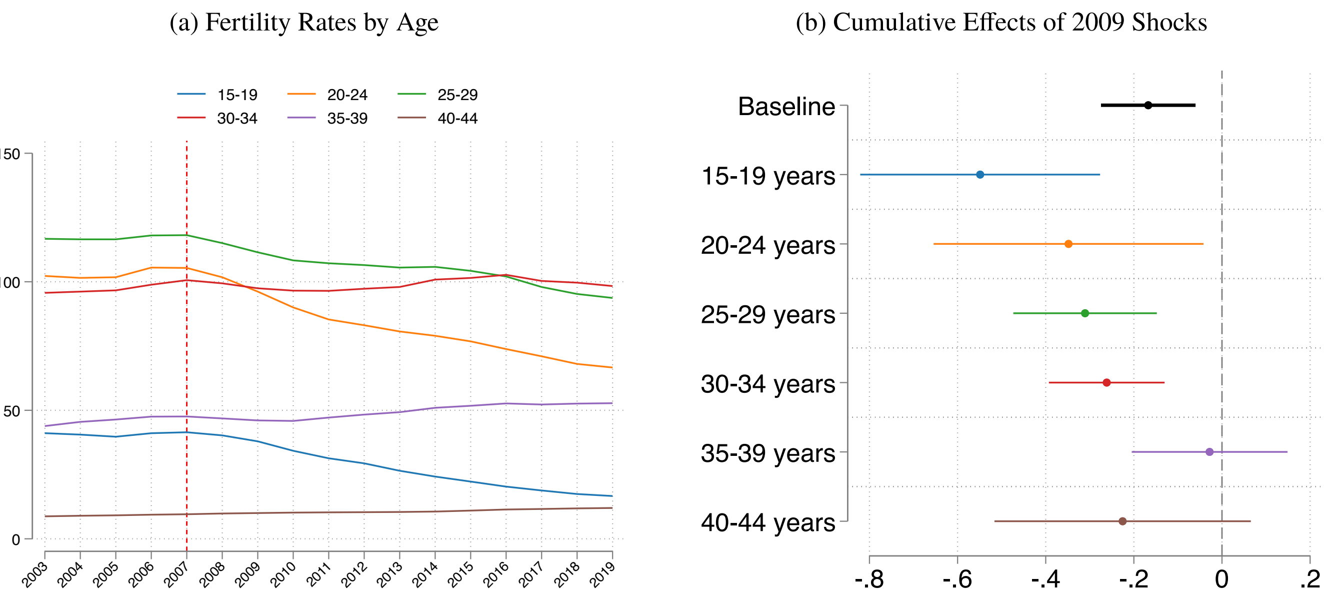



(b) Cumulative Effects of 2009 Shocks




*Notes*: Fertility rates specific to White and Black or African American are obtained from Bridged Race Statistics, while values for Hispanic or Latino are from fertility by Origin records. The red dashed line indicates 2007. Lines in (b) indicate 95% confidence intervals.

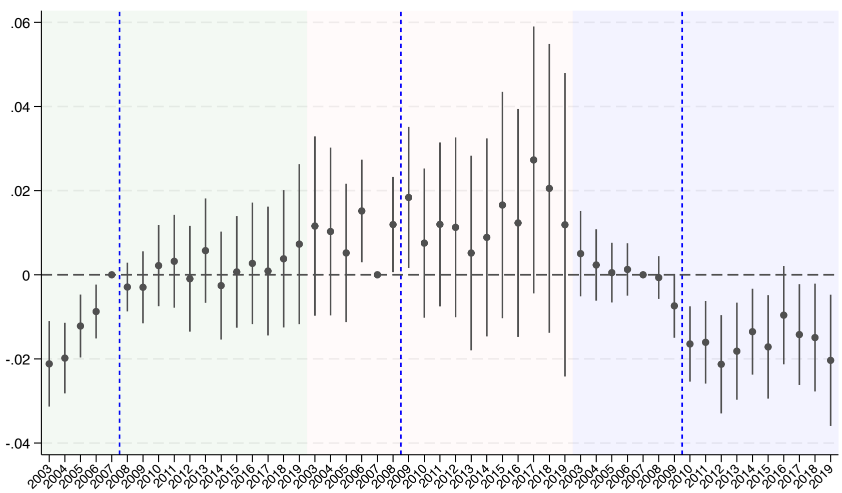
Figure 13: Heterogeneous Effect of Credit Supply Shocks by Age



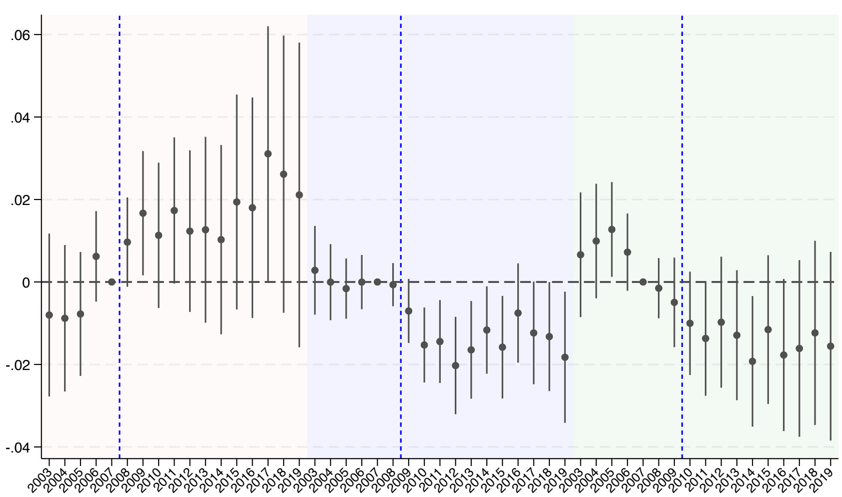

*Notes*: The red dashed line indicates 2007. Lines in (b) indicate 95% confidence intervals.

Figure 14: The Effect of Credit Shocks on Fertility with Other Year Credit Shocks

(a) 2007



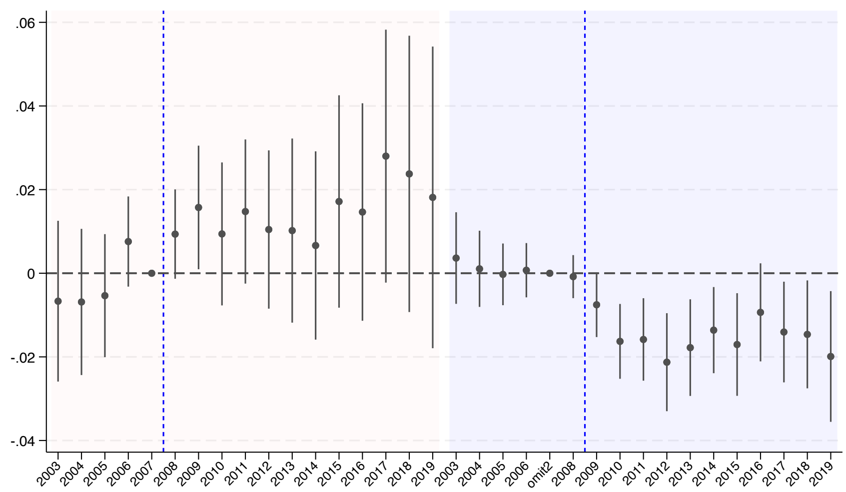

(b) 2010



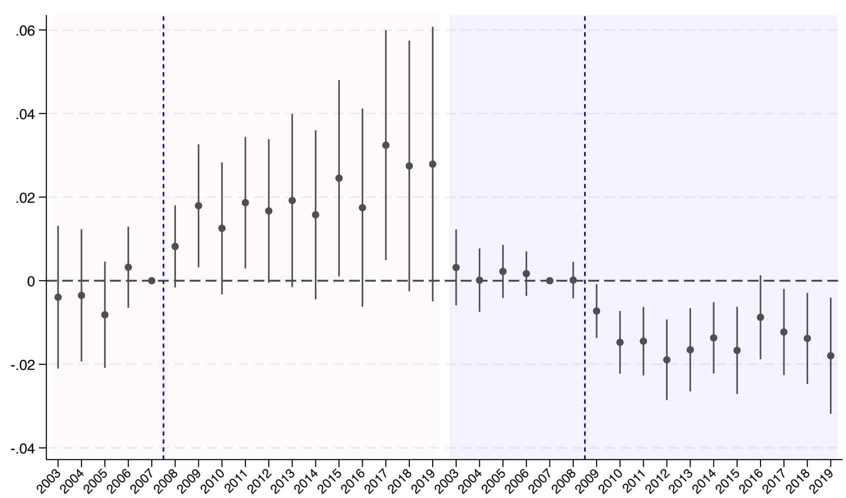

*Notes*: The plots present the estimated effect of credit shocks from HMDA on the log of fertility rates. The red area represents the estimates of the impact of the 2008 shocks, the blue area represents the impact of the 2009 shocks. The green area (a) corresponds to the 2007 shocks, and (b) represents the 2010 shocks.

Figure 15: The Effect of Credit Supply Shocks from HMDA on Fertility Rates by Loan Measures

(a) Log Dollar Amount



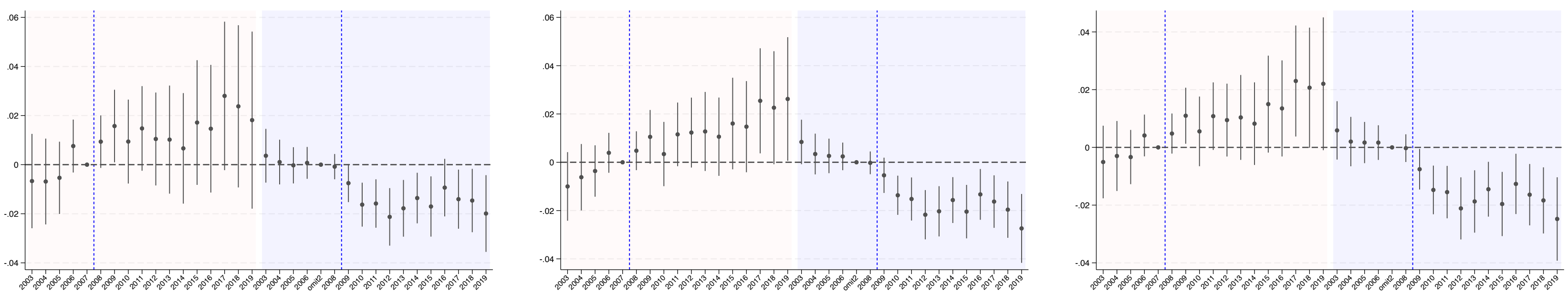

(b) Log Number of Loan




*Notes*: Each panel shows the estimated results by different loan measures.

Figure 16: The Effect of Credit Supply Shocks from HMDA on Fertility Rates by Regression Weights

(a) County Share (b) Bank Share (c) Geometric Mean



*Notes*: Each panel shows the estimated results by different weights. The geometric mean is a mean of county and bank share.

Table 1: Data Sources for County-level Variables

| Data Type | Variable | Data Source |
|---|---|---|
| Labor Market | Per capita Income, Per Capita Earnings, Average Earnings | Local Area Personal Income |
| | Employed, Civilian Labor Force, Unemployment Rates | US Department of Agriculture (USDA) |
| Housing Market | Housing Price Index (HPI) | Federal Housing Finance Agency (FHFA) |
| | Homeownership Rates | Decennial Census (2000), American Community Survey (ACS, 2010 and 2015) |
| Population | Total, Population by Age, Gender, Race, Origin | The Surveillance, Epidemiology, and End Results (SEER) program |

Table 2: The Effect of Credit Shocks on Loan Origination

| | CRA | | HMDA | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Shock_{2008} * I[year = 2008]$ | -0.063*** | -0.061*** | -0.065*** | -0.054*** |
| | (-3.45) | (-3.32) | (-4.51) | (-3.43) |
| $Shock_{2008} * I[year = 2009]$ | -0.067*** | -0.070*** | -0.082*** | -0.093*** |
| | (-3.50) | (-3.85) | (-5.50) | (-5.59) |
| $Shock_{2008} * I[year = 2010]$ | 0.028 | 0.018 | -0.106*** | -0.125*** |
| | (1.05) | (0.74) | (-7.99) | (-8.38) |
| $Shock_{2009} * I[year = 2009]$ | -0.030 | -0.029 | -0.067*** | -0.074*** |
| | (-1.37) | (-1.35) | (-7.09) | (-7.01) |
| $Shock_{2009} * I[year = 2010]$ | -0.086** | -0.076** | -0.050*** | -0.055*** |
| | (-2.01) | (-2.04) | (-6.85) | (-6.23) |
| Observations | 32867 | 32853 | 30613 | 30609 |
| $R^2$ | 0.306 | 0.509 | 0.469 | 0.654 |
| Controls | | X | | X |

t statistics in parentheses

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

Table 3: Summary Statistics

| | 2007 | | % Change in 2008 | | % Change in 2009 | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Birth Outcomes | | | | | | |
| Fertility Rates | 69.28 | 9.99 | -2.54 | 2.46 | -6.21 | 3.99 |
| Birth Rates | 14.80 | 2.52 | -1.79 | 2.43 | -4.73 | 3.95 |
| Age of Mothers | 27.80 | 1.37 | 0.18 | 0.46 | 0.56 | 0.62 |
| Birth Weights | 3265.65 | 59.03 | -0.02 | 0.40 | -0.04 | 0.45 |
| LMP Age | 38.55 | 0.20 | 0.09 | 0.20 | 0.09 | 0.23 |
| Market Outcomes | | | | | | |
| Employment to Population Ratio | 0.63 | 0.06 | -1.36 | 1.34 | -6.07 | 2.65 |
| Unemployment Rates | 4.59 | 1.27 | 28.79 | 18.48 | 108.20 | 39.49 |
| Per Capita Income | 41971.80 | 10528.06 | 2.57 | 3.55 | -1.79 | 4.60 |
| Per Capita Earnings | 28017.86 | 7691.89 | 0.09 | 4.53 | -4.79 | 5.35 |
| Average Earnings | 50332.09 | 10202.07 | 1.52 | 3.37 | 1.18 | 4.09 |
| Housing Price Index (HPI) | 169.01 | 41.24 | -6.36 | 7.97 | -13.65 | 13.19 |
| Population | | | | | | |
| Female Percentage | 0.51 | 0.01 | 0.00 | 0.11 | 0.02 | 0.21 |
| Population Aged 15-49 Percentage | 0.51 | 0.04 | 0.84 | 0.42 | 1.68 | 0.78 |
| Black Percentage | 0.12 | 0.13 | 1.35 | 1.91 | 2.67 | 3.66 |
| Hispanic Percentage | 0.12 | 0.14 | 3.45 | 2.16 | 6.70 | 3.97 |

*Notes:* This table presents the means and standard deviations for 515 counties. For birth outcomes, the female population is used as a weight. For market outcomes, the total population is used as a weight. The population is not weighted. The column (1) and (2) represent the means and standard deviations in 2007. The last four columns are percentage changes using the base year 2007. The Housing Price Index (HPI) uses the base year 2000.

Table 4: Cumulative Effect of the Credit Supply Shocks on Birth Outcomes

| | Fertility rates (1) | Birth rates (2) | Age of mother (3) | Birth weights (4) | Lmp Gestational age (5) |
|---|---|---|---|---|---|
| CRA | | | | | |
| Shock2008 | -0.034 | -0.073* | 0.001 | 0.001 | -0.002 |
| | (0.039) | (0.039) | (0.010) | (0.005) | (0.002) |
| Shock2009 | -0.184*** | -0.147*** | 0.021 | -0.011* | 0.004 |
| | (0.059) | (0.049) | (0.015) | (0.006) | (0.003) |
| HMDA | | | | | |
| Shock2008 | 0.178 | 0.143 | 0.065* | -0.021 | -0.010* |
| | (0.120) | (0.126) | (0.034) | (0.019) | (0.006) |
| Shock2009 | -0.167*** | -0.171*** | 0.002 | -0.007 | 0.002 |
| | (0.055) | (0.055) | (0.013) | (0.006) | (0.003) |

*Notes:* This table provides the results for testing the linear combination of the estimated cumulative effect of the credit supply shocks on log birth outcomes. Standard errors are in parentheses. Shock2008 is the cumulative effect of the 2008 credit supply shock, $\sum_{j=2008}^{2019} \hat{\theta}_j^{2008}$, Similarly, Shock2009 is the cumulative effect of the 2009 credit supply shock, $\sum_{j=2009}^{2019} \hat{\theta}_j^{2009}$. Standard errors are clustered at the county level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 5: Cumulative Effect of the Credit Supply Shocks on Market Outcomes

| | Emp-to-pop ratio (1) | Unemployment rates (2) | Per capita income (3) | Per capita earnings (4) | Average earnings (5) | HPI (6) |
|---|---|---|---|---|---|---|
| CRA | | | | | | |
| Shock2008 | 0.007 | -0.153** | 0.017 | 0.014 | 0.012 | -0.015 |
| | (0.016) | (0.063) | (0.025) | (0.037) | (0.028) | (0.042) |
| Shock2009 | -0.021 | 0.088 | -0.045 | -0.092* | -0.072* | -0.087 |
| | (0.016) | (0.072) | (0.037) | (0.055) | (0.043) | (0.056) |
| HMDA | | | | | | |
| Shock2008 | 0.033 | -0.026 | -0.173* | -0.260* | -0.213* | -0.083 |
| | (0.043) | (0.185) | (0.094) | (0.145) | (0.115) | (0.092) |
| Shock2009 | -0.024 | 0.014 | 0.015 | 0.009 | 0.016 | -0.026 |
| | (0.016) | (0.069) | (0.025) | (0.035) | (0.030) | (0.050) |

*Notes:* This table provides the results for testing the linear combination of the estimated cumulative effect of the credit supply shocks on the growth rate of market outcomes. Standard errors are in parentheses. Standard errors are in parentheses. Shock2008 is the cumulative effect of the 2008 credit supply shock, $\sum_{j=2008}^{2019} \hat{\theta}_j^{2008}$, Similarly, Shock2009 is the cumulative effect of the 2009 credit supply shock, $\sum_{j=2009}^{2019} \hat{\theta}_j^{2009}$. Standard errors are clustered at the county level. $^*$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

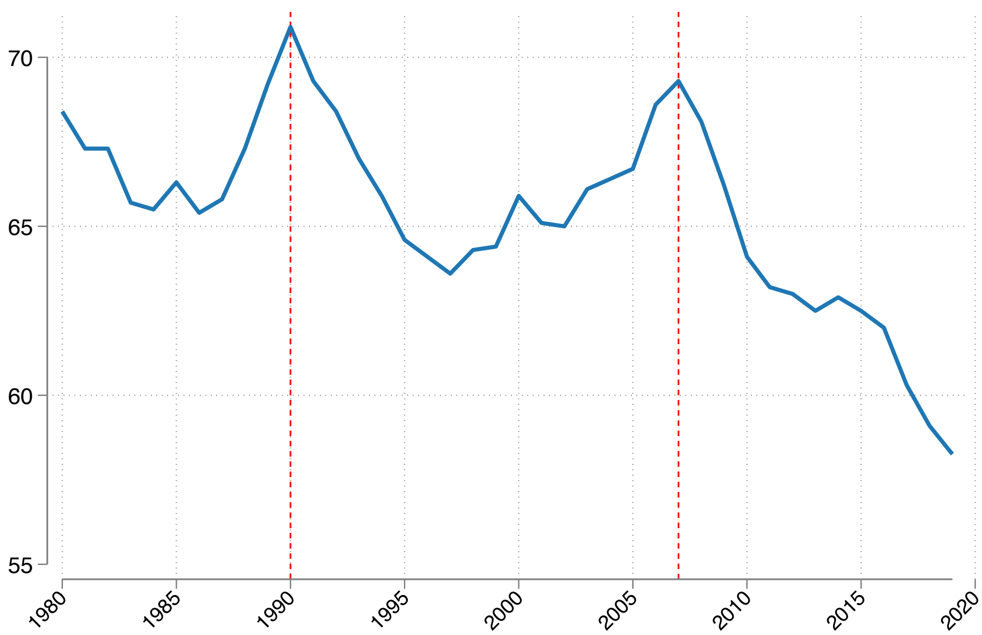
# For Online Publication

"Credit Supply Shocks and Fertility: Long-Term Consequences"

*Kim, Kim, and Park (2023)*

# A Supplemental Figures and Tables

Figure A1: The Trend of Fertility Rates from 1980 to 2019

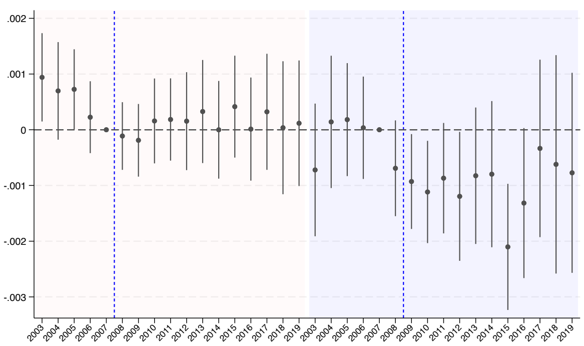



*Notes*: Data are from the National Center for Health Statistics. Health, United States, 2020-2021: Table Brth. Hyattsville, MD. Available from: https://www.cdc.gov/nchs/hus/contents2020-2021.htm#Table-Brth

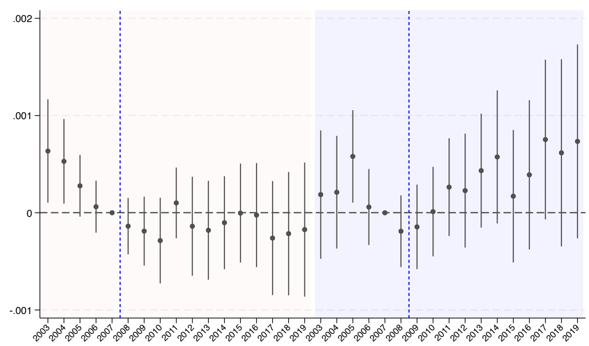
Figure A2: The Effect of Credit Supply Shocks on Infant Health

**CRA**

(a) Birth Weights

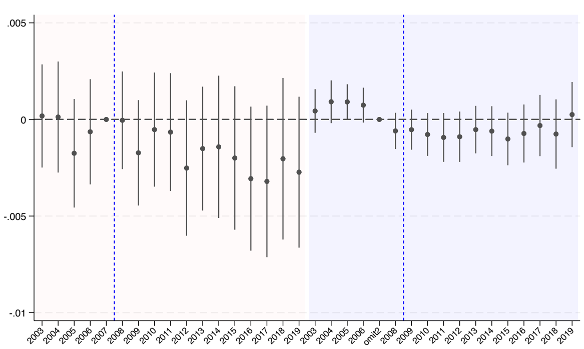



(b) LMP Gestational Age

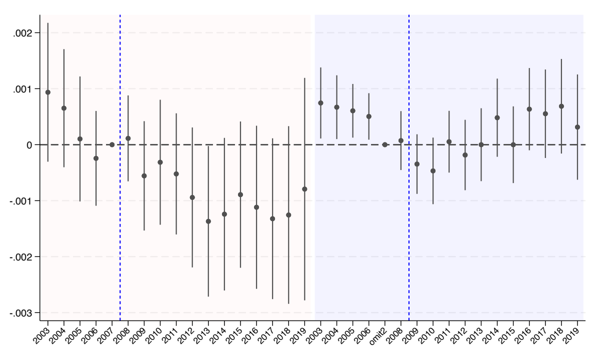



**HMDA**

(c) Birth Weights



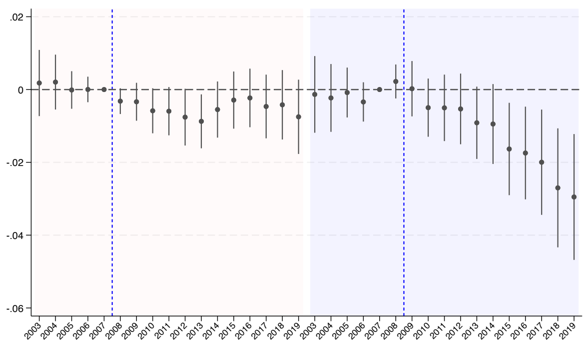

(d) LMP Gestational Age



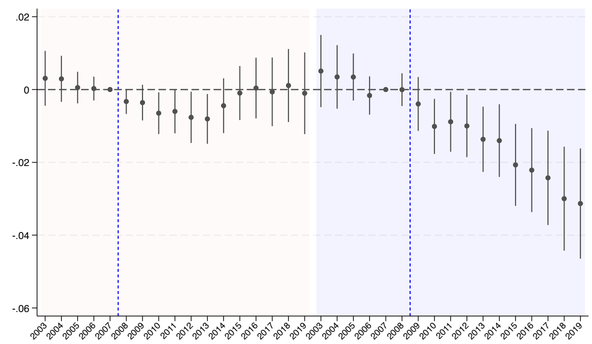

*Notes*: In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dashed blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of birth outcomes.

Figure A3: The Effect of Credit Supply Shocks from CRA on Birth Decisions

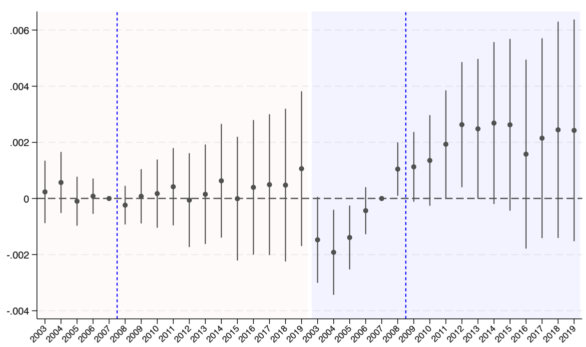
(a) Birth Rates



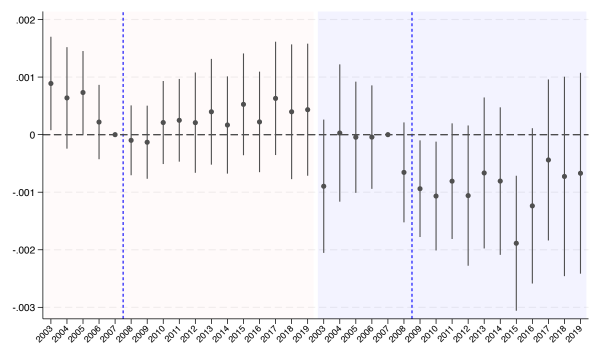
(b) Fertility Rates



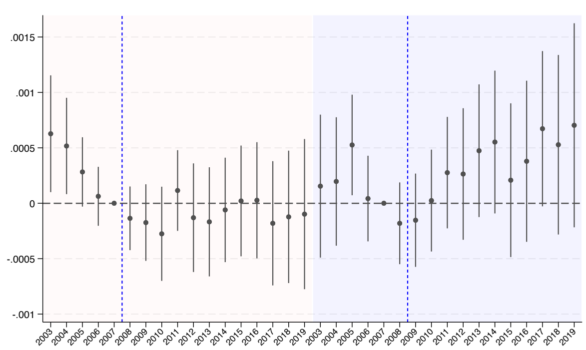
(c) Age of Mothers



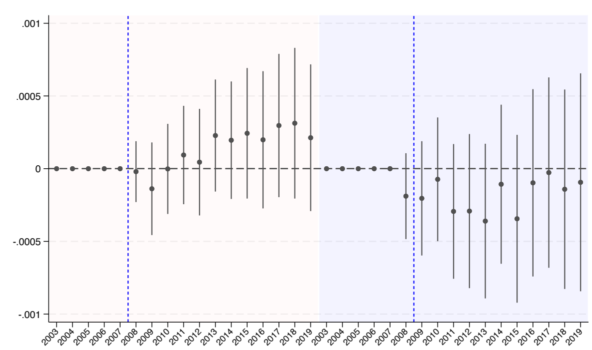
(d) Birth Weights



(e) LMP Gestational Age



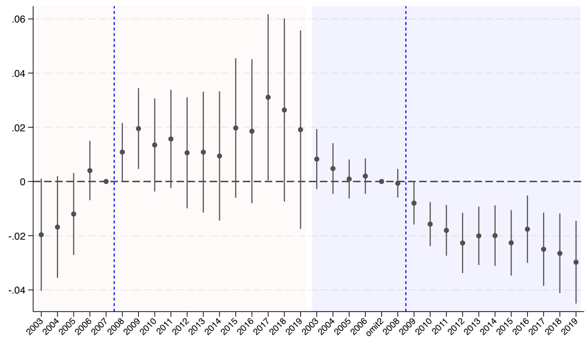
(f) OE Gestational Age



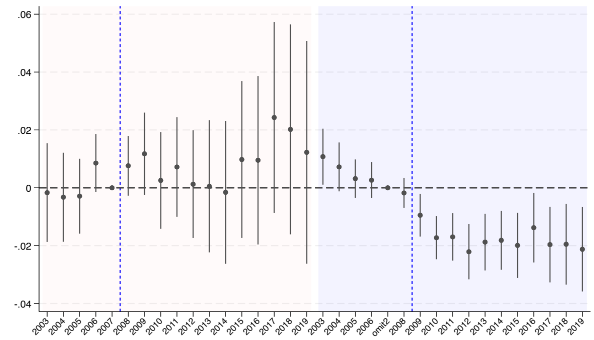
*Notes*: It plots the baseline estimates without controls. In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dotted blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of birth outcomes.

Figure A4: The Effect of Credit Supply Shocks from HMDA on Birth Decisions

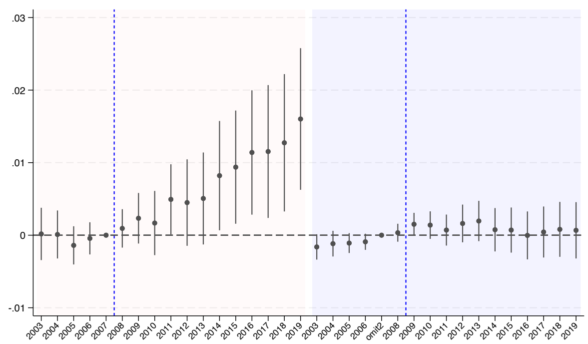
(a) Birth Rates



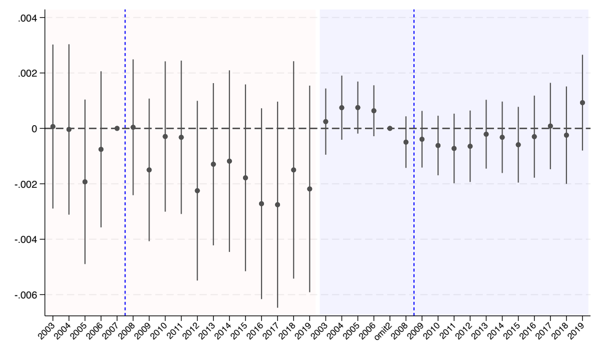
(b) Fertility Rates



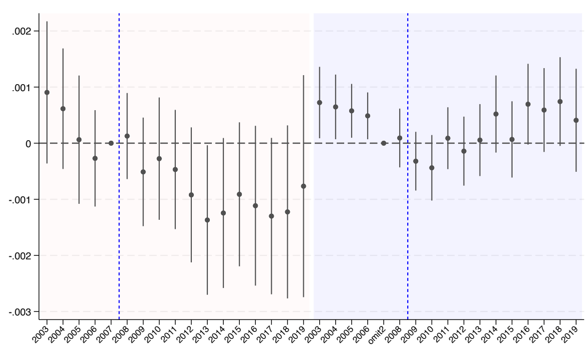
(c) Age of Mothers



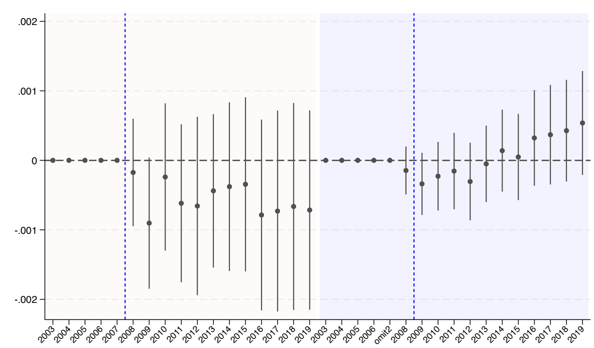
(d) Birth Weights



(e) LMP Gestational Age



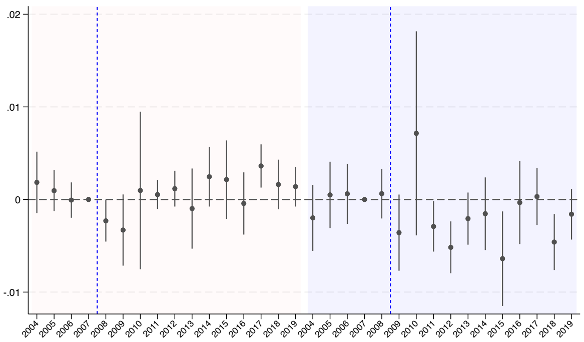
(f) OE Gestational Age



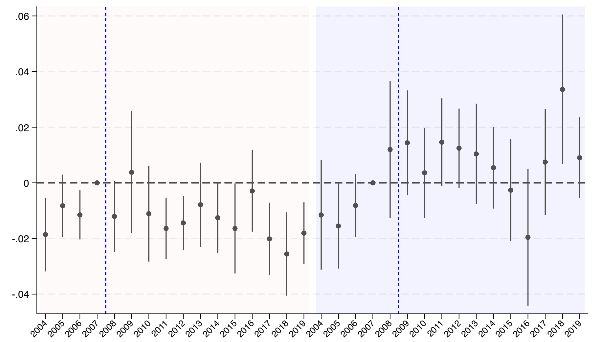
*Notes*: It plots the baseline estimates without controls. In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dotted blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of birth outcomes.

Figure A5: The Effect of Credit Supply Shocks from CRA on Market Variables

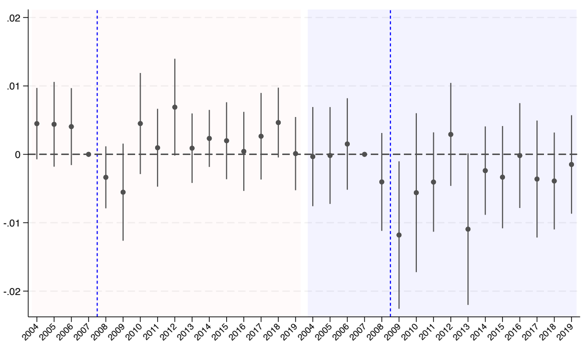
(a) Employment-to-Pop Ratio



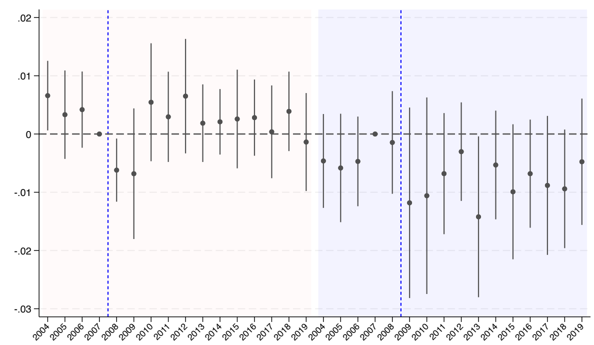
(b) Unemployment Rates



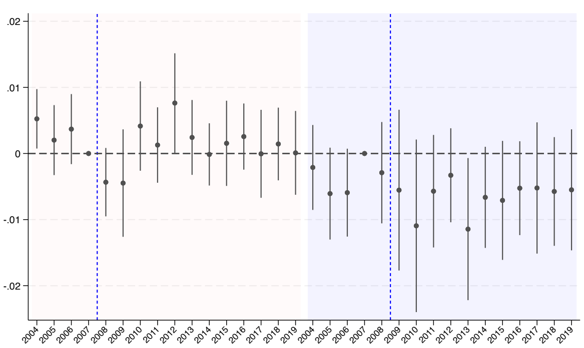
(c) Per Capita Income



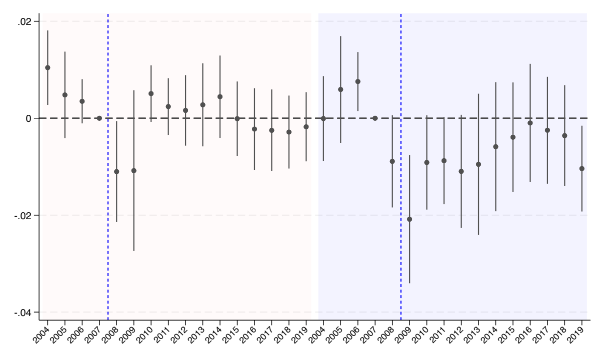
(d) Per Capita Earnings



(e) Average Earnings



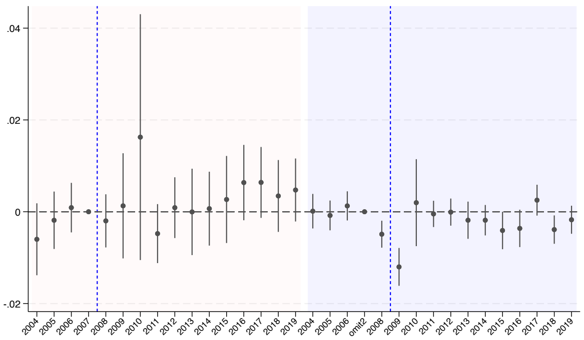
(f) HPI



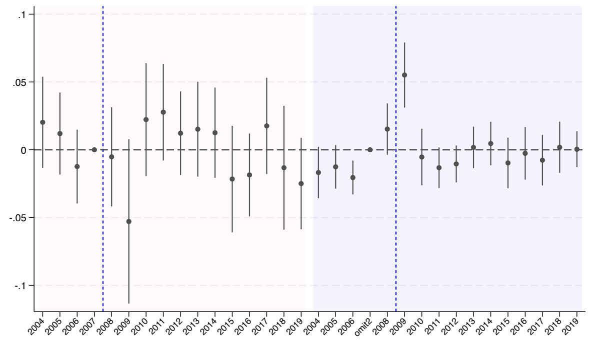
*Notes*: It plots the baseline estimates without controls. In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dotted blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of birth outcomes.

Figure A6: The Effect of Credit Supply Shocks from HMDA on Market Variables

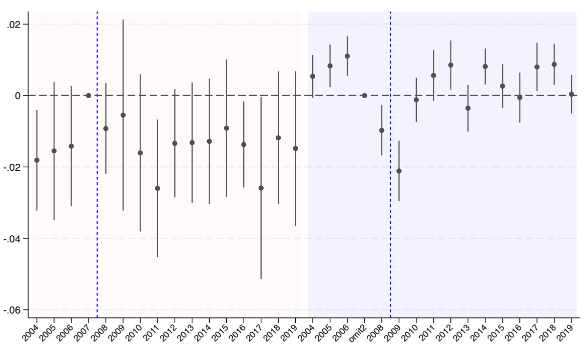
(a) Employment-to-Pop Ratio



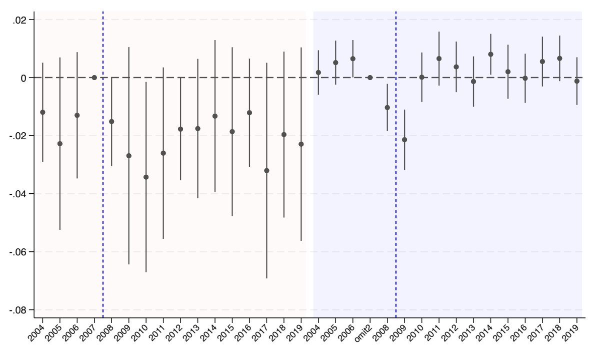
(b) Unemployment Rates



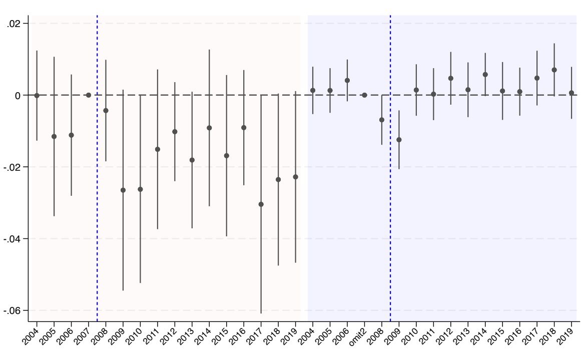
(c) Per Capita Income



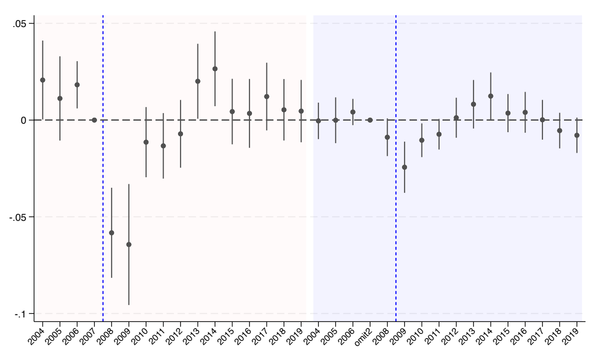
(d) Per Capita Earnings



(e) Average Earnings



(f) HPI



*Notes*: It plots the baseline estimates without controls. In the red graph region, the estimates for the 2008 credit supply shocks are plotted. The 2009 credit supply shock estimates are plotted in the blue graph region. The dotted blue line corresponds to the years 2008 and 2009, respectively. The baseline is 2007. The dependent variables are the log of birth outcomes.