The Intangible Gender Gap: An Asset Channel of Gender Inequality*

Carlos F. Avenancio-León† Leslie Sheng Shen‡

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PRELIMINARY

Abstract

We propose an "asset channel of inequality" that contributes to gender inequities. We establish that industries with low (high) gender pay gaps have high (low) shares of tangible assets. Because asset tangibility determines firms' ability to collateralize assets and borrow, credit conditions affect industries differently. We show that credit expansions further reduce the pay gap in low-pay-gap industries while leaving it unaffected in high-pay-gap industries, making low-pay-gap industries more appealing for women. Consequently, gender sorting across industries increases, which then cements gender roles and accentuates workplace gender bias. Ultimately, credit expansions help women "swim upstream" but also reinforce glass ceilings.

JEL Classification: J71, O16

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†Indiana University—Bloomington, Kelley School of Business. Email: cfavenan@iu.edu.

‡Federal Reserve Board. Email: leslie.shen@frb.gov.

I. Introduction

Changes in financial conditions—credit contractions and expansions—are frequent[1] and have been shown to affect income inequality (Beck, Levine, and Levkov 2010, Philippon and Reshef 2012). But how do financial conditions affect group inequality? To explore this question, we focus on the connection between financial conditions and gender inequality. We propose an "asset channel of inequality" and show that it, in particular, drives the persistence of gender inequities. When financial conditions change, differences in firms' ability to collateralize assets restructure the set of productive investments held by the firm; this restructuring propels changes in labor demand both across industries and, due to preexisting gender imbalances, across gender lines. When these shifts in labor demand benefit women at the bottom of the pay distribution but not at the top, changes in financial conditions may simultaneously help women "swim upstream" and reinforce the glass ceiling.

In this paper, we document these dynamics by showing how financial deregulation reduced the gender pay gap at the bottom of the pay distribution while propelling gender sorting out of the top. We establish that industries with high gender pay gaps have higher wages and less tangible assets; conversely, industries with low gender pay gaps have lower wages and more tangible assets. Because asset tangibility determines firms' collateral and ability to borrow, and thus choice of project and ensuing labor demand, financial deregulation has different effects on workers from industries with different levels of tangibility. In more equitable industries (i.e., industries with a lower pay gap and more tangible assets), firms increase borrowing and take on more positive NPV projects in response to financial deregulation, which increases their demand for labor. In more inequitable industries (i.e., industries with a higher pay gap and more intangible assets), firms do not significantly change their borrowing but must relinquish marginally positive NPV projects in response to increased labor competition from the more equitable industries, which lowers their demand for labor. Differences in labor demand between equitable industries and inequitable industries, together with higher relative pay for women in the more equitable industries, lead to gender sorting between the more equitable and inequitable industries. We further show that this sorting accentuates workplace gender bias by cementing gender roles.

Our findings contribute to the understanding of the persistence and evolution of the gender

1. Over the past few decades, prominent instances of financial shocks include the waves of financial deregulation in the United States, the 2008 financial crisis, potential COVID-19 credit crunch, etc.

pay gap. Gender inequities in the labor market have been large and persistent. While pay for men and women has narrowed, especially during the 1980s, women still earn, on average, 20 percent less than men (Blau & Kahn, 2017). In addition, the narrowing of the gender pay gap took place at the bottom and center of the wage distribution rather than at the top, and progress slowed afterwards (Blau & Kahn 1997, 2017). Our findings suggest that the waves of financial deregulation in the 1980s, by differentially affecting wages by industry and inducing gender sorting across industries, contributed to the bottom-up narrowing of the gender pay gap, and by cementing gender roles, made gender inequities persistent.

Our analysis proceeds in three steps. First, we exploit variation in interstate and intrastate U.S. bank deregulation to estimate the effects of credit expansions along the gender pay gap distribution across industries. Because pay for men and women converged significantly during the 1980s, as we noted above, we fix pay gap levels by industry prior to 1980 and categorize industries into high pay gap, medium pay gap, and low pay gap based on their preexisting pay gap levels. We find that while relative wages for women did not change in the high-pay-gap industries in response to banking deregulation, they increased by 5% in the low-pay-gap industries, controlling for Mincerian traits (education, experience, and experience squared). These results are robust to alternative methods of industry categorization.

Second, we explore the role of assets in linking changes in credit conditions to the gender pay gap. We begin by documenting the industry-level relationship between gender pay gaps and asset tangibility: The share of tangible assets is consistently and materially lower in the high-pay-gap industries than in the low-pay-gap industries. This differentially affects the ability of the two types of industries to post assets as collateral. We then show that asset tangibility funnels changes in credit conditions by differentially affecting firm borrowing, investment decisions, and demand for workers across the two types of industries. More specifically, in response to bank deregulation, the low-pay-gap (or high-asset-tangibility) industries increased borrowing, further shifted their asset composition towards tangible assets, and increased demand for labor. In contrast, the high-pay-gap (or low-asset-tangibility) industries did not change borrowing behavior, further shifted their asset composition towards intangible assets as evidence by increased R&D expenditures, and lowered labor demand. Changes across all these dimensions point to a restructuring of the labor market.

This restructuring of the labor market altered the dynamics of gender through the interplay of two main forces. One, the low-pay-gap industries, despite being more equitable, are on average low paying, while the high-pay-gap industries are high paying. Two, surpluses in the high-pay-gap industries, owing to low female representation in these industries, disproportionately accrued to male workers.[2] Moreover, these rents make men relatively more likely to transition into the high-pay-gap industries. In contrast, the low-pay-gap industries compete for workers with low risk of transitioning out of lower-paying industries into higher-paying industries, which are more likely to be women. This competition induces the low-pay-gap industries to increase relative pay for women, which leads to higher women participation in them as a byproduct.

Increases in the relative pay in lower-paying (but more equitable) jobs combined with low female representation in high paying jobs alters the opportunity cost for women relative to men. This creates incentives for women to select into more equitable but lower-paying industries, or, conversely, abstain from participating in less equitable but higher-paying ones. Indeed, we document that following bank deregulation, women are more likely to stay in the low-pay-gap industries and exit the better-paying high-pay-gap industries. This sorting behavior leads to persistence of the gender pay gap by perpetuating gender imbalances across industries. Furthermore, higher participation in lower-paying industries makes women more vulnerable to economic downturns: We show that credit contractions disproportionately reduce women's wages in the low-pay-gap industries, reverting the gains from credit expansions.[3]

Lastly, we show that this asset channel of inequality has downstream implications: the resulting differences in gender sorting may cement gender roles in the long run. Individuals, both male and female, may interpret the differences in sorting and the resulting gender imbalance through gendered lens and conclude that women are less suitable for some jobs, or that it is less important for women to pursue a career, or that staying at home is a comparative advantage for women. We directly test for changes in gender norms of this sort by testing how bank deregulation, through industrial composition, affects measures of sexism derived from General Social Survey (GSS) data. We find that, indeed, following bank deregulation, attitudes toward women in the workplace worsen. These effects are stronger for men than for women and, also, stronger for individuals with children.

On net, gains in the relative pay for women in the lower-paying industries offset any losses arising from gender sorting (i.e., women sorting into lower-paying industries) at the extensive margin, leading to an overall reduction in the gender pay gap. Nevertheless, the reduction comes

2. This is consistent with documented empirical facts in the recent literature. See, Card, Cardoso, and Kline 2016 and Barth, Kerr, and Olivetti 2017. It is also consistent with the empirical findings documenting a positive relationship between innovative investments and rent sharing with workers (Van Reenen 1996) and that rents can be disproportionately shared with male workers (Black & Strahan 2001; Kline et al. 2018).

3. See Appendix E for an analysis of the effects of credit contraction on the gender pay gap.

at the cost of increased sorting that polarizes gender imbalances across industries, and changes in gender norms that reflect such polarization. This transformation in gender inequities – rather than an unqualified decline in the pay gap – may have been a contributing factor to the slow progress in pay convergence between women and men after the 1980s.

Contribution to the Literature This paper furthers the understanding of the determinants of gender inequities and, in particular, the role of financial conditions on the evolution of gender inequities in the labor market. As such this paper contributes to several lines of research in labor economics and finance.

First, we contribute to research on what factors affect the persistent gap in pay between genders. Previous studies in this area emphasize one of several general hypotheses regarding the persistence of the gender pay gap: lack of temporal flexibility in the structure of jobs in the labor market (Goldin 2014), cultural differences that translate into differences in choices (Goldin, 2006), and gender differences in bargaining power (Babcock and Laschever, 2003). We propose an alternative channel that complements these mechanisms and highlight how gender inequities can transition across dimensions of the labor market.

Second, while previous literature has documented the differences in earnings between women and men over the life cycle (Barth Et Al. 2017; Goldin Et Al. 2017), the determinants that explain the relationship between gender sorting into particular firms, occupations, or industries, and lower pay are less understood. One approach to assess this relationship is to evaluate whether external conditions force women to sort into lower paying firms (e.g. flexible hours, Goldin 2014; home production, Albanesi and Olivetti 2009). Nevertheless, evidence also finds that job pay decreases synchronously with increased women participation (Levanon et al. 2009). This finding suggests that approaching the relationship between pay and gender sorting from the perspective of the employer may be informative: why female-dominated firms become lower paying? Our contribution advances this question by showing how credit conditions can exacerbate differences in pay across industries, and then how, along with other determinants like flexible hours, those differences in pay may lead to sorting across gender lines and the accentuation of gender norms.

Third, we contribute to the literature on the real effects of financial liberalization[4] by showing that credit liberalization propels changes in labor demand across industries and the size of the

4. See, for example, King and Levine (1993), Demirguc-Kunt and Maksimovic (1998), Rajan and Zingales (1998), Beck and Levine (2004), Jayaratne and Strahan (1996), Cetorelli and Strahan (2006), and Beck, Levine, and Levkov (2010).

gender pay gap within industries in a way that can influence industry gender composition and gender norms. In this regard, the paper closest to ours is Black and Strahan (2001), which shows that gender gaps narrow within the banking sector following banking deregulation as rents available for sharing with workers decrease with competition. However, our paper differs considerably as it focuses on the gendered labor dynamics triggered by differences in collateral when financial conditions change.

Fourth, by documenting an asset (as collateral) channel that drives inequality, we contribute to the literature on equitable finance that attempts to dissect the financial mechanisms that lead to economic redistribution (e.g., Beck, Levine, and Levkov 2010).

II. Data & Methodological Approach

Our goal is to evaluate how changes in credit conditions alter the cross-industry dynamics of the gender pay gap, and in particular, whether they differentially affected the pay gaps of industries by their (ex-ante) equitability. In other words, do changes in credit amplify preexisting equitability or inequitability within industries? To capture exogenous changes in credit conditions across industries, we exploit the temporal and spatial variation in U.S. bank deregulation. In this section, we first provide background on the U.S. bank deregulation and discuss how we categorize industries by their equitability. Then we explain the data and our empirical approach.

II.1 Intrastate and Interstate Banking Deregulation

The events and effects of U.S. bank deregulation during the 1970s–90s have been well documented starting with Jayaratne and Strahan 1996. There were two main sets of deregulation events in the banking industry.[5] The first one was the removal of restrictions on branching within states which largely happened between 1970 and 1994. In line with the literature, we refer to this event as intrastate bank deregulation or simply branch deregulation.

The other deregulation event was the removal of restrictions on cross-state ownership of banks.[6] Following the lead of Maine, states started allowing entry of out-of-state bank holding companies with legislative changes taking place from 1978 to 1992 for all states but Hawaii. As is standard in the literature, we henceforth refer to this event as interstate bank deregulation.

5. See, for example, Jayaratne and Strahan (1997).
6. The Douglass Amendment to the 1956 Bank Holding Company Act effectively prohibited bank holding companies from acquiring banks outside the states where their headquarters resided. This prohibition continued to be effective unless states actively allowed those acquisitions.

II.2 Industry Equitability Categorization

To proxy for each industry's preexisting equitability, we categorize industries by their pay gap levels in the first five years of CPS data (1976–1980, which is prior to our estimation sample period).[7] We categorize industries into high-, medium-, and low-pay-gap. The high-pay-gap industries are defined as the industries in the top quartile of the preperiod pay gap distribution using the 1990 Census Industry Codes (CIC). The low-pay-gap industries are those in the bottom quartile, and the medium-pay-gap industries are those in between. We discuss the stability of this categorization in Subsection II.5.

II.3 Data

Our main data comes from the March Supplement of the Current Population Survey (CPS) for years 1976–2014.[8] We restrict our sample to working-age full-time full-year workers in the private sector. To ensure that our estimates are not driven by industrial organization changes within the finance industry (Black & Strahan 2001), we exclude individuals working in the Finance, Insurance, and Real Estate (FIRE) industries. Our primary variable of interest is individual hourly wage.[9] The CPS also contains individual demographic information such as race, gender, and age, as well as individual and household-level information that allows us to explore other outcomes and potential mechanisms, including type of employer (public vs. private), occupation and industry, previous year occupation and industry, county/state of work, and educational attainment. The CPS contains probability sampling weights for each individual that indicate their representativeness in the population. We use these sampling weights in all our specifications.

We supplement the CPS data with the Compustat data to evaluate the effects of bank deregulation on firm R&D spending and measures of profitability per employee (to assess efficient use of labor). We also use the GSS data to construct indexes of sexism following Charles, Guryan, and Pan 2018, which are used to evaluate the effects of bank deregulation on changes in gender norms. We describe our empirical approach to test the effects of bank deregulation on gender norms in Section V.[10]

7. The estimation sample spans the years 1981 to 2014. The preperiod choice is driven by both data restrictions and the importance of the 1980s decade for understanding the evolution of the pay gap (Blau & Kahn, 2017).

8. We start the analysis in 1976 because states in the CPS data can only be identified separately starting in the 1977 survey (which cover data from 1976), similar to Beck, Levine, and Levkov (2010). In Appendix I.1, as a robustness, we conduct our analysis using an expanded dataset that starts in 1968.

9. We use the log transformation of this outcome as our dependent variable.

10. In Appendix Section E, we also evaluate vulnerability of women to contractions in credit, using data from the FDIC call reports on mergers.

II.4 Empirical Specification

We employ a generalized differences-in-differences design, exploiting cross-state, cross-year variation in the timing of intrastate and interstate banking deregulation, to estimate the causal effect of changes in credit conditions on the cross-industry dynamics of the gender pay gap. Specifically, we estimate the differential labor market outcomes for female workers relative to male workers across industries, by their preperiod equitability, in response to banking deregulation.

Let $\Omega = \{High, Medium, Low\}$ denote the classifications of industries into low-, medium-, and high-pay-gap industries based on the preperiod pay gap, and I_j^k is a dummy variable indicating whether industry j falls into classification $k \in \Omega$. The high- and low-pay-gap industries are defined as industries in the top and bottom 25%, respectively, of 1976–1980 gender pay gap using the 1990 Census Industry Codes (CIC). We provide more details on this classification scheme in the next subsection.

Our primary empirical specification takes the following form:

$$\begin{aligned} Y_{ijst} \quad = \quad & \alpha + \sum_{k\in\Omega} \beta_k D_{st} \times I_j^k + \sum_{k\in\Omega} \gamma_k D_{st} \times I_j^k \times F_i + \sum_{k\in\Omega} \delta_k I_j^k \times F_i \\ & + \sum_{k\in\Omega} \zeta_k I_j^k + \pi X_{ijst} + \tau_{t,female} + \mu_{s,female} + \epsilon_{ijst} \end{aligned} \tag{1}$$

where D_{st} is a dummy denoting whether deregulation has taken place in state s and year t, F_i indicates whether individual i is female, X_{ijst} is a vector of demographic controls including Mincerian traits (education, experience, experience squared), race, and marital status, and $\tau_{t,female}$ and $\mu_{s,female}$ are time-gender and state-gender fixed effects, respectively. Single order F_i term is absorbed by fixed effects.

II.5 Stability of Industry Equitability Categorization

Our empirical analysis has the embedded assumption that the rank of industries by equitability is stable prior to 1980. We conduct several analysis to test the stability of the equitability categorization. We note that legislative changes leading to interstate deregulation for all states took place after our categorization period (1976–1980), except for Maine which took place in 1978. However, about a third of intrastate deregulation changes happened before our categorization period, which raises the possibility that our industry categorization is contaminated by deregulation, specifically by intrastate deregulation. In Appendix A, we perform four tests to show that our choice of industry categorization is stable and not a result of our treatment. First, we repeat our interstate deregulation analysis excluding Maine. Second, we show that our categorization is not sensitive to dropping the seventeen states (Amel 1993) with intrastate (branch) deregulation prior to 1980. Third, we show that alternative categorization methods, including using the 1968–1972 CPS data, yields the same results.[11] Fourth, throughout all tables, we present results using both interstate and intrastate bank deregulation and show that the estimates are virtually identical.

II.6 Summary Statistics

Employment Summary Statistics. In Table (1.A), we present summary statistics on characteristics of male and female workers across all industries (columns 1 and 2) and in the low- and high-pay-gap industries separately (columns 3-6). Female labor force participation is visibly higher in the low-pay-gap industries at 41.9%, while the high-pay-gap industries have a larger female participation rate (38.3%) than the full sample average (34.9%). The differences in female participation between the low- and high-pay-gap industries are stable over time (Appendix Figure 5.A). Hourly wages are \$5.43 lower for women than for men in the high-pay-gap industries on average, but the difference is only \$0.99 in the low-pay-gap industries. This translates into a percentage difference of -33 and -8.5%, respectively. Overall, women earn \$3 dollars (22%) less than men for each hour of work. Years of education for women are similar across industry categories at around 13.4 years of schooling in both the high- and low-pay-gap industries. For men, workers in the high-pay-gap industries have an additional 1.4 years of schooling on average. Age of workers is similar across industries and across genders, ranging from 39.7 to 40.9 years of age. Experience is higher for men than for women by between 0.6 and 0.7 years across all industries.

The low-pay-gap and high-pay industries exhibit visible differences in their employment of hourly-paid positions, as shown in Appendix Figure (5.B). The low-pay-gap industries employed a higher fraction of hourly-paid positions (around 61% of their total employees), and the share decreased in the high-pay-gap industries between 1990 and 2014 (from 50% to 40%).[12] Moreover, the hourly-paid positions are held mostly by women in both industries, and a decline in hourly-paid positions in the high-pay-gap industries is attributed to men.

The two types of industries also exhibit different occupational needs. Using the occupational task measure developed by Autor, Levy, and Murnane 2003 from the *Dictionary of Occupational Titles* (DOT), we classify an occupation as routine, or nonroutine and cognitive, or manual. As shown in Appendix Figure (3.A), the high-pay-gap industries rely more on workers performing

11. We discuss the alternative methods and results in Appendix I.

12. We plot the fraction of hourly-paid positions by industry only during the period 1990–2014 because of data availability constraint.

nonroutine cognitive tasks, and their reliance increase steeply over time (left panel). In contrast, the low-pay-gap industries employ a higher fraction of workers to perform nonroutine manual tasks, and the share employed by the high-pay-gap industries steadily drops over time from more than 20% in 1980 to near 10% in 2014 (right panel). Lastly, there are no significant differences between the low and high-pay-gap industry in their reliance on routine jobs for either manual or cognitive tasks as shown in Appendix Figure (3.B). The share of routine task jobs declined in both industries over the sample period, with a more notable decreasing trend in the high-pay-gap industries. The declining trend may be attributed to the rise in computer technology, as routine tasks are more vulnerable to substitution by computers (Autor, Levy, and Murnane 2003). Overall, Appendix Figure (3) shows that the main difference in occupational need between the low- and high-pay-gap industries lies in their reliance on workers performing different types of nonroutine tasks.

Firm Summary Statistics. In Table (1.B), we present summary statistics on characteristics of public firms across all industries (column 1) and in the low- and high-pay-gap industries (column 2 and 3, respectively). Compared to firms in the high-pay-gap industries, firms in the low-pay-gap industries have slightly higher assets (a statistically insignificant difference of 3%), more workers, and higher revenues and income by worker. The high-pay-gap industries have lower book leverage (48 vs. 54%), higher Tobin's Q (1.09 vs. 0.92), and lower levels of tangibility (0.22 vs. 0.55) than the low-pay-gap industries.

We find that the low-pay-gap industries are more reliant on external financing and more capital intense than the high-pay-gap industries. We compute debt-to-asset ratios (for secured debt, debt notes, and long-term debts) and leverage by industries in Table (2). The low-pay-gap industries are consistently more reliant on debt than the high-pay-gap industries regardless of the debt instrument. The low-pay-gap industries are twice as likely to use secured debt, debt notes, and long-term debt than the high-pay-gap industries are, and their leverage is 7.4% higher. Furthermore, the low-pay-gap industries are more capital intense than the high-pay-gap industries throughout our estimation period. In Figure (1), we plot total assets, total plant and equipment, and total tangibility per employee by industries. Regardless of instruments, the low-pay-gap always exhibit higher capital intensity throughout the entire period than the high-pay-gap industries.

The difference in reliance on external financing and capital as well as employment needs across industries serve as an important ground for divergent industrial response following bank deregulation, which eventually leads to restructuring of labor market.

Industry Summary Statistics: Frontier Industries and the Pay Gap. Table 3 lists industries exhibiting the highest and lowest pay gaps (panel A) and the fastest and slowest growth (panel B). Overall, service-oriented industries exhibit the highest pay gaps, which include Legal services, Advertising, Accounting services, Physicians, and Dentists. Agricultural and Care industries exhibit more equitable pay. Pay gaps in Physicians and Dentists offices are mostly driven by high levels of occupational segregation, where women dominate care taking activities like nursing.

Table 3.B shows that the industries exhibiting the highest levels of growth in employment from 1980 to 2000 are the high-pay-gap industries. Among the top 10 fastest-growing industries, seven are in the high-pay-gap category (including Computer and Data Processing Systems and Management and Public Relations Services), and only one in the low-pay-gap category (Agricultural Chemicals). In contrast, the slowest growing industries exhibit no obvious differences in their pay gap level: four industries exhibit low pay gap while three exhibit high pay gap levels.

It is also the case that the high-pay-gap industries typically pay more than the low-pay-gap industries throughout the entire sample period (Figure 2.A). Compared to the low-pay-gap industries, average pay is around 21% higher in the high-pay-gap industries. Furthermore, that difference is driven almost exclusively by higher wages for men (Figure 2.A). Combined with observations from Table 3.B, the data suggest that women benefited less from industry growth. Relative to the low-pay-gap industries, the high-pay-gap industries exhibit significantly higher growth in both employment and pay during the sample period.

III. Credit Conditions and Gender Inequality

Table (4) presents the estimation results on the differential effects of banking deregulation on wages by gender in low-pay-gap and high-pay-gap industries based on Equation (1). Columns (1)–(4) show results on the effects of intrastate deregulation, and columns (5)–(8) show those on the effects of interstate deregulation. All specifications control for Mincerian traits (education, experience, experience squared), marital status, race, state-gender dummies and year-gender dummies. Columns (2)–(4) and (6)–(8) additionally control for age-gender dummies.

Our results show significant heterogeneity in the effects of banking deregulation on wages across industries and gender. While the overall wage across industries declined by 4% in response to (intrastate and interstate) banking deregulation on average, wage in high-pay-gap industries increased by 4% more than the average. In other words, wage for workers in the high-pay-gap industries increased by 8% relative to the medium- and low-pay-gap industries.

Zooming into the effects of banking deregulation on wages by gender across industries, we find significant differential effects between low-pay-gap and high-pay-gap industries. In low-pay-gap industries, relative wages for women increased by about 5% in response to banking deregulation, as the decrease in wages accrues mostly to men. As shown in Figure 7 Panel A, this relative increase took place immediately after deregulation. In contrast, female workers experienced no relative increase in their pay in high-pay-gap industries. These results indicate that bank deregulation improves wage parity between men and women only in lower-paying jobs.

These differential effects in pay by gender accrue to pre-banking deregulation wage differentials between low- and high-pay-gap industries by gender. For men, average pay is 21% higher in high-pay-gap than low-pay-gap industries, controlling for education and experience. The corresponding difference for women is only 7%.A similar stylized fact can be observed in Figure (2). When we incorporate the effects of bank deregulation, the difference in wage between high-pay-gap than low-pay-gap industries amplifies to 29% for men and 11% for women.

Balance & Pre-Trends Standard assumptions for difference-in-difference regressions require no significant difference between treatment and control groups and no pre-trends. We show there is balance, i.e., observable characteristics are similar treatment and control groups to mitigate concerns that unobservable characteristics are driving the results, and no pre-trend.

We provide corroborating evidence that our research strategy approximates an “apples-to-apples” comparison in which we should be less concerned about unobservable institutional differences confounding our estimation. Appendix Figure (B.1) presents differences in average state characteristics for states with bank deregulation just before it passed against states where deregulation has not passed and will not pass within the following year. Panel A provides estimates for intrastate deregulation while Panel B does the same for interstate deregulation. These differences in average state characteristics provide evidence regarding the use of our design. Most average characteristics are not different at the five percent level and are economically small in magnitude and precise.

The characteristic that varies the most in our sample is the percentage of the workforce that is black. States deregulating intrastate branching have on average 0.6% more black workers (the average total is 6%), while states deregulating intrastate branching have 0.006% fewer black workers (the average total is 7.5%). Both estimates are highly imprecise. Percentage of nonroutine manual workers is the most different between deregulating and nonderegulating states with a difference of 1.5% for intrastate deregulation (average total is 26.5%) and 2.1% for interstate deregulation (average total is 26.4%).

We can indirectly assess the parallel-trends identifying assumption in a few ways. First, we can examine preperiod trend differences. Appendix Figure (B.2) provides such first piece of evidence in support of our assumption of parallel trends. The figure presents differences in average state yearly trends for states with bank deregulation just before it passed against states where deregulation has not passed and will not pass within the following year, across a wide range of characteristics. As before, Panel A provides estimates for intrastate deregulation while Panel B does the same for interstate deregulation. All average trends are not different at the five percent level and are economically small in magnitude and precise, including percentage of black workers and percentage of nonroutine manual workers.

An alternative way to provide supporting evidence in favor of the parallel-trends assumption is by observing the behavior of outcomes of interest around deregulation years in an event study. To this end, Figure (3) plots the raw likelihood of working in the high- and low-pay-gap industries by gender between 10 years prior and 10 years after intrastate deregulation. The likelihood is computed by assigning -1 to workers in the low-pay-gap industries, 1 to workers in the high-pay-gap industries, and 0 otherwise, and taking the average of the indicators by gender in each period using CPS data.

It is not clear whether reduction in wage gap reduces overall wage gap due to sorting, which we address in the next section. To this end, we perform two simple Oaxaca-Blinder decompositions, shown in Appendix Section D and show that intensive margin effects dominate.

IV. The Role of Assets

In this section, we show that asset tangibility serves as a key force driving the relationship between credit conditions and gender inequality.

IV.1 Asset Tangibility and Gender Pay Gap: Overview and Hypotheses

We first document a new stylized fact on the relationship between asset tangibility and gender pay gap. In Panel A of Figure (1), we plot asset tangibility per employee for low-pay-gap and high-pay-gap industries, where the pay gap level is categorized using the CPS data between 1976 and 1980 as in Section II.3. As shown, more equitable industries tend to have a significantly higher share of tangible assets. Conversely, more inequitable industries have a higher share of intangible assets. This empirical pattern holds not only on a per worker basis but also as a share of total assets (Panel B of Table 1). Relatedly, we observe that high-pay-gap industries have more physical assets and lower total asset on a per worker basis than low-pay-gap industries (Panel B and C of Figure 1). Overall, the observe relationship between asset tangibility and gender pay gap suggests that low-pay-gap industries are less capital intensive.

How does asset tangibility drive the effects of banking deregulation on gender inequality? First, the tangibility of assets affects firm borrowing. Second, differences in firm borrowing lead to differential investment decisions and demand for workers. Third, imbalances in demand for workers across genders lead to differential effects on gender pay gap in high-asset-tangibility and low-asset-tangibility industries.

Asset Tangibility and Firm Borrowing. The tangibility of assets affects firm borrowing because high- and low-tangible assets differ in debt capacity. Williamson (1988) and Shleifer and Vishny (1992) stress the importance of asset redeployability, or asset's potential for alternative uses, for debt capacity. In case default occurs, assets can be seized by creditors and redeployed, increasing the value available to creditors. This reasoning is particularly relevant for tangible assets. Tangible assets can sustain more external financing by increasing the value available to creditors when default occurs (Almeida & Campello 2007). On the other hand, intangible assets, which can be, for example, in the form of R&D or brand name, contain limited capacity for pledgeability as collateral, even though they can provide the firm with a competitive edge (Lev 2001).

Given the differences in pledgeability between tangible and intangible assets, bank deregulation could lead to differential firm borrowing behavior between high-asset-tangibility and low-asset-tangibility industries. While bank deregulation increases access to credit in general, we conjecture that it has a greater effect on borrowing in industries with more tangible assets (i.e., industries with a lower pay gap), as the higher pledgeability of tangible asset enhances borrowing capacity. On the other hand, borrowing in industries with more intangible assets (i.e., industries with a higher pay gap) may not be affected as much, as intangible assets are harder to post as collateral.

Hypothesis 1: *In response to bank deregulation, low-pay-gap industries, which have a higher share of tangible assets, are more likely to increase firm borrowing, while borrowing in high-pay-gap industries, which have a lower share of tangible assets, is likely to remain unaffected.*

From Firm Borrowing to Asset Composition and Labor Decisions. Differences in firm borrowing in response to banking deregulation could have divergent effects on investment and labor decisions. The relaxation of financial constraints following deregulation allows firms to dig into an untapped pool of positive NPV projects. While bank deregulation relaxes financial constraints in general, it has a stronger impact on investment in tangible assets, as tangible assets can be collateralized.[13] This investment is likely to increase demand for labor in industries in which financial constraints are relaxed more—the low-pay-gap industries with higher share of tangible assets prior to deregulation.

Hypothesis 2a: *The low-pay-gap industries, because of their higher share of tangible assets (which help to relax financial constraints more following bank deregulation), are more likely to increase investment in tangible assets and increase labor demand.*

The increase in labor demand in industries with more tangible assets exerts upward pressure on wages. For industries with more intangible assets, the increase in wage puts mildly positive NPV projects (the marginal projects) into negative territory, which should prompt them to relinquish these projects—a *downscale-to-quality* mechanism. In this case, the average revenue per employee and the average wage in low-asset-tangibility industries should increase. Conversely, the average revenue per employee is expected to decline in high-asset-tangibility industries, as they take on more positive (but lower and more marginal) NPV projects.[14] In search for higher NPV projects, the low-asset-tangibility industries are likely to substitute into more intangible investment, such as R&D, which would face less competition from high-asset-tangibility industries.

Hypothesis 2b: *In high-pay-gap industries with more intangible assets, average revenue per employee is expected to increase, and firms are more likely to substitute into investing in R&D. In low-pay-gap industries, the average revenue per employee is expected to decline, as they take on more positive (but lower) NPV projects.*

13. For example, in a car purchase, the car itself can be used as a collateral, which relaxes the financial constraint for that investment.

14. The reason for the increase (decrease) in average revenue per employee in low-asset-tangibility (high-asset-tangibility) industries can be elucidated through a simple example. Consider two projects, Project 1 and Project 2. The revenue before wage for Project 1 and 2 is 100 and 50, respectively, and each requires one employee. If wage moves from 49 to 51, only the first project will be taken. The average revenue would increase from 75 to 100. This scenario corresponds to the expected effect in low-asset-tangibility industries in our context. Conversely, if a firm initially invests in the first project and wage goes down from 51 to 49, it will take on the second project, which drags down its average revenue. This scenario corresponds to the expected effect in high-asset-tangibility industries in our context.

From Labor Decisions to the Gender Pay Gap. How do these asset composition and labor decisions affect the gender pay gap? The effect stems from the optimal hiring decisions by the low-pay-gap (or high-asset-tangibility) industries whose demand for labor has increased because of banking deregulation. In particular, we argue that any potential gender imbalance in hiring decisions by the high-pay-gap (or low-asset-tangibility) industries would affect hiring in low-pay-gap industries. In the following, we discuss the mechanisms through an illustrative example. In Appendix A, we formalize the argument in a model.

Consider two types of employers: high-pay employers who can pay high wages (e.g., Amazon) and low-pay employers who can't (e.g., the Washington Post), all else equal. In our context, the high-pay employers correspond to firms in the low-asset-tangibility or high-pay-gap industries, and the low-pay employers correspond to firms in the high-asset-tangibility or low-pay-gap industries: As shown in Figure (2a), wages in the high-pay-gap industries are 3% higher than those in the median-pay-gap industries during the sample period of 1980–2000, while wages in the low-pay-gap industries pay workers wages are 18% lower than the average wage. There are two potential gendered hiring approaches: employers who hire based on employee skill and, by optimizing skills, statistically discriminate against a particular group (statistical discrimination), and employers who hire employees strictly based on taste on gender (taste discrimination). When the low-pay employers look to hire an employee based on a specific skill, e.g., writing, it can choose between two sets of employees. Both sets have similar writing skills but one has superior computer science skills. The optimal choice for the low-pay employer is to hire the employee from the group with less adequate computer science skills. (Why? Otherwise, they would have to pay the reservation wage for a computer scientist.) If it is the case that there is a gender imbalance in the employee pool for high-pay employers, then the low-pay employer would necessarily have the reverse gender imbalance through a *reverse statistical discrimination* mechanism. An alternative gendered hiring practice is when the employers have particular taste about the gender of the employee. When the high-pay employer taste-discriminates against one gender, it is optimal for the low-pay employer to hire from the employee group that is taste-discriminated against—a *reverse taste discrimination* mechanism.

We do not take a stance on whether high-pay employers statistically or taste discriminate. What we are arguing is that if either is the case, reverse discriminatory practices would be optimal for the low-pay employers. This argument is broadly related to Arrow (1973).

Based on these mechanisms, the low-pay-gap industries in our context would hire more from the employee group that is discriminated against by the high-pay-gap industries. If the high-pay-gap industries statistically or taste discriminate against women, then it is optimal for the low-pay-gap industry to hire women over men. This leads to an increased demand for women that puts upward pressure on women's relative wages.

Hypothesis 3: *Following bank deregulation, the relative wage for women would increase in low-pay-gap industries, as their labor demand for women increases relative to high-pay-gap industries.*

IV.2 Firm Borrowing

We first test whether banking deregulation differentially affected firm borrowing between low-pay-gap (or high-asset-tangibility) and high-pay-gap (or low-asset-tangibility) industries (Hypothesis 1). Specifically, we examine the effects on firm overall debt growth, long-term debt growth, and debt ratio. Table (5) shows the results on the effects of bank deregulation on firm borrowing changes for industries that had higher or lower gender pay gap prior to deregulation, as specified in Equation (1).

The results show that both debt and long-term debt increased in the low-pay-gap industries in response to deregulation. Specifically, intrastate deregulation increased overall debt and long-term debt growth by 5 log points in these industries. On the other hand, there was no significant growth in debt in the high-pay-gap industries, but their debt ratio declined, which suggests that non-debt financing increased in these industries.

Overall, the results are consistent with our hypothesis. Low-pay-gap industries, which have more tangible assets prior to deregulation, increase borrowing in response to deregulation and the resulting relaxation of financial constraints, as the higher pledgeability of tangible assets enhances their borrowing capacity. On the other hand, high-pay-industries, which have more intangible assets prior to deregulation, do not significantly change their borrowing, as intangible assets are harder to post as collateral.

IV.3 Firm Asset Composition and Labor Decisions

Next we proceed to test whether banking deregulation differentially affected firm asset composition and labor decisions between low-pay-gap and high-pay-gap industries.

Asset Composition. First, we examine how deregulation affected tangible asset composition, as measured by the share of tangible assets, in the two types of industries (Hypothesis 2a). Columns (1)–(3) in Table (6) show the results. Industries with low pay gap prior to deregulation significantly increased their relative investment in tangible assets. Specifically, intrastate and interstate deregulation increased their relative investment in tangible assets by 2 log points. On the other hand, high-pay-gap industries did not significantly change their tangible asset composition.

These results support our hypothesis. Banking deregulation is expected to relax financial constraints more for low-pay-gap industries because they have more tangible assets prior to deregulation, which can be collateralized. Additional investment in tangible assets are easier to make because these assets can be collateralized as well. Therefore, low-pay-gap industries increase their relative investment in tangible assets in response to deregulation.

Labor Demand. This increase in relative investment by low-pay-gap industries is likely to increase their relative demand for labor. To examine whether that is the case, we plot the difference in labor share between the high-pay-gap and low-pay-gap industries before and after banking deregulation, as illustrated by the solid black line in Figure (3). Recall that the high-pay-gap and low-pay-gap industries are categorized based on whether their pay gap falls in the top and bottom quartile, respectively, of the pay gap distribution from 1976 to 1980. In other words, by construction, the share of labor in the high-pay-gap and low-pay-gap industries each makes up 25% of total labor market at the period of construction. Thus, the difference in labor share between high-pay-gap and low-pay-gap industries is roughly zero before deregulation, as shown by the solid black line. In the years after deregulation, the difference in labor share between high-pay-gap and low-pay-gap industries turned negative, which indicates a change in labor demand towards to low-pay-gap industries and away from high-pay-gap industries.

We complement this empirical finding on the change in labor demand at the extensive margin with within-firm estimations using Compustat data. Columns (1)–(3) of Table (7) show results from estimations of the differential effects of banking deregulation on firm employment between high-pay-gap and low-pay-gap industries. Based on the estimates in column (3), employment in low-pay-gap industries increased by 7 log points (relative to the omitted medium-pay-gap industries) in response to banking deregulation, controlling for firm and state-year fixed effects and firm controls. On the other hand, employment in high-pay-gap industries decreased by 4 log points, although this estimate is not statistically significant. These estimates are robust to alternative specifications (columns 1 and 2).

Project Composition. Next, we test whether banking deregulation differentially affects average revenue per employee between high-pay-gap and low-pay-gap industries (Hypothesis 2b). The increase in labor demand in low-pay-gap industries exerts upward pressure on wage, which should change the composition of projects that are undertaken by both types of industries, as we explained in Section IV.1. We test for this effect, and the results are shown in columns (4)–(6) in Table (7). The results in column (6) indicate that relative revenue per employee increased by 13 log points in the high-pay-gap industries in response to banking regulation, controlling for firm and state-year fixed effects and firm controls. This result is consistent with the idea that high-pay-industries relinquish marginal projects when the marginal cost exceeds marginal revenue (downscale-to-quality), increasing the average revenue per employee. In contrast, relative revenue per employee declined in the low-pay-gap industries in response to banking regulation, as relaxation of financial constraint allows them to undertake additional lower positive NPV projects. Based on the estimates in column (4), revenue per employee in the low-pay-gap industries declined by more than 12 log points relative to the medium-pay-gap industries following deregulation, which implies a total decline of 17 log points (as revenue per employee decreased by 5 log points on average across industries). Most of the relative decline goes away with the inclusion of firm controls (column 6), which implies that revenues per employee declined by at least 5 log points in the low-pay-gap industries, just as in the medium-pay-gap industries.

Revenue per employee proxies for surplus absorbed by all stakeholders of the firm, including creditors, employees, and the employer itself. We devise an approach to decompose the total surplus into components absorbed by the employers, the employees, or others such as creditors. We first remove potential surplus absorbed by the creditors by dropping non-operating expenses from revenue. This corresponds to testing for the differential effects of banking deregulation on net income + operating expense per employee between high-pay-gap and low-pay-gap industries. Net income captures the surplus absorbed by the employers and does not include wages, while operating expense is driven in large part by wages—the surplus absorbed by employees. Next, we focus on net income solely as the dependent variable, or surplus solely absorbed by employers.

Columns (7)–(9) of Table (7) show the results on net income + operating expense per employee, and columns (10)–(12) show those on net income alone. First notice that estimates using net income + operating expense per employee as the dependent variable are similar to those using revenue per employee. This suggests that the results on revenue per employee are not driven by changes in credit conditions such as interest rates. Based on the results in column (9), net income + operation expense increased by 13 log points in response to banking deregulation, which is the same as the estimate on revenue (column 6). At the same time, net come per employee increased by a lower amount (9 log points, based on column 12). This means that operating expenses, including wages, are absorbing part of the effects. The differences in outcomes between the two sets of results proxy the change in surplus absorbed by the employees. Taken together, our results show that the relative increase in revenues absorbed by workers in high-pay-gap industries is around 4 log points. On the other hand, the net relative loss for low-pay-gap industries is around -4 log points.

We compare the estimates on the relative changes in revenue absorbed by workers to those on wages from Table (4). The two sets of estimates are of the same magnitude. As shown in Table (4), banking deregulation increased (decreased) the absolute wages in the high-pay-gap (low-pay-gap) industries by 4 log points, the same as our estimates on relative increase (decrease) in revenues absorbed by workers in the two industries. We also study the increase in absolute wages using an event study version of Eq. (1) following Borusyak & Jaravel (2017). As illustrated in Figure (4) Panel B, absolute wages in the high-pay-gap industries sharply increased after deregulation, while pre-trends are statistically indistinguishable from zero.

Project Substitution. As the high-pay-gap industries relinquish marginal projects, it is likely that they substitute into more intangible investments such as R&D, where there is less labor competition from low-pay-gap industries. We test the differential effects of banking deregulation on R&D investment for low-pay-gap and high-pay-gap industries. The results are shown in columns (4)–(6) of Table (6). Based on the estimates in column (4), R&D spending in high-gender-pay-gap industries increased by 31 log points more than other industries following banking deregulation. This difference is driven in part by a reduction in R&D spending in low- and medium-gender-pay-gap industries.[15] The results are robust to the inclusion of state×year fixed effects and firm controls.

IV.4 Gender Pay Gap

Differences in asset composition and labor decisions in the two types of industries will affect gender pay gap if there is differential hiring decisions by gender in either industry, as we explained in Section IV.1. To explore whether there is differential hiring practices by gender, we first examine the difference in labor share between the high-pay-gap and low-pay-gap industries for women and men before and after banking deregulation, as illustrated by the dotted red and blue lines, respectively, in Figure 3. The data shows that there was a sharp transition from high-pay-gap to low-pay-gap

15. The reduction is consistent with the findings in Chava et al. (2013), who document a decline in innovation following intrastate deregulation.

industries for women in the years after deregulation. While some men also transitioned towards the low-pay-gap industries immediately after deregulation, the extent of the transition is more muted, and men are equally represented in both types of industries in the subsequent years. This evidence suggests gendered differences in hiring decisions in the high-pay-gap and low-pay-gap industries in response to a change in credit condition.

To further confirm differences in hiring decisions by gender between the two types of industries, we estimate the effects of bank deregulation on the probability of transitioning from low-pay-gap to high-pay-gap industries, or vice versa. The results are shown in columns (1)–(2) and columns (5)–(6) in Table (8). We measure industry-to-industry transition using a dummy variable that takes the value 1 for individuals who moved from a low-pay-gap to a high-pay-gap industry and vice versa during the previous year, and 0 otherwise. A negative estimate means that workers are more likely to stay in the same industry, and a positive estimate means that they are more likely to transition. The results show that high-pay-gap industries are more likely to retain workers than medium-pay-gap industries by 5 log points following deregulation on average, while low-pay-gap industries are more likely to lose workers by about 7 log points. However, this pattern reverses when we zoom in on women. Relative to men, women are more likely to remain in low-pay-gap industries by 6 log points and more likely to leave high-pay-gap industries by 4 log points.

In the presence of differential hiring patterns between men and women in high-pay-gap industries, low-pay-gap industries should compete more for female workers than male workers, which would exert an upward pressure on the relative wage for women in the low-pay-gap industries. As we discussed in Section III and shown in Table (4), relative wages for women increased by about 5% in low-pay-gap industries in response to banking deregulation, while there was no significant change in their pay in high-pay-gap industries.

To further confirm that the change in relative wage for women is driven by differential hiring patterns in the two types of industries, we separately estimate Equation (1) for workers in occupations with low or high risk of cross-industry transition. For occupations with high risk of cross-industry transition, banking deregulation should have a stronger effect on worker wage, as increases in worker demand are more likely to spillover from industry to industry. We categorize the risk of transition for each occupation by the rate at which workers switch from low into high-pay-gap industries or vice versa. Occupations with switching rate less than the median are categorized as low-transition-risk occupations, and those with above median switching rate are categorized as high-transition-risk industries. The results are shown in Table (9). Columns (1)–(2) and (5)–(6)

show the effects of intrastate and interstate deregulation, respectively, for workers in occupations with low risk of transitioning, and columns (3)–(4) and (7)–(8) show estimates for workers in occupations with high risk of transitioning. In low-pay-gap industries, relative wages for women with low-transition-risk occupations risk increase by about 1–2% after deregulation but this increase is not statistically significant. However, for women with high-transition-risk occupations, relative wages significantly increase by 4–5%. The result that the relative increase in women's wage is concentrated in high-transition-risk occupations support the idea that differential hiring patterns across industries is driving result.

Furthermore, we evaluate how much compensation it takes to lure workers from high-pay-gap to low-pay-gap industries. As shown in columns (4)–(6) of Table (8), it takes an additional 5–6% increase in wages to lure a male worker from a high-pay-gap to a low-pay-gap following deregulation. For women, it takes only about 1–2%. In total, luring a male worker from a high-pay-gap to a low-pay-gap industry would require an increase of 10–12%, while for women it takes only 1–3%.

To summarize, we have shown that asset tangibility drive the effects of banking deregulation on gender inequality by (i) affecting firm borrowing differentially across industries, (ii) leading to differential changes in investment decisions and demand for workers, and (iii) creating imbalances in demand for workers across genders, which results in differential effects on gender pay gap in high-asset-tangibility and low-asset-tangibility industries.

IV.5 Robustness

In this subsection, we conduct three main sets of robustness analyses. We evaluate (i) potential alternative mechanisms driving our main results on the effects of banking deregulation on gender pay gap across industries; (ii) results based on alternative ways of categorizing industries, including by asset tangibility; and (iii) additional robustness tests controlling for industry-level characteristics.

Alternative Mechanisms. Supply-side channels may contribute to our main results on the differential effects of bank deregulation on gender pay gap in low-pay-gap and high-pay-gap industries as well as the results on differential industry transitions between women and men. To examine whether that is the case, we perform a series of analyses.

First, we account for composition changes in the labor force by controlling for Mincerian traits $\times$ gender (education-gender, experience-gender, and experience^2-gender) in all our specifications, following the standard practice in the literature.

Second, we examine whether changes in wages are consistent with a change in demand for workers or a change in worker supply. For example, if there is a supply-side shift in preference toward a particular industry by one gender, then the relative wages for workers of that gender should decline; in contrast, if there is an increase in the demand for workers by a particular industry, wages in that industry should increase. Our results from Table (4) and Table (8) show that relative wages for women increases in the low-pay-gap industries while more women transition towards these industries. Taken together, these results suggest that it is unlikely that differential industry transitions and changes in wages are driven by supply-side forces.

Third, we analyze whether credit expansion from bank deregulation differentially affected labor participation between women and men, which could affect their relative wages. As bank deregulation may change household lending, are banks lending disproportionately more to borrowers of a particular gender and thus generating differences in the labor participation patterns between these two groups? We test this question by examining whether bank deregulation differentially affected labor market participation of one gender group by improving its (i) housing outcomes (residential choices allow moving into opportunity), (ii) transportation outcomes (easier commute allows better job prospects), and (iii) self-employment opportunities.

In Appendix Tables (G.5) and (G.6), we evaluate the differential effects of intrastate and interstate deregulation, respectively, on housing and transportation outcomes using the CPS and Census data. In columns (1), (2), and (3), we evaluate the effect of deregulation on home ownership, likelihood of moving into a different residence, and likelihood of holding a mortgage, respectively. Panels A, B, and C report results for workers in all industries, low-pay-gap industries, and high-pay-gap industries, respectively. The coefficient of interest is $Deregulation \times Female$. For all three housing outcome measures across all three panels, estimates are economically small and statistically indistinguishable from zero, which show that residential choices of female workers are not differentially affected by credit expansion from bank deregulation. In columns (4)–(5), we conduct a similar analysis focusing on car ownership and transportation time to work (in minutes) as measures of work commute. For all three panels, estimates of the coefficient of interest are economically small and statistically insignificant, which indicate that transportation outcomes were not affected in a gendered way by deregulation. These two sets of results suggest that differential access to credit between men and women is unlikely to drive our main results.

In Appendix Table (G.7), we show results on the effects of deregulation on self-employment incorporated rates (columns 1-3), self-employment unincoporated rates (columns 4-6), and incorporation rates conditional on self-employment (columns 7-9). Panel A reports estimates using intrastate deregulation, while Panel B shows results using interstate deregulation. The coefficient of interest is again $Deregulation \times Female$. In Panel A, we find that the effects of intrastate bank deregulation on self-employment measures by gender are not statistically significant or economically meaningful for any of the measures of self-employment. However, in Panel B we see that the effects of interstate bank deregulation are statistically significant and larger for workers in low-pay-gap industries (around 1% increase). Nevertheless, we do not believe the effects of interstate deregulation on self-employed incorporated rates by gender contribute to our main results in Table (4) for two reasons. First, the estimates in Table (4) are nearly identical for intrastate and interstate deregulation. If differential self-employment incorporated were a first-order driver of the main results, the effects on self-employment incorporated intrastate and interstate deregulation should be similar, but they are not. Moreover, the effects of deregulation on self-employment incorporated are close to zero for intrastate deregulation. Second, the difference in the estimates of interstate bank deregulation on self-employment incorporated by gender between the low-pay-gap and high-pay-gap industries are small in magnitude. If differential self-employment incorporated were a main driver of the main results, it must be the case that self-employment incorporated affects the main results differently in low-pay-gap and high-pay-gap industries.

A limitation of our analysis is that we cannot observe whether credit relaxation helped individuals to invest in their skills in a gendered way, which could then affect differences in industrial-occupational choice across genders in a way that does not require divergent industrial responses. Nevertheless, there are two pieces of indirect evidence challenge this conjecture. First, the initial changes in hiring patterns and relative wages in low-pay-gap industries were sharp (Figure **??**). This is inconsistent with the conjecture of finance propelling gendered-differences in skill investments as a main explanation for our results, as investments in skills tend to occur with a time lag. This, of course, does not preclude the possibility that finance-propelled gendered investments in skills is a complementary mechanism to the main mechanism put forward in this paper. Second, we will show in the next subsection that repeating the analysis of Table (4) by worker skills yields similar results, suggesting that the results stem from changes in wage premia for specific tasks rather than occupational upgrading or downgrading due to gendered changes in skill.

Alternative Categorizations In section IV.1, we showed that there is a close relationship between gender pay gap and industries' asset tangibility. Since this is a study on the transformation of gender inequities, conceptually, we have decided to focus on divergent industrial responses to deregulation along their preexisting gender pay gap levels. We should expect our results to be robust to categorizing industries by asset tangibility. In the following, we show that our main results hold if we categorize industries by asset tangibility.

Appendix Table (I.10) shows estimates from Equation (1) categorizing industries by low and high levels of asset tangibility instead of by pre-existing gender pay gap levels. We document that, following deregulation, wages increased in low-tangibility industries (analogous to high-pay-gap industries) while wages at high-tangibility industries (analogous to low-pay-gap industries), and overall wages went down. Our analysis controls for county and year fixed effects as well as for Mincerian traits. Following deregulation, wages for workers in low-tangibility-industries increased by around 5–7% relative to other industries. This wage increase in low-tangibility industries is of similar magnitude to the estimates documented using our preferred categorization by preexisting pay gap levels. Changes in relative wages for women using this categorization also yields estimates similar to the ones documented in the main results. In high-tangibility industries (analogous to low-pay-gap industries), female relative wages increased by around 3–5%. In Appendix Table (J.11), we show that the results on the effects of bank deregulation on firm borrowing are also robust to categorizing industries by low and high levels of asset tangibility.

Other Industry-Level Robustness We could think that fixed industrial characteristics differentially affect men and women in a way that is not triggered by deregulation. In particular, we might think that the riskiness of an industry (proxied by earnings volatility or leverage) or the availability of growth opportunities (proxied by Tobins' q) might explain the relative changes in wages for men and women. In Appendix Table (H.8) we show that the inclusion of these industry level characteristics (duly interacted with a female dummy indicator) does not change our main results.

V. Downstream Effects: Shaping Gender Norms

We have shown that credit expansions, through gendered labor market dynamics, lead to gender differences in pay and in sorting across industries. In this section, we test whether these differences changes views on gender norms.

Papers have pointed out that gender norms may lower women's wages and their labor market participation (Charles, Guryan, and Pan 2018) and affect women's career choices (Crawford and MacLeod 1990; Ceci, Williams, and Barnett 2009; Bottia et al. 2015). Conversely, differences in sorting and opportunity cost, real and perceived, could create ripe conditions for the creation and reinforcement of gender norms. Workers, spouses, and observers may interpret the gender differences in pay and in sorting we document through gendered lens and assume biased views, or validate previously formed ones, on women and their role in the workplace. For example, they may regard women as less suitable for some jobs, as having a comparative advantage for staying at home, or that their careers should be subordinated to those of their husband's. We test for such changes in views using data from the GSS.

V.1 Empirical Specification and Variable Measures

Specifically, we conjecture that the effects of credit expansion on gender norms are more pronounced in places geared towards having a bimodal industrial structure with a higher concentration of both the low-pay-gap and high-pay gap industries, rather than nonbimodal industrial structures, e.g., industrial structures with only one type of industry. The gendered dynamics we document should be more pronounced in a bimodal industrial structure because it allows more opportunities to switch between the low-pay-gap and high-pay gap industries.

To test our hypothesis on the effects of credit expansion on gender norms about the workplace, we estimate the following specification using the GSS:

$$Sexism_{irt} = \alpha + \beta_1 Spread_r \times DP_{rt} + \beta_2 DP_{rt} + \delta_r + \gamma_t + \varepsilon_{irt} \tag{2}$$

where $Sexism$ is a measure of workplace sexism, $Spread$ is a measure of the spread (or degree of polarization) of available industrial choices for a worker, DP is a measure of credit expansion, or changes in bank deregulation changes, adapted for the geographic design of the GSS, and δ_r and γ_t denote year and region fixed effects, respectively. The coefficient of interest is β_1.

Measure of Workplace Sexism. We adopt a measure of workplace sexism following Charles, Guryan, and Pan 2018. The GSS asks its respondents about their attitudes on women's role in the workplace, family, and society. We focus on responses to the three questions pertaining to beliefs about the role of women in the workplace: "Should women work?"; "Wife should help husbands career first."; "Better for man to work, women tend home." Respondents either approve/agree or disapprove/disagree with a given statement. For each question, we assign a value of one when the response reflects biased views against women and zero otherwise. To generate a standardized measure of sexism in the workplace, we then subtract individual responses to each question by the average response of entire population in 1977, a pre-treatment period, and divide it by the standard deviation of the initial response of the entire population in 1977, following Charles, Guryan, and Pan 2018. The standardized measure reflects where each individual belief stands in the spectrum of workplace sexism relative to the pre-treatment average.

Measure of Industrial Spread. We hypothesize that credit affects gender norms through the gendered labor market dynamics we document and the resulting gendered sorting across the high- and low-pay-gap industries. Through this mechanism, the public's views on gender roles should be affected more acutely in areas where gendered industrial composition is more pronounced and sorting is most likely to occur. When industrial composition in an area is characterized by a fifty-fifty split between jobs in the low-pay-gap and jobs in the high-pay-gap industries, the differential opportunity cost of choosing an industry over another between men and women is at its highest. By comparison, when areas are dominated by a single type of industry, the differential opportunity cost must, trivially, be zero, as there is no de facto choice to be made. In short, higher industrial spread accentuates the dynamics of sorting, and lower industrial spread mitigates them. We proceed to formalize this notion in a measure that quantifies the degree of industrial spread within a geographic area.

To measure the spread of industries in terms of pay gap, we classify each industry by the distance of its pay gap to the median-pay-gap industry. If it belongs to the top 25th percentile in terms of pay gap, i.e., the high-pay-gap industries, it is assigned a value of 1. If it belongs to the bottom 25th percentile, it is assigned a value of -1. Industries between the 25th and 75th percentiles, the median-pay-gap industries, are given a value of 0. The discrete values in each category represent the distance to the middle so that we can express the spread between industries as a composite of distances between any two industries. For any two industries, the longest possible distance is 2. The spread is the expected value over pairwise combinations of workers. By taking the expected value, the largest possible spread is normalized to be 1.

Formally, for every worker in a region, the overall industrial spread is the average pairwise distance between the industries of every two workers in a given region g:

$$Spread_g = \frac{1}{N^2} * \sum_{\forall i,j \in g}^{N} |x_i - x_j|, \tag{3}$$

where $x_i \in \{-1, 0, 1\}$ is the value of the industry to which worker i belongs, and N is the number of workers in region g.

The larger the spread is, the more margin for gendered dynamics to occur, which would lead to an environment more susceptible to the creation and reinforcement of gender norms.

Measure of Deregulation Penetration. GSS public data reports geographic affiliation of interviewee only at the region level. It divides nation into nine different regions. Since bank deregulation changes occur at the state-level, we construct a penetration measure for each region-year to capture the proportion of the population affected by the new regulatory framework. This is, penetration refers to the proportion of individuals in region r affected by bank deregulation for each year t. Deregulation Penetration (DP) is defined as follows:

$$DP_{rt} = \sum_{s \in r} D_{st} * \frac{pop_{st}}{pop_{rt}} \tag{4}$$

where pop_{st} denotes the population count living in state s in year t, pop_{rt} denotes the total population living in region r in year t, and, as before, D_{st} is a dummy variable indicating that deregulation had taken place before time t. We use this measure as our treatment variable for credit expansion.

V.2 Effects of Deregulation on Gender Norms

We report the results in Table (10). We find that, following credit expansion, gender bias increases in areas with a higher degree of industrial spread between the high- and low-pay-gap industries, and this increase is driven mostly by men and households with children. In column (1), we find that following deregulation, workplace sexism in areas with industrial spread of 1, or a fully polarized geographical area, increased by 2.71 standard deviations relative to an area with an industrial spread of 0, or no polarization, based on our index of workplace sexism. The average industrial spread in our sample is 0.75. This effect is greater for households with children (an increase of 3.27 standard deviations for areas with industrial spread of 1, as shown in column 2). Both estimates are large and statistically significant. One explanation for the stronger effects among people with children involves differential opportunity costs. As we previously document, the differences in earnings between the high-pay-gap and low-pay-gap industries are larger for men than for women and increase following deregulation. This means that the opportunity cost of staying at home also increases for men in places with the highest industrial spread, making households with children more likely to support gendered views about the workplace.

We also run our analysis separately for men and women in columns (3)–(6) and (7)–(10), respectively. In particular, we zoom in on the responses to individual questions on workplace sexism in the survey in columns (4)–(6) and (8)–(10). We find that men are driving the main overall effect. Men are more likely to hold the views that women should not work, prioritize their husband's career, or stay at home. For men, coefficients in each of the individual questions are large, statistically significant, and similar across questions. Among women, the results across the three questions on workplace sexism are more varied, revealing more complex views about the role of women in the workplace. Based on the results on the overall index of workplace sexism, we find that women's views on gender norms did not exhibit a statistically significant change following deregulation (albeit the coefficient is still positive). Overall, the results indicate that gender norms about women in the workplace are mostly driven by males, and such views accentuated among male workers following the credit expansion.

VI. Conclusion

This paper proposes an asset channel of inequality that drives the persistence of gender inequities. We show that, through this channel, financial deregulation reduced the gender pay gap at the bottom of the pay gap distribution and induced gender sorting out of the top of the distribution. Specifically, we document that industries with high gender pay gaps have a low share of tangible assets, and industries with low gender pay gaps have a high share of tangible assets. Because asset tangibility determines firms' collateral and ability to borrow, project selection, and labor demand, financial deregulation (which increases credit access) has different effects on workers who belong to industries with distinct levels of asset tangibility. In more equitable industries (i.e., industries with a lower pay gap and more tangible assets), firms increase borrowing and increases their demand for labor in response to financial deregulation. In more inequitable industries (i.e., industries with a higher pay gap and more intangible assets), firms do not significantly change their borrowing but lower their demand for labor. Differences in labor demand between equitable industries and inequitable industries, together with higher relative pay for women in the more equitable industries, lead to gender sorting between the more equitable and inequitable industries. We further demonstrate that this sorting cements gender roles, which then accentuates workplace gender bias and reinforces glass ceilings.

Our results have implications for understanding the evolution of the gender pay gap. Our findings suggest that the waves of financial deregulation in the 1980s contributed to the bottom-up narrowing of the gender pay gap by propelling a reduction in pay gap in lower-paying industries. In addition, these findings shed light on why gender inequities remain persistent by showing how relative gains that are heterogeneous across economy sectors can lead to gender sorting, and that this gender sorting across industries worsens sexism toward women. As gender roles cement, glass ceilings become harder to break.

More broadly, the asset channel we document may play a role in other settings, affecting not only gender inequities but also other forms of inequality. Through this channel, credit conditions could trigger changes in labor market dynamics across industries, affecting workers in complex ways that could potentially compound preexisting inequities along different dimensions. These dimensions are potentially policy relevant and interesting avenues for further research.

References

Aghion, Philippe, and Peter Howitt. 1992. "A Model of Growth Through Creative Destruction." *Econometrica:* 323–351.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005a. "Competition and innovation: An inverted-U relationship." *The Quarterly Journal of Economics* 120 (2): 701–728.

Aghion, Philippe, Philippe Askenazy, Nicolas Berman, Gilbert Cette, and Laurent Eymard. 2012. "Credit constraints and the cyclicality of R&D investment: Evidence from France." *Journal of the European Economic Association* 10 (5): 1001–1024.

Aghion, Philippe, Robin Burgess, Stephen Redding, and Fabrizio Zilibotti. 2005b. "Entry liberalization and inequality in industrial performance." *Journal of the European Economic Association* 3 (2-3): 291–302.

Aghion, Philippe, Antonin Bergeaud, Gilbert Cette, Rémy Lecat, and Hélène Maghin. 2018. *The inverted-U relationship between credit access and productivity growth.* Technical report. London School of Economics and Political Science, LSE Library.

Albanesi, Stefania. 2019. *Changing Business Cycles: The Role of Women's Employment.* Working Paper, Working Paper Series 25655. National Bureau of Economic Research.

Albanesi, Stefania, and Claudia Olivetti. 2009. "Home production, market production and the gender wage gap: Incentives and expectations." *Review of Economic dynamics* 12 (1): 80–107.

Almeida, Heitor, and Murillo Campello. 2007. "Financial constraints, asset tangibility, and corporate investment." *The Review of Financial Studies* 20 (5): 1429–1460.

Amore, Mario Daniele, Cedric Schneider, and Alminas Žaldokas. 2013. "Credit supply and corporate innovation." *Journal of Financial Economics* 109 (3): 835–855.

Ashenfelter, Orley, and Timothy Hannan. 1986. "Sex discrimination and product market competition: The case of the banking industry." *The Quarterly Journal of Economics* 101 (1): 149–173.

Autor, David H, Frank Levy, and Richard J Murnane. 2003. "The skill content of recent technological change: An empirical exploration." *The Quarterly journal of economics* 118 (4): 1279–1333.

Ballot, Gérard, Fathi Fakhfakh, and Erol Taymaz. 2006. "Who benefits from training and R&D, the firm or the workers?" *British journal of industrial relations* 44 (3): 473–495.

Barth, Erling, Sari Pekkala Kerr, and Claudia Olivetti. 2017. *The Dynamics of Gender Earnings Differentials: Evidence from Establishment Data.* Working Paper, Working Paper Series 23381. National Bureau of Economic Research.

Beck, Thorsten, Ross Levine, and Alexey Levkov. 2010. "Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States." *The Journal of Finance* 65 (5): 1637–1667.

Becker, Gary S. 1957. *The Economics of Discrimination.* Univ. Chicago Press.

Bellucci, Andrea, Alexander Borisov, and Alberto Zazzaro. 2010. "Does gender matter in bank–firm relationships? Evidence from small business lending." *Journal of Banking & Finance* 34 (12): 2968–2984.

Bennedsen, Morten, Elena Simintzi, Margarita Tsoutsoura, and Daniel Wolfenzon. 2019. *Do firms respond to gender pay gap transparency?* Working Paper, Working Paper Series 25435. National Bureau of Economic Research.

Bertrand, Marianne, Antoinette Schoar, and David Thesmar. 2007. "Banking Deregulation and Industry Structure: Evidence from the French Banking Reforms of 1985." *The Journal of Finance* 62 (2): 597–628.

Bewley, Truman F. 1995. "A depressed labor market as explained by participants." *The American Economic Review* 85 (2): 250–254.

Black, Sandra E, and Alexandra Spitz-Oener. 2010. "Explaining Women's Success: Technological Change and the Skill Content of Women's Work." *The Review of Economics and Statistics* 92 (1): 187–194.

Black, Sandra E., and Philip E. Strahan. 2002. "Entrepreneurship and Bank Credit Availability." *The Journal of Finance* 57 (6): 2807–2833.

———. 2001. "The Division of Spoils: Rent-Sharing and Discrimination in a Regulated Industry." *American Economic Review* 91 (4): 814–831.

Blanchflower, David G, Phillip B. Levine, and David J. Zimmerman. 2003. "Discrimination in the small-business credit market." *Review of Economics and Statistics* 85 (4): 930–943.

Blau, Francine D., and Lawrence M. Kahn. 1997. "Swimming upstream: Trends in the gender wage differential in the 1980s." *Journal of labor Economics* 15:1–42.

———. 2017. "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature* 55 (3): 789–865.

Breza, Emily, Supreet Kaur, and Yogita Shamdasani. 2017. "The morale effects of pay inequality." *The Quarterly Journal of Economics* 133 (2): 611–663.

Card, David, Ana Rute Cardoso, and Patrick Kline. 2016. "Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women." *The Quarterly Journal of Economics* 131 (2): 633–686.

Card, David, Francesco Devicienti, and Agata Maida. 2013. "Rent-sharing, holdup, and wages: Evidence from matched panel data." *Review of Economic Studies* 81 (1): 84–111.

Card, David, Alexandre Mas, Enrico Moretti, and Emmanuel Saez. 2012. "Inequality at work: The effect of peer salaries on job satisfaction." *American Economic Review* 102 (6): 2981–3003.

Charles, Kerwin Kofi, Jonathan Guryan, and Jessica Pan. 2018. *The Effects of Sexism on American Women: The Role of Norms vs. Discrimination.* Working Paper, Working Paper Series 24904. National Bureau of Economic Research.

Chava, Sudheer, Alexander Oettl, Ajay Subramanian, and Krishnamurthy V. Subramanian. 2013. "Banking deregulation and innovation." *Journal of Financial Economics* 109 (3): 759–774.

Clark, Andrew E, and Andrew J Oswald. 1996. "Satisfaction and comparison income." *Journal of public economics* 61 (3): 359–381.

Demirgüc-Kunt, Asli, and Vojislav Maksimovic. 1998. "Law, Finance, and Firm Growth." *The Journal of Finance* 53 (6): 2107–2137.

Demsetz, Harold. 1982. "Barriers to entry." *The American economic review* 72 (1): 47–57.

Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Ecnomic Review* 104 (4): 1091–1119.

———. 2006. "The Quiet Revolution That Transformed Women's Employment, Education, and Family." *American Ecnomic Review* 96 (2): 1–21.

Goldin, Claudia, Sari P. Kerr, Claudia Olivetti, and Erling Barth. 2017. "The Quiet Revolution That Transformed Women's Employment, Education, and Family." *American Ecnomic Review* 107 (5): 110–114.

Hall, Bronwyn H, and Josh Lerner. 2010. "The financing of R&D and innovation." In *Handbook of the Economics of Innovation,* 1:609–639. Elsevier.

Hart, Oliver, and John Moore. 1994. "A theory of debt based on the inalienability of human capital." *The Quarterly Journal of Economics* 109 (4): 841–879.

Jayaratne, Jith, and Philip E. Strahan. 1996. "The Finance-Growth Nexus: Evidence from Bank Branch Deregulation." *The Quarterly Journal of Economics* 111 (3): 639–670.

King, Robert G., and Ross Levine. 1993. "Finance and Growth: Schumpeter Might Be Right." *The Quarterly Journal of Economics* 108 (3): 717–737.

Kline, Pat, Neviana Petkova, Heidi Williams, and Owen Zidar. Forthcoming. "Who Profits from Patents? Rent-sharing at Innovative Firms." *Quarterly Journal of Economics.*

Lemmon, Michael, and Michael R. Roberts. 2010. "The Response of Corporate Financing and Investment to Changes in the Supply of Credit." *The Journal of Financial and Quantitative Analysis* 45 (3): 555–587.

Levanon, Asaf, Paula England, and Paul Allison. 2009. "Occupational Feminization and Pay: Assessing Causal Dynamics Using 1950-2000 U.S. Census Data." *Social Forces* 88 (2): 865–892.

Mellor, Earl F, and Steven E Haugen. 1986. "Hourly paid workers: who they are and what they earn." *Monthly Lab. Rev.* 109:20.

Nguyen, Hoai-Luu Q. 2019. "Are Credit Markets Still Local? Evidence from Bank Branch Closings." *American Economic Journal: Applied Economics* 11 (1): 1–32.

Rajan, Raghuram, and Luigi Zingales. 1998. "Financial Dependence and Growth." *American Economic Review* 88 (3): 559–86.

Rice, Tara, and Philip E. Strahan. 2010. "Does Credit Competition Affect Small-Firm Finance?" *The Journal of Finance* 65 (3): 861–889.

Shleifer, Andrei, and Robert W Vishny. 1992. "Liquidation values and debt capacity: A market equilibrium approach." *The Journal of Finance* 47 (4): 1343–1366.

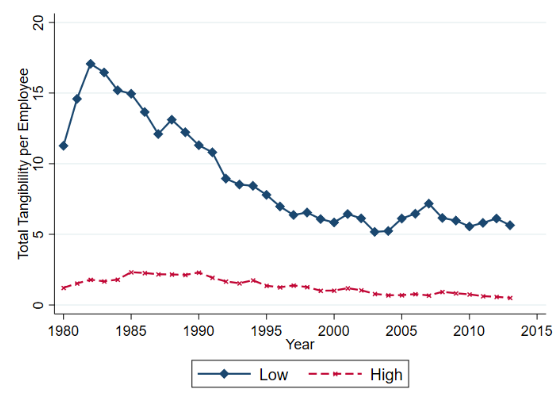
Smirlock, Michael, Thomas Gilligan, and William Marshall. 1984. "Tobin's q and the Structure-Performance Relationship." *The American Economic Review* 74 (5): 1051–1060.

Van Reenen, John. 1996. "The Creation and Capture of Rents: Wages and Innovation in a Panel of U.K. Companies." *The Quarterly Journal of Economics* 111 (1): 195–226.

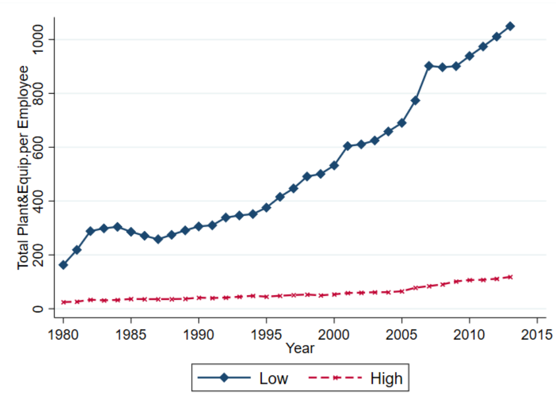
Williamson, Oliver E. 1988. "Corporate finance and corporate governance." *The Journal of Finance* 43 (3): 567–591.

Figure 1: Industry Assets by Pay Gap

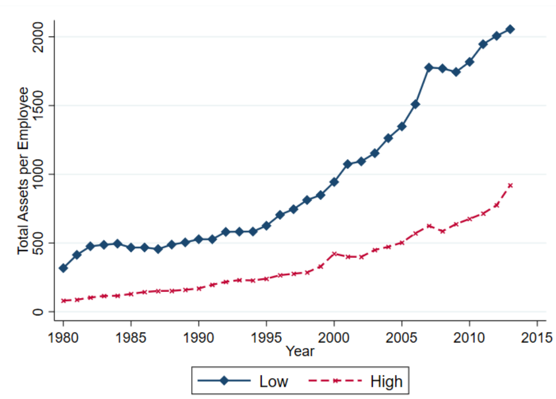
Panel A: Asset Tangibility per Employee



Panel B: Total Plant and Equipment per Employee



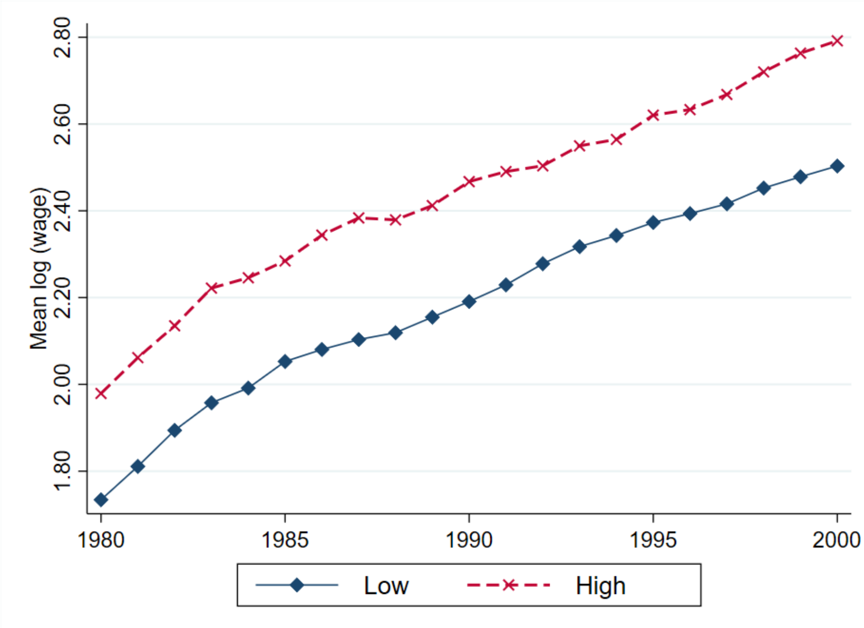
Panel C: Total Assets per Employee



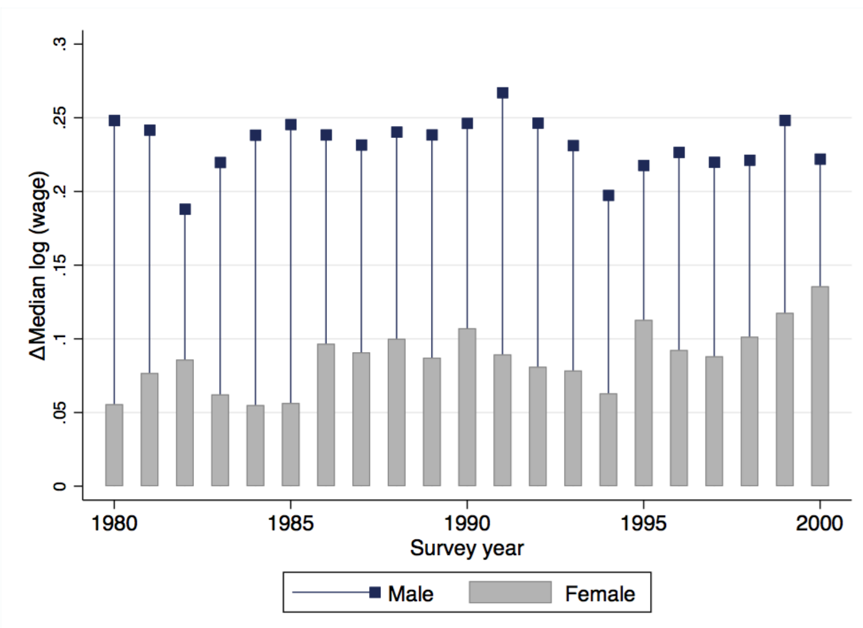
Notes: This figure plots three measures of assets for the low-pay-gap and high-pay-gap industries between 1980 and 2014 using Compustat. Panel A shows total asset tangibility per employee; Panel B shows total plant and equipment per employee; and Panel C shows total assets per employee. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution.

Figure 2: Industry Wage by Pay Gap

Panel A: Average Industry Wage for the Low and High-Pay-Gap Industries

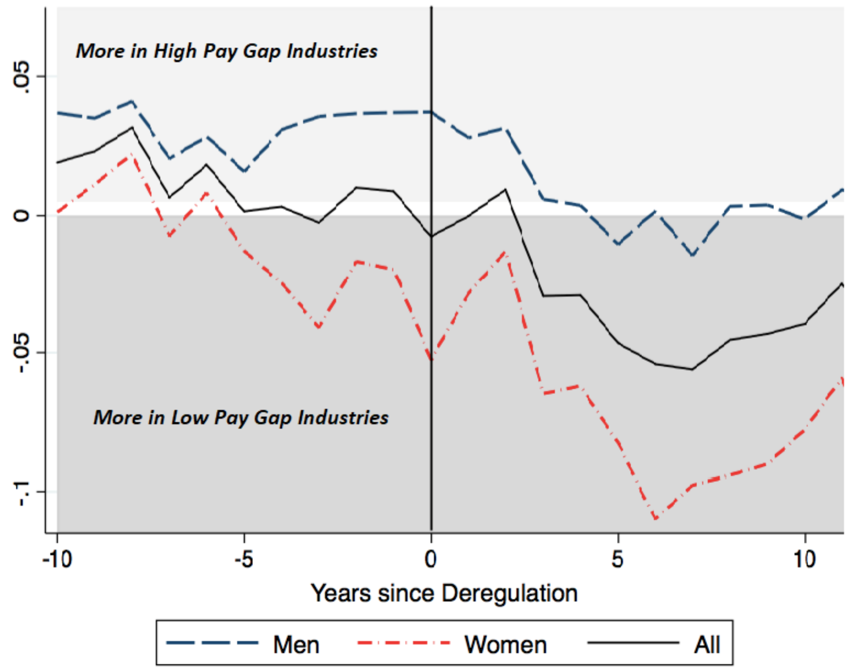


Panel B: Differences in Median Wage between High and Low- Pay-Gap Industries



NOTES: Panel A plots the average industry wage for the high and low-pay-gap industries. Panel B plots the difference in median log wage between the high-pay-gap and the low-pay-gap industries by gender. The difference in median log wage between the two industries is computed by subtracting the median log wage of each gender in the low-pay-gap industries from that of the same gender in the high-pay-gap industries. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. Data source: CPS.

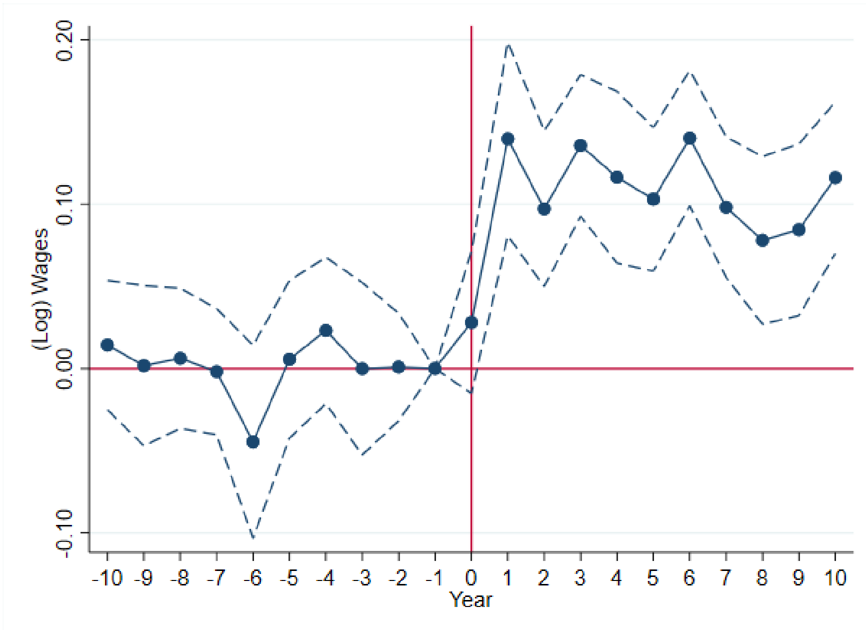
Figure 3: Changes in Labor Force Participation in Low and High-Pay-Gap Industries



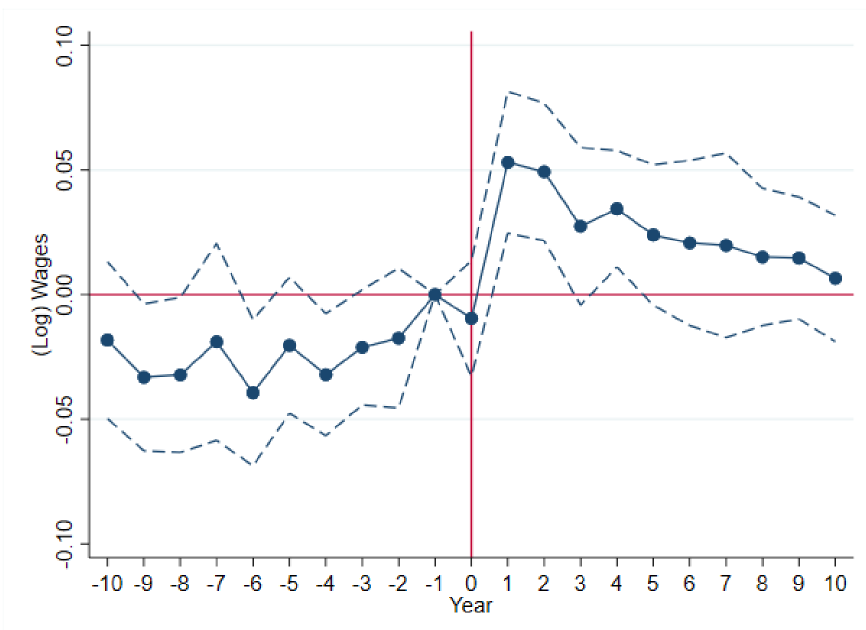
Notes: This figure plots the likelihood of working in the high- and low-pay-gap industries 10 years before and 10 years after intrastate banking deregulation (deregulation corresponds to $t = 0$), for all workers (black line) and by gender (women in red and men in blue), using raw CPS data. Workers in the low-pay-gap industries are assigned a value of -1; workers in the high-pay-gap industries are assigned a value of 1; and workers in all other industries are assigned a value of 0. The likelihood of working in a particular industry is calculated as the average of the indicators in each period. Values greater than 0 mean higher likelihood of working in the high-pay-gap industries, and values less than 0 mean higher likelihood of working in the low-pay-gap industries. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution.

Figure 4: Effects of Bank Deregulation on Gender Pay Gap: Event Studies

Panel A: Relative Wages in the Low-Pay-Gap Industries



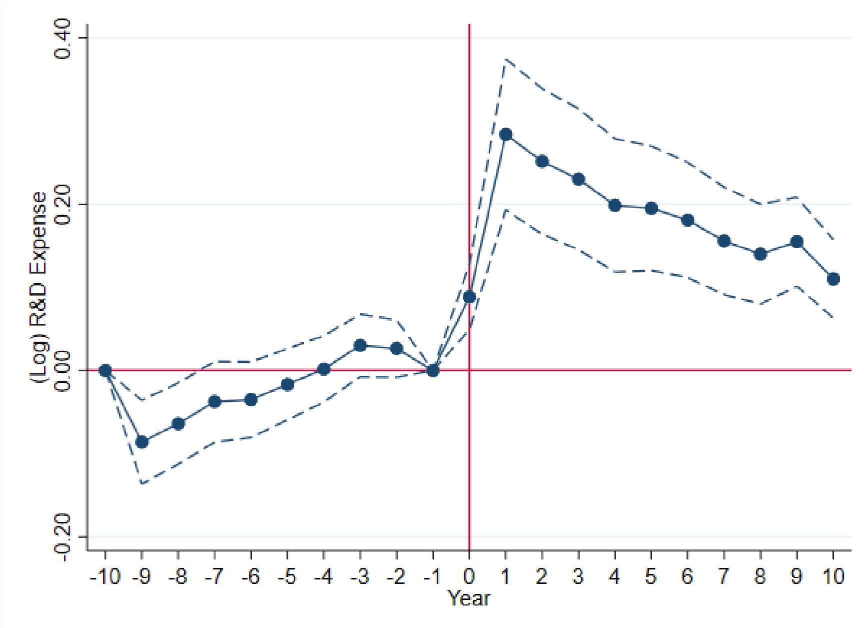
Panel B: Absolute Wages in the High-Pay-Gap Industries



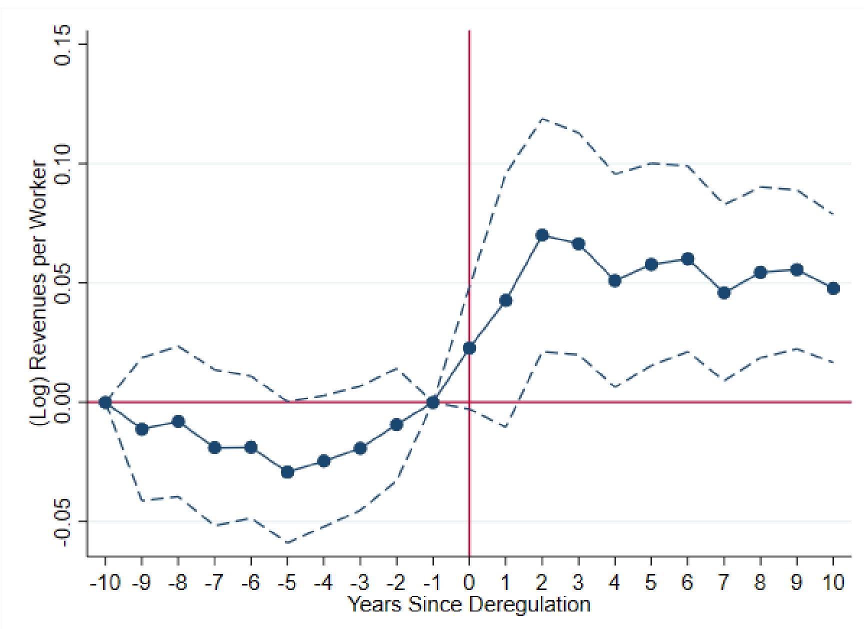
Notes: This figure shows two main wage outcomes from Table (4), based an event study of Equation (1) using (log) wage as the dependent variable, state fixed effects, year fixed effects, and Mincerian controls. Panel A shows the coefficients on the interaction of female × dummies for years since deregulation in the low-pay-gap industries. Panel B shows the coefficients on the dummies for years since deregulation for the high-pay-gap industries. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution.

Figure 5: Effects of Bank Deregulation on R&D and Firm Revenue: Event Studies

Panel A: R&D Spending in the High-Pay-Gap Industries



Panel B: Revenue Per Worker in the High-Pay-Gap Industries



Notes: This figure shows outcomes on R&D spending and firm revenue from Table (6), based an event study of Equation (1) using (log) wage as the dependent variable, state fixed effects, year fixed effects, and Mincerian controls. Panel A and B show the coefficients on the dummies for years since deregulation for the high-pay-gap industries. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution.

Table 1: Summary Statistics

Panel A: Summary Statistics for Individuals (CPS)

	All		Low		High	
	Men	Women	Men	Women	Men	Women
Wage (hourly)	$13.65	$10.65	$11.61	$10.62	$16.54	$11.11
	($1.97)	($1.97)	($1.98)	($1.96)	($2.54)	($2.04)
Education (years)	13.1	13.3	12.6	13.4	14.0	13.4
	(2.9)	(2.6)	(3.2)	(2.5)	(2.7)	(2.6)
– HS Grad &Equiv(%)	21.7	22.4	22.6	22.6	15.1	20.0
	(41.3)	(41.7)	(41.8)	(41.8)	(35.8)	(40.0)
– College(%)	16.6	18.2	13.7	18.0	24.8	19.4
	(37.2)	(38.6)	(34.4)	(38.5)	(43.2)	(39.5)
– Post-College(%)	4.5	5.0	4.2	4.6	7.0	4.4
	(20.7)	(21.8)	(20.1)	(21.0)	(25.5)	(20.5)
Age	40.7	40.2	40.1	40.2	40.9	39.7
	(10.3)	(10.2)	(10.4)	(10.3)	(10.2)	(10.1)
Experience	27.6	26.9	27.4	26.8	26.9	26.3
	(10.8)	(10.8)	(11.0)	(10.8)	(10.6)	(10.8)
Participation(%)	65.1	34.9	58.1	41.9	61.7	38.3

Panel B: Summary Statistics for Public Firms

	All	Low	High
Revenue per Employee($)	242.4	418.3	224.8
	(1,055.8)	(1,666.7)	(852.4)
Net Income per Employee($)	-31.7	-14.0	-45.7
	(873.8)	(652.7)	(925.5)
Net Income + Operating Expense per Employee($)	195.7	278.3	194.3
	(910.0)	(1,344.4)	(737.2)
Employees	6.0	5.5	4.5
	(20.2)	(15.0)	(17.9)
Total Assets($)	1,325.8	1,367.3	1,326.4
	(10,427.3)	(6,376.7)	(12,935.6)
Tobin's Q	1.02	0.92	1.09
	(0.45)	(0.37)	(0.49)
Book Leverage	0.51	0.55	0.47
	(0.68)	(1.43)	(0.30)
Tangibility	0.29	0.55	0.20
	(0.24)	(0.26)	(0.17)
Firms	10,089	1,612	5,981

Notes: This table reports summary statistics for the main analysis sample using the Current Population Survey (CPS) (Panel A) and Compustat (Panel B) from 1976–2014. The CPS main sample is restricted to working-age full-time full-year workers in the private sector excluding FIRE industries. Hourly wages are derived from annual wage income, usual weekly hours worked, and number of weeks worked. Tobin's Q, book leverage, and tangibility are defined as follows: Tobin's Q is the ratio of total assets + shares outstanding × share price − common equity to total assets; book leverage is the ratio of short-term debt + long-term debt to short-term debt + long-term debt + stockholders equity; tangibility is the ratio of Property, Plant, and Equipment to total assets. For additional details, see Section II.3.

Table 2: Reliance on External Financing by Industries

	All		Low		High	
	Mean	sd	Mean	sd	Mean	sd
	Panel A: All					
Debt-to-Asset – Secured	0.085	0.144	0.125	0.174	0.061	0.119
Debt-to-Asset – Notes	0.066	0.120	0.106	0.152	0.045	0.096
Debt-to-Asset – Long-term	0.163	0.192	0.236	0.211	0.123	0.171
Leverage	0.496	0.270	0.533	0.266	0.459	0.270
	Panel B: Pre-Deregulation					
Debt-to-Asset – Secured	0.106	0.152	0.128	0.174	0.085	0.127
Debt-to-Asset – Notes	0.085	0.127	0.105	0.148	0.065	0.105
Debt-to-Asset – Long-term	0.179	0.179	0.206	0.201	0.147	0.155
Leverage	0.507	0.252	0.510	0.282	0.482	0.238
	Panel C: Post-Deregulation					
Debt-to-Asset – Secured	0.082	0.143	0.124	0.174	0.059	0.118
Debt-to-Asset – Notes	0.064	0.119	0.106	0.153	0.043	0.095
Debt-to-Asset – Long-term	0.161	0.193	0.242	0.213	0.122	0.172
Leverage	0.495	0.272	0.538	0.263	0.457	0.273

NOTES: This table reports summary statistics of debt-to-asset ratios and leverage by industry using Compustat data. Panel A reports the average and standard deviation for the entire sample period from 1976 to 2014; Panel B reports those for the period before deregulation; Panel C reports those for the period after deregulation. For details, see Section II.3.

Table 3: Industry Descriptions

Panel A: Highest and Lowest Pay Gap Industries

Top 10 Industries	Bottom 10 Industries
Offices and Clinics of Dentists	Agricultural Production, Crops
Offices and Clinics of Physicians	Gasoline Service Stations
Legal Services	Grain Mill Products
Drug Stores	Religious Organizations
Computer and Data Processing Services	Nursing and Personal Care Facilities
Advertising	Social Services
Miscellaneous Fabricated Textile Products	Household Appliance Stores
Management and Public Relations Services	Beverage Industries
Miscellaneous Professional and Related Services	Oil and Gas Extraction
Accounting, Auditing, and Bookkeeping Services	Residential Care Facilities, without nursing

Panel B: Fastest and Slowest Growing Industries

Top 10 Industries	Pay Gap Level	Bottom 10 Industries	Pay Gap Level
Computer and data processing services	High	Private households	Med
Agricultural chemicals	Low	Agricultural production, crops	Low
Research, development, and testing services	Med	Apparel and accessories, except knit	High
Management and public relations services	High	Variety stores	High
Drugs	High	Footwear	Low
Electric light and power	High	Retail florists	Med
Engineering, architectural, and surveying services	High	Knitting mills	Med
Computers and related equipment	High	Beauty shops	Low
Petroleum refining	High	Eating and drinking places	Low
Electric and gas, and other combinations	Med	Laundry, cleaning, and garment services	High

Notes: Panel A lists the top 10 and bottom 10 industries in terms of pay gap. Panel B lists the top 10 and bottom 10 industries in terms of employment growth. Pay gap is the difference between the mean log wage of male and female employees by industry during the years before and after bank deregulation using CPS. The sample is restricted to industries that hired at least 100 female and 100 male employees during the sample period, which encompasses 105 industries (out of 189 total industries) in the CPS 1990 industry classification codes. For details, see Section II.3.

Table 4: Effects of Bank Deregulation on Gender Pay Gap

	Intrastate Deregulation				Interstate Deregulation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deregulation × Female	-0.02	-0.02	-0.02	-0.02	-0.02**	-0.02**	-0.02*	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – Low PG Industry	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – High PG Industry	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation	-0.04***	-0.04***	-0.04***	-0.04***	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – Low PG Industry	-0.00	-0.00	0.00	0.00	0.01*	0.01*	0.01**	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – High PG Industry	0.08***	0.08***	0.08***	0.08***	0.10***	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – Low PG Industry	0.12***	0.12***	0.12***	0.13***	0.13***	0.13***	0.12***	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – High PG Industry	-0.02*	-0.02*	-0.03**	-0.02**	-0.03***	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Low PG Industry	-0.18***	-0.18***	-0.18***	-0.18***	-0.19***	-0.19***	-0.19***	-0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High PG Industry	0.03***	0.03***	0.03***	0.02***	0.02**	0.02**	0.02***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	815,627	815,627	815,627	815,627	815,627	815,627	815,627	815,627
State × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age × Gender	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Marital Status × Gender	No	No	Yes	No	No	No	Yes	No
Race × Gender	No	No	No	Yes	No	No	No	Yes

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

Notes: This table reports the difference-in-differences estimates of the effects of bank deregulation on gender pay gap from Equation (1). Columns (1)–(4) report the effects of intrastate deregulation as the treatment, and columns (5)–(8) report the effects of interstate deregulation as the treatment. Deregulation is a dummy variable that takes the value one for the years after deregulation and 0 otherwise. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. High-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. High PG is a dummy variable that takes the value one for high-pay-gap industries and 0 otherwise. Low PG is a dummy variable that takes the value one for low-pay-gap industries and 0 otherwise. All specifications control for Mincerian traits×gender, state×gender, and year×gender fixed effects. Columns (2)–(4) and (6)–(8) additionally control for age×gender fixed effects. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Effects of Deregulation on Firm Borrowing

	Debt Growth			Long Term Debt Growth			Debt Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intrastate – High PG Industry	-0.02	-0.02	-0.02	-0.03	-0.03	-0.02	-0.19***	-0.17***	-0.15***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.05)
Intrastate – Low PG Industry	0.06**	0.05*	0.05*	0.07***	0.05**	0.05**	-0.01	0.03	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)	(0.08)	(0.08)
Intrastate	0.04**			0.03			0.13**		
	(0.02)			(0.02)			(0.05)		
N	65,379	65,330	64,283	65,432	65,383	64,317	65,422	65,373	64,323
Interstate – High PG Industry	-0.03**	-0.02	-0.02	-0.04**	-0.03	-0.02	-0.13***	-0.11***	-0.10***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)
Interstate – Low PG Industry	0.01	0.02	0.01	0.01	0.00	-0.00	-0.02	0.00	-0.02
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)
Interstate	0.05***			0.06**			0.11***		
	(0.02)			(0.03)			(0.04)		
N	65,379	65,330	64,283	65,432	65,383	64,317	65,422	65,373	64,323
Firm FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FX	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm Controls	No	No	Yes	No	No	Yes	No	No	Yes

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

NOTES: This table reports the estimates of the effects of bank deregulation on firm debt. The dependent variable is debt growth in columns (1)–(3), long-term debt growth in columns (4)–(6), and debt ratio in columns (7)–(9). Intrastate is a dummy variable that takes the value one for the years after intrastate deregulation and 0 otherwise. Interstate is a dummy variable that takes the value one for the years after interstate deregulation and 0 otherwise. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. High-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. High PG is a dummy variable that takes the value one for high-pay-gap industries and 0 otherwise. Low PG is a dummy variable that takes the value one for low-pay-gap industries and 0 otherwise. All specifications control for firms, state, and year fixed effects. Columns (2), (5), (8), and (11) additionally control for state×year fixed effects. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Effects of Deregulation on Tangible Asset Share by Firm

	% Tangible			R&D Spending		
	(1)	(2)	(3)	(4)	(5)	(6)
Intrastate – High PG Industry	-0.00	-0.01	-0.01	0.31***	0.32***	0.32***
	(0.00)	(0.01)	(0.00)	(0.06)	(0.05)	(0.03)
Intrastate – Low PG Industry	0.02***	0.02***	0.02***	-0.09	0.01	0.09
	(0.01)	(0.01)	(0.01)	(0.08)	(0.09)	(0.07)
Intrastate	-0.00			-0.29***		
	(0.01)			(0.06)		
N	68,407	68,355	60,593	41,535	41,387	36,541
Interstate – High PG Industry	-0.01**	-0.01**	-0.01***	0.35***	0.33***	0.29***
	(0.00)	(0.00)	(0.00)	(0.05)	(0.04)	(0.03)
Interstate – Low PG Industry	0.02***	0.02***	0.01***	-0.12*	-0.07	0.01
	(0.00)	(0.01)	(0.01)	(0.07)	(0.08)	(0.06)
Interstate	-0.00			-0.22***		
	(0.00)			(0.04)		
N	68,407	68,355	60,593	41,535	41,387	36,541
Firm FX	Yes	Yes	Yes	Yes	Yes	Yes
Year FX	Yes	Yes	Yes	Yes	Yes	Yes
State FX	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FX	No	Yes	Yes	No	Yes	Yes
Firm Controls	No	No	Yes	No	No	Yes

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

NOTES: This table reports the estimates of the effects of bank deregulation on asset tangibility and R&D. The dependent variable is the log (tangible assets / total assets) in columns (1)–(3) and log(R&D expenditure) in columns (4)–(6)). Intrastate is a dummy variable that takes the value one for the years after intrastate deregulation and 0 otherwise. Interstate is a dummy variable that takes the value one for the years after interstate deregulation and 0 otherwise. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. High-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. High PG is a dummy variable that takes the value one for high-pay-gap industries and 0 otherwise. Low PG is a dummy variable that takes the value one for low-pay-gap industries and 0 otherwise. All specifications control for firms, state, and year fixed effects. Columns (2), (5), (8), and (11) additionally control for state×year fixed effects. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Effects of Deregulation on Revenue Per Employee

	Employment			Revenue Per Employee			Net Income+Operating Expense Per Employee			Net Income Per Employee		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intrastate – High PG Industry	-0.04	-0.04	-0.04	0.09***	0.09**	0.13***	0.09***	0.09***	0.13***	0.07	0.05	0.09**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)
Intrastate – Low PG Industry	0.11***	0.08**	0.07**	-0.12***	-0.12***	0.00	-0.13***	-0.13***	0.00	-0.11	-0.08	0.04
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.07)	(0.06)	(0.05)
Intrastate	-0.04			-0.05*			-0.03			-0.01		
	(0.03)			(0.02)			(0.02)			(0.04)		
N	70,899	70,842	69,570	70,748	70,690	62,515	69,576	69,517	61,586	52,453	52,369	46,562
Interstate – High PG Industry	-0.06***	-0.05**	-0.04	0.13***	0.12***	0.12***	0.12***	0.11***	0.11***	0.05**	0.04	0.07*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Interstate – Low PG Industry	0.13***	0.11***	0.10***	-0.13***	-0.11***	-0.01	-0.16***	-0.14**	-0.03	-0.15**	-0.11	0.02
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.07)	(0.06)
Interstate	0.01			-0.04*			-0.01			0.03		
	(0.01)			(0.02)			(0.03)			(0.03)		
N	70,899	70,842	69,570	70,748	70,690	62,515	69,576	69,517	61,586	52,453	52,369	46,562
Firm-level FX:												
Firm FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FX	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

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

Notes: This table reports the estimates of the effects of bank deregulation on employment, revenues per employee, and net income per employee by industry at state level. The dependent variable is log(number of employees) in columns (1)–(3), log(revenue / number of employees) in columns (4)–(6), log([net income + operating expense] / number of employees) in columns (7)–(9), and log(net income / number of employees) in columns (10)–(12). Interstate is a dummy variable that takes the value one for the years after interstate deregulation and 0 otherwise. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. High-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. High PG is a dummy variable that takes the value one for high-pay-gap industries and 0 otherwise. Low PG is a dummy variable that takes the value one for low-pay-gap industries and 0 otherwise. All specifications control for firms, state, and year fixed effects. Columns (2), (5), (8), and (11) additionally control for state×year fixed effects. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Effects of Deregulation on Transitions

	Intrastate				Interstate			
	Industry Transition		Δ Wage		Industry Transition		Δ Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deregulation × Female – Low PG Industry	-0.06***	-0.06***	0.00	0.00	-0.05***	-0.05***	-0.02	-0.03
	(0.01)	(0.01)	(0.04)	(0.04)	(0.01)	(0.01)	(0.05)	(0.05)
Deregulation × Female – High PG Industry	0.04***	0.04***	-0.04	-0.04	0.04***	0.04***	-0.07	-0.08
	(0.00)	(0.00)	(0.03)	(0.04)	(0.00)	(0.00)	(0.05)	(0.05)
Deregulation – Low PG Industry	0.07***	0.07***	-0.02	-0.02	0.06***	0.06***	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Deregulation – High PG Industry	-0.05***	-0.05***	0.04*	0.03*	-0.04***	-0.04***	0.03	0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)
Female – High PG Industry	-0.09***	-0.09***	-0.05**	-0.05**	-0.08***	-0.08***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
High PG Industry	0.14***	0.14***	0.06***	0.05***	0.12***	0.12***	0.06***	0.05***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
N	509,956	509,956	20,511	20,511	509,956	509,956	20,511	20,511
County × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes

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

Notes: This table reports the difference-in-differences estimates of the effects of bank deregulation on workers mobility using the same set of controls and indicators in Equation (1). In columns (1)–(2) and (5)–(6), the dependent variable is a dummy that takes the value one for workers who transition from the low-pay-gap to the high-pay-gap industries or vice versa. In columns (3)–(4) and (7)–(8), the dependent variable is the change in log(wage) for those who transitioned between the high- and low-pay-gap industries. Deregulation is a dummy variable that takes the value one for the years after deregulation and 0 otherwise. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. High-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. High PG is a dummy variable that takes the value one for high-pay-gap industries and 0 otherwise. Low PG is a dummy variable that takes the value one for low-pay-gap industries and 0 otherwise. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. Even-numbered columns add marriage and race controls. For details, see Section **??**. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Effects of Deregulation on Gender Pay Gap By Risk of Transition

	Intrastate				Interstate			
	Low Risk		High Risk		Low Risk		High Risk	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deregulation × Female	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01	-0.03	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Deregulation × Female – Low PG Industry	0.02	0.01	0.05***	0.04***	0.01	0.01	0.03**	0.03*
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – High PG Industry	0.01	0.01	0.02	0.01	0.02*	0.02*	-0.00	0.00
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Deregulation	-0.03**	-0.03**	-0.04***	-0.04***	-0.06***	-0.06***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – Low PG Industry	0.01	0.01	0.01	0.02	0.02*	0.02*	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – High PG Industry	0.05***	0.05***	0.09***	0.09***	0.08***	0.08***	0.13***	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – Low PG Industry	0.05***	0.05***	0.16***	0.15***	0.05***	0.05***	0.15***	0.14***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – High PG Industry	-0.02*	-0.03**	-0.08***	-0.08***	-0.02**	-0.02**	-0.09***	-0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Low PG Industry	-0.11***	-0.11***	-0.25***	-0.24***	-0.12***	-0.12***	-0.26***	-0.25***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High PG Industry	0.01	0.01	0.06***	0.06***	0.01	0.01	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	405,392	405,392	391,373	391,373	402,088	402,088	400,529	400,529
State × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age × Gender	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Marital Status × Gender	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Race × Gender	No	Yes	Yes	Yes	No	Yes	Yes	Yes

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

Notes: This table reports the difference-in-differences estimates of Equation (1) for workers with occupations at low or high risk of cross-industry transitions. Columns (1)–(3) reports the estimates for workers with occupations in the low-transition-risk group. Columns (4)–(6) reports the estimates for workers with occupations in the high-transition-risk group. Deregulation is a dummy variable that takes the value one for the years after deregulation and 0 otherwise. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. High-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. High PG is a dummy variable that takes the value one for high-pay-gap industries and 0 otherwise. Low PG is a dummy variable that takes the value one for low-pay-gap industries and 0 otherwise. All specifications control for Mincerian traits×gender, state×gender, and year×gender fixed effects. Columns (2) and (4) additionally control for age×gender, marital status×gender, and race×gender fixed effects. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Effects of Deregulation on Gender Norms

	All	With Children	Men				Women			
	Workplace Sexism	Workplace Sexism	Workplace Sexism	Women Should Not Work	Husband Career First	Women Stay Home	Workplace Sexism	Women Should Not Work	Husband Career First	Women Stay Home
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Intrastate Deregulation										
Intrastate × Industrial Spread	2.71***	3.27***	4.36***	4.75**	4.78**	4.45*	1.52	3.25***	-0.16	-2.72
	(0.91)	(0.90)	(1.63)	(2.18)	(1.83)	(2.37)	(1.13)	(1.22)	(2.05)	(2.04)
Intrastate Penetration	-0.12***	-0.08**	-0.12**	-0.09	-0.10	-0.12*	-0.12***	-0.13***	-0.11*	-0.20***
	(0.03)	(0.03)	(0.05)	(0.06)	(0.07)	(0.06)	(0.04)	(0.05)	(0.07)	(0.06)
N	33,786	24,484	14,745	8,574	6,604	12,495	19,041	11,339	8,707	16,035
Panel B: Interstate Deregulation										
Interstate × Industrial Spreading	2.73**	2.92***	3.72**	3.19*	5.58***	6.10**	2.02**	2.28*	1.22	1.04
	(1.09)	(0.99)	(1.61)	(1.80)	(1.81)	(2.63)	(0.98)	(1.19)	(2.68)	(2.71)
Interstate Penetration	-0.06	-0.01	-0.05	-0.17**	-0.07	-0.10	-0.07	-0.16**	-0.13	-0.05
	(0.04)	(0.05)	(0.05)	(0.08)	(0.09)	(0.07)	(0.05)	(0.07)	(0.08)	(0.10)
N	33,786	24,484	14,745	8,574	6,604	12,495	19,041	11,339	8,707	16,035
Year FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

NOTES: This table reports estimates of the effects of bank deregulation on gender norms at regional level using the General Social Survey (GSS) survey data. The dependent variables are standardized measures of workplace sexism based on response to the three questions pertaining to beliefs about the role of women in the workplace: "Should women work?"; "Wife should help husbands career first."; "Better for man to work, women tend home." For each question, we assign a value of one when the response reflects biased views against women and zero otherwise. We then standardize the values by subtracting individual responses to each question by the average response of entire population in 1977, a pre-treatment period, and dividing it by the standard deviation of the initial response of the entire population in 1977. For industrial spread, we classify each industry by the distance of its pay gap to the median-pay-gap industry. If it belongs to the top 25th percentile in terms of pay gap, i.e., the high-pay-gap industries, it is assigned a value of 1. If it belongs to the bottom 25th percentile, it is assigned a value of ?1. Industries between the 25th and 75th percentiles, the median-pay-gap industries, are given a value of 0. Industrial spread is the expected value over pairwise combinations of workers based on Equation 3. Deregulation penetration is a measure of the proportion of individuals in each region-year affected by bank deregulation, calculated based on Equation 4. See Section V.1 for more detailed descriptions of variable construction. All specifications control for year fixed effects and region fixed effects. Bootstrapped errors reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendices

Table of Contents

A. Divergent Industrial Responses to Credit Expansions: Literature Overview and Conceptual Framework

A.1 Creative Destruction in Different Industries: Literature Overview

Credit as a catalyzing force for competition has been readily studied through the lens of creative destruction (King & Levine 1993). Creative destruction produces monopoly rents that persist until new waves of technology arrive (Aghion & Howitt 1992). Implementation of new technologies can potentially foster entry of new firms (e.g., Black and Strahan 2002; Guiso et al. 2004; Cetorelli and Strahan 2006; Zarutskie 2006; Bertrand et al. 2007; Kerr and Nanda 2009) which may catalyze the general entrepreneurial process. This process promotes innovation *ex post* by allowing for many business attempts with some of them rendering success (Kerr and Nanda 2009).

Alternatively, incumbents can erect barriers to entry by *ex-ante* commiting to make investments that lower the profitability for new entrants (Spence 1977, 1979; Dixit 1980). These investments need not be desirable for the incumbent firm before the threat of new entrants (Spence 1979), but might become optimal after such threat. This divergent response should lead to a negative relationship between firm entry and monopolisitic rents.[16] Theoretical work predicts these divergent responses (Aghion et al. 2005a), which also finds empirical support in the context of eroding barriers to entry through industrial delicensing (Aghion et al. 2005b) and in the relationship between access to credit and productivity growth (Aghion et al. 2018). In our context, barriers to entry are differentially eroded through differences in the pledgeability of assets (i.e., industries with more tangible assets have higher debt capacity due to the higher pledgeability of tangible assets), a point we elaborated on in subsection IV.1.

This source of heterogeneity in the emergence of technological process can cause significant changes in the labor force industrial composition as it will increase demand for skilled workers in industries with higher monopoly rents – causing those rents to not be fully absorbed by firms (Aghion & Howitt 1992) – while inducing substitution away from those workers in low monopoly rent industries. This should increase absolute wages in the high surplus industries, increase relative wages for the substitute class of workers in low surplus industries, and have an undeterminate effect on the absolute wages in low surplus industries depending on the size of displaced workers in all industries.

A.2 Conceptual Framework: Cross-Industry Labor Dynamics After Credit Expansions

We now explore what occurs to labor markets when credit expansions differentially opens up the availability of new positive NPV projects or ventures.

Consider two industries $i \in \{L, H\}$ and j. Every period, each industries engages in routine ventures and new ventures. New ventures require extra capital but generate monopolistic profits π_i per worker. Firms hire workers for both routine and new ventures. Workers in routine ventures are paid at a competitive spot wage w^T. Workers for new venture roles must be trained for a time

16. The channels through which financial liberalization foster creative-destruction include fostering improvements in the allocation of investment and management of risk (Bencivenga and Smith 1991; Greenwood and Jovanovic 1990; King and Levine 1993), entry and exit of firms (e.g., Black and Strahan 2002; Guiso et al. 2004; Cetorelli and Strahan 2006; Zarutskie 2006; Bertrand et al. 2007; Kerr and Nanda 2009), and innovation (Amore et al. 2013; Chava et al. 2013).

t before working. A subset of workers of size K also are trainable in nonroutine tasks. Cross-industry competition for workers occurs only through the trainability dimension and not through other aptitudes. New ventures can only hire trainable workers, and try to hire $M < \frac{K}{2}$ trainable workers.

The cost associated with training a worker, $t\pi_i$, is akin to a replacement cost and generates a quasi-rent that must be bargained between the worker and the firm in a bilateral monopoly.[17] Bargaining is governed by a Nash protocol where workers have bargaining power β.

Industry H is less competitive than industry L, and thus generates higher profits from the new ventures than industry L, i.e., $\pi_H > \pi_L$.[18] The wage for a trainable worker in industry H is:

$$w_H^I = w^T + \beta t \pi_H$$

This is, the worker is more productive in a new venture and captures part of that productivity in the form of higher wages, which is consistent with the findings of Van Reenen (1996) documenting a large rent-sharing elasticity in innovative firms.

Group membership $g \in \{a, b\}$ need not be correlated with the productivity of workers. Without loss of generality assume group membership is orthogonal to worker productivity,[19] and that the owners of the means of production in industry H do not have any monetary incentive to preferentially hire from any group, but neither do they prevent preferential hiring by group. For idiosyncratic reasons, during the hiring process in industry H, workers of group a are weakly preferred to workers of group b, with a positive probability that group a is strictly prefer to group b.[20] New ventures in industry H hire λM workers of group a and $(1-\lambda)M$ workers of group b.

New ventures in industry L pay wages that are above the traditional market wage, but that are strictly below wages at new ventures in industry H. Workers can be poached. As a consequence, they are not indifferent to hiring decisions in industry H. In particular, industry L sets wages such that they are indifferent between hiring a worker of group a or b. This implies that:

$$w_{L,b}^I = w^T + \beta t \pi_L \Big(1 - \frac{M}{K}(1-\lambda)\Big)$$

$$w_{L,a}^I = w^T + \beta t \pi_L \Big(1 - \frac{M}{K}\lambda\Big)$$

and therefore:

$$w_{L,b}^I - w_{L,a}^I = \beta t \pi_L \frac{M}{K}\Big(2\lambda - 1\Big) > 0.$$

We summarize as follows:

Pay Gaps In High and Low Surplus Industries. When an industry with high surplus disproportionately shares rent with workers of group a, industries with low surplus will find optimal to

17. The replacement cost assumption in our analysis is consistent with recent empirical evidence from Kline et al., 2018, who show that firms disproportionately share rents with workers with high replacement costs. More on this below.

18. This is due to pledgeability differences explained in subsection IV.1.

19. Skills correlated with group membership amplify this problem. For example, highly educated workers may be deemed overqualified relative to workers with similar experience in a task with low complexity, especially when the replacement cost is high (Bewley 1995).

20. We make this assumption without loss of generality since the problem is symmetric for members of group a or b.

disproportionately hire or pay more to workers of group b.

The replacement cost assumption finds support in recent empirical evidence. Kline et al. (2018) find that firms disproportionately share rents with workers with high replacement costs, and that these workers are mostly men. Since the group disproportionately benefited is men, according to our framework, women will benefit in industries with lower surpluses. We will test this throughout the paper.

It is important to remark that the cross-industry dynamics not only apply to when group refers to gender; it extends to multiple other dimensions documented to matter in the labor market. For example, our framework predicts a set of findings in Beck et al. (2010), in which that the value of other noneducation characteristics, e.g. experience, for low pay jobs should increase if demand for another proxy for skill, e.g. education, increases in high paid jobs. In that finding, group a refers to workers with high education, and group b are workers with low education (but other noneducation traits). Beck et al. (2010) overall finding is that following deregulation inequality decreases, converging from the bottom of the education distribution. The findings of this paper connect the findings of Beck et al. (2010) with those of Blau & Kahn (1997) by showing that deregulation generates bottom-up convergence in the gender pay gap.

B. Balance

B.1 Balance in Covariates

B.2 Balance in Covariates' Trends

C. Occupational Differences Across Industries

C.1 Unequal Industries' Worker Skills are Mostly Nonroutine Cognitive; Equitable Industries' Worker Skills are Mostly Nonroutine Manual

In terms of employment composition, high and low pay gap industries differ mostly along their nonroutine skills. High pay gap industries employ a labor force with high levels of nonroutine cognitive skills while low pay gap industries employ mostly nonroutine manual skill workers (Figure 3). This is consistent with high pay gap industries' high levels of intangible assets and, also, with the low levels of external financing (Hart & Moore 1994). In terms of routine skills, routine cognitive and routine manual skills were largely concentrated on high pay gap industries at the start of the decade, but through out the 80s, 90s, and 00s they steadily converged to a low share of routine workers similar to that of low pay gap industries. High and low pay gap industries differ mostly along their nonroutine skills.

Mellor and Haugen (1986) document that in 1984 nonhourly paid workers work more hours than hourly paid workers, with women overrepresented in hourly paid positions. In our distinction between high and low pay gap industries, we document similar findings. Men are only slightly more likely to work in high pay gap industries than women are, but those differences accentuate when we focus on type of work. Women are disproportionately overrepresented in hourly paid work (Figure 5). These differences are consistent with the findings of Goldin (2014) emphasizing the role of long working hours and temporal flexibility in explaining the gender pay gap.

The nature of skills can affect sorting of workers across different industries and through those cross-industry dynamics directly affect the compensation for workers and the relative differences between groups of workers. We will explore these dynamics in detail now in the following subsection. But a word of caution is warranted first, differences in skills are sufficient to drive and amplify cross-industry labor dynamics, but they are not necessary. So while we document there are skill differences by gender in these industries, we must acknowledge that other factors such as taste discrimination, differences in referral networks, or even hiring procedures or algorithms might, on their own or in addition, be a source of cross-industry labor dynamics. Furthermore, taste or networks can lead to differences in skills, and vice versa. With that disclaimer in mind, we can proceed to discuss the nature of cross-industry labor dynamics.

D. Bottom-Up Convergence in Pay? Oaxaca-Blinder Decompositions

Our results demonstrate convergence in pay in low-pay-gap industries. Does the convergence lead to an unambiguous reduction in the gender pay gap? To address this question, we perform two simple Oaxaca-Blinder decompositions, estimated one year before and five years after banking deregulation. The results are shown in Appendix Table (1). In columns (1), (3), and (5), we show that low-pay-gap industries's contribution to the overall pay gap lowers from $-$ 0.013 log points pre-deregulation to -0.039 log points post-deregulation, netting to a reduction of -0.026 log points. During the same period, high-pay-gap industries' contribution to the pay gap lowers from $+0.034$ log points to $+0.022$ log points. Overall, the net effect is a reduction of 0.038 log points in the pay gap or about 34.4% of the total decline during that period. The effects are mostly bottom-up driven. Out of the 34.4% contribution, 69% is driven by low pay gap industries. Moreover, after deregulation low pay gap industries explain -12.5% of the pay gap – that is a -9.4% change from pre-deregulation levels. In contrast, high pay gap industries after deregulation still contribute $+7.0\%$ to the pay gap.

However, Blau & Kahn (1997) find that the gender pay gap converges despite rising labor market inequality. In Table (D.1) we confirm that is true also in our setting.

E. Reversal of Fortune: Vulnerability to Credit Contractions

We have shown that credit liberalization increase relative wage for women in low paying-low pay gap industries. These increases do not stem from higher revenues in these industries but from the response of low pay gap industries to higher revenues in already high paying industries. A natural question to ask is whether these gains are permanent, or if they disappear when the risk of workers transitioning into higher paying industries, male workers in particular, dissipates. In other words, if changes in access to credit reduce the pay gap for women in some industries, it is important to know if economic reversals in the form of credit contractions have the opposite effect: women's wages becoming vulnerable to credit contractions.

Vulnerability of women's wages goes hand in hand with changes in the cyclicality of women's employment. Since the 1991 recession, female employment cyclicality has started to resemble that of male's (Albanesi 2019). Moreover, female labor participation has been associated with increases in total factor productivity, while reduced female participation growth (which would follow declines in female wages) is connected with jobless recoveries, affecting overall economic performance (Albanesi 2019).

Additional Data Sources For our analysis on credit contractions, we use bank mergers that led to branch closings as our treatment. We use two alternative methods to pinpoint mergers that work as credit supply shocks. For both methods we restrict to mergers occurring during the 2000s but prior to the Great Recession, in order to avoid capturing many of the mergers that occurred *because* of the recession. We use the FDIC Call Reports and Summary of Deposits to identify business combinations and branch closings.

In our first method, we select mergers with the largest transfer of branches. This is important since the credit shock should be strong enough to affect labor markets – which are typically larger than census tract. For that reason, we restrict to mergers with more than 1000 branches acquired. This leaves us with two specific mergers: the merger of Firstar Corporation with U.S. Bancorp in

2001, and the merger of Bank of America and FleetBoston Financial in 2004.

Alternatively, as a form of robustness, we run our analysis using mergers that exactly conform to Nguyen (2018). As she does, we choose mergers where both Buyer and Target held at least $10 billion in premerger assets, and the branch network of each bank overlaps in at least one Census tract.

Empirical Specification Nguyen (2018) shows that post-merger branch consolidation reduces local small business lending. In contrast to bank deregulation which occurred at state level, bank mergers led to credit contraction at county levels mostly by limiting access to local branches. Since the effects stemming from bank mergers are more localized, we focus on the effects of credit contractions at the county rather than state level.

We can assess whether a reduction in credit increases the gender pay gap in low pay gap industries. In order to do so, again define $\Omega = \{High, Medium, Low\}$ to be the classifications of industries into low, medium, and high preperiod pay gap industries, and I_j^k is a dummy indicating whether industry j falls into classification $k \in \Omega$. We now have the following specification:

$$\begin{aligned} Y_{ijct} \quad = \quad & \alpha + \sum_{k\in\Omega} \beta_k D_{ct} \times I_j^k + \sum_{k\in\Omega} \gamma_k D_{ct} \times I_j^k \times F_i + \sum_{k\in\Omega} \delta_k I_j^k \times F_i \\ & + \sum_{k\in\Omega} \zeta_k I_j^k + \pi X_{ijst} + \tau_{t,female} + \mu_{s,female} + \epsilon_{ijst} \end{aligned} \qquad (5)$$

for

$$D_{ct} = Post_{mt} \times Close_{cm}$$

where i denotes individual, c denotes county, m denotes merger deal and t denotes time. $Post_{mt}$ equals 1 if merger m precedes year t, $Close_{cm}$ is a dummy equal to 1 if a branch has closed in county c after merger m.

Effects of Bank Mergers on Gender Pay Gaps We intend to test whether, following weakened credit conditions and absent better job prospects for workers at high paying-high pay gap industries, credit-induced relative wage gains for women in low pay gap industries disappears, i.e., relative wages for women would decline. We find that is the case. Table 2 reports effects of bank mergers on wages. While high and median pay gap industries are largely unaffected by bank mergers, low pay gap industries show a reduction in the wages of women of about 3 to 4%, while wages for men increase by about 2%. All in all, the pay gap increases by about 6%. Importantly, workers in high pay gap industries are unaffected. The results are robust to the inclusion of controls including age, race, and marital status.

Jointly, our results so far show that credit expansions alter workers' calculus of industry choice in a gendered way. However, our bank merger analysis highlights that this effect is not permanent. Credit contractions can make disappear the gains female workers had obtained in low pay gap industries while not affecting the gains male workers enjoyed in high pay gap industries. Consequently, the emergence of labor dynamics leave women more vulnerable to deterioration of economic conditions.

F. Categorization Robustness to Excluding Always-Treated States

A potential concern is that the low-pay gap or high-pay-gap classifications are endogenous outcomes, and thus we cannot include always-treated states in our analysis. For our main categorization, whereby industries are categorized during the 5 year window spanning 1976 to 1980, there are seventeen always-treated states for intrastate deregulation and one always-treated state for interstate deregulation (Maine).[21]

To mitigate this concern, we show that excluding all seventeen always treated states does not change industry categorization. Appendix Table (F.3) shows that all High Pay Gap industries remain classified High Pay Gap after excluding always treated states. Only one industry classified as Low Pay Gap was reclassified after excluding always treated states: Lumber and building material retailing (CPS ind1990 = 580) moved from low pay gap to medium pay gap. Overall, a total of only two industries changed classification – the other being Electric light and power (CPS ind1990 = 450) which moved from medium pay gap to high pay gap.

To further mitigate any concerns we have provided throughout the paper: (1) estimates using interstate deregulation as a comparison; (2) estimates using a categorization whereby industries are categorized during the 5 year window spanning 1968 to 1972 (Appendix Table I.9), which reduces always treated states to thirteen; and (3) categorization using industry measures of asset tangibility (Table I.10). All estimates are very similar in direction, magnitude, and statistical significance.

G. Effects on Direct Lending to Worker

G.1 Effects of Bank Deregulation on Gender Differences in Housing and Transportation

One potential concern is that financial deregulation operates by directly affecting the worker instead of operating through the assets of the firm. To mitigate these concerns, we estimate Eq. (1) using household outcomes which would directly benefit from increased access to credit: homeownership, holding a mortgage, car ownership, moving into new dwelling (potentially triggered by relocating for a better job), and transportation time (potentially triggered by commutting to a better job). All these dimensions are potentially affected by financial constraints.

We report estimates in Tables (G.5) and (G.6). While it is not clear whether relaxing financial constraints for any of these dimensions would lead to the cross-industry we have documented in the paper, it is reassuring to find no economic or statistically meaningful gender differences following deregulation along any of these dimensions for both intrastate and interstate deregulation.

G.2 Effects of Bank Deregulation on Gender Differences in Self-Employment

Another potential concern is that financial deregulation may affect self-employment opportunities for women. We can test this directly by estimating Eq. (1) using self-employment as an outcome. Self-employment can become easier, if financial constraints are relaxed, or harder, if relaxing the financial constraints of bigger firms makes it harder for individuals to compete.

We report estimates in Table (G.7) by type of self-employment for: (1) all industries, (2) Low Pay Gap industries only, and (3) High Pay Gap industries only. Panel A shows estimates for intrastate deregulation, while Panel B shows effects for interstate deregulation. Intrastate deregulation does not have an effect on gender differences in self-employment for any of the three industry categories and for any type of self-employment. Interstate deregulation does not have economically meaningful effects on gender differences in unincorporated self-employment. In contrast, for incorporated self-employment, there are small but statistically significant gender differences in incorporated self-employment of between 0.69 and 1.04%. These effects are mostly driven by lower

21. Interstate deregulation estimates excluding Maine presented in Table (F.4).

rates of incorporated self-employment among men than increases among women. Despite this, it is not likely that these gender differences in incorporated self-employment for interstate deregulation are driving our core results since the core results hold for both intrastate and interstate deregulation.

H. Controlling for Tobin's Q, Earnings Volatility and Leverage by Gender

In Table (H.8) we show the robustness of the main findings when controlling for proxies for industrial risk taking and Tobins' Q by gender.

I. Alternative Categorizations

In this appendix section, we repeat the main estimates of this paper (Table 4) using alternative ways of categorizing workers. In particular, we categorize industries by (i) using 1968–1972 as the categorization period instead of 1976–1980, (ii) by asset tangibility, or (iii) according to worker skills required in each occupation. We show that our main results do not meaningfully change if we follow an alternative categorization procedure. Further analysis on this robustness exercise is contained in Subsection IV.5.

I.1 Analysis with Categorization by Industrial Gender Pay Gap in 1968–1972 (Instead of 1976–1980)

The main analysis in the text starts in 1976 because states in the CPS data can only be identified separately starting in the 1977 survey. Less precise state identifiers exist, however, for earlier years. Using these imprecise identifiers we can repeat Table (4) using data starting in 1968, which is the earliest year where workers can be classified into full-time full-year status. The results are presented in Table (I.9). The results are generally similar to those presented in the main text.

I.2 Analysis with Categorization by Asset Tangibility

I.3 Analysis with Occupational Categorization into Nonroutine Cognitive or Nonroutine Manual Task

J. More on Tangibility

K. Unstaggered DiD Estimates

Throughout the paper we showed difference-in-differences estimates of the effects of financial deregulation on the gender pay gap using a staggered treatment design. This has been the practice in the literature. Nevertheless, recent papers have shown that in estimating difference-in-differences with a staggered design and heterogeneous treatment effects some events might be negatively weighted (Abraham & Sun, 2018). We can validate the robustness of our main results using a staggered treatment design by showing that the results we obtain when aligning events by event-time instead of calender-time remain similar. We hereinafter refer to this as the "unstaggered" DiD design.

Our "unstaggered" DiD design approach is similar to Cengiz et al. (2019). For each deregulation event and an X-year bandwidth around the event year, we create event-specific datasets whereby:

1. Only observations at calendar years that fall within the X-year bandwith around are kept in the sample; and

2. Observations from other states deregulating within the X-year bandwidth around the event year are excluded.

These two conditions mean that for each deregulation event all states that did not experience a regulation change serve as a control group (a more stringent criterion that provides a cleaner control group) and, also, that there is no other deregulation event contaminating the estimates. For each event h, we define event-time, T, as years since event h, that is, $T =$ calendar-year $t-$event-h-year. Notice that for each event, controls also have event-year time T defined relative to event-year h. Pooling all datasets, we run a similar equation to Eq. 1:

$$\begin{aligned} Y_{ijst} \quad = \quad & \alpha + \sum_{k \in \Omega} \beta_k D_{st} \times I_j^k + \sum_{k \in \Omega} \gamma_k D_{st} \times I_j^k \times F_i + \sum_{k \in \Omega} \delta_k I_j^k \times F_i \\ & + \sum_{k \in \Omega} \zeta_k I_j^k + \pi X_{ijst} + \tau_{T,female} + \mu_{s,female} + \rho_h + \epsilon_{ijst} \end{aligned} \tag{6}$$

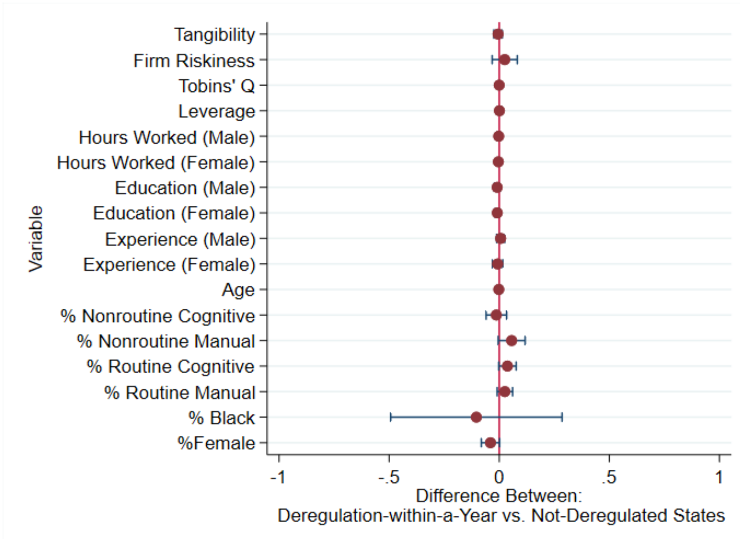
where now time fixed effects, $\tau_{T,female}$, are now defined based on event-time, T, instead of calendar-time, T, while ρ_h indicates event fixed effects. As we mentioned, by aligning events by event-time and dropping from the control group all states who had deregulated during the X-year bandwidth, this specification gets closer to the canonical DiD model and avoids the negative weighting of some events.

We estimate equation 6 for bandwidths $X \in \{1, 3, 5\}$ for both intrastate and interstate deregulation events. Table K.13 shows our results. The coefficient on Deregulation $\times$ Female for Low Pay Gap Industries, the main estimate of interest, ranges from 0.03 to 0.07, which is in the same direction and of a comparable magnitude to the coefficients reported on Table 4. Another important coefficient of interest, Deregulation $\times$ for High Pay Gap Industries, is also on the same direction and statistically significant, although under this more stringent specification the magnitudes are smaller. Other estimates are generally of a similar magnitude to the ones reported in Table 4.

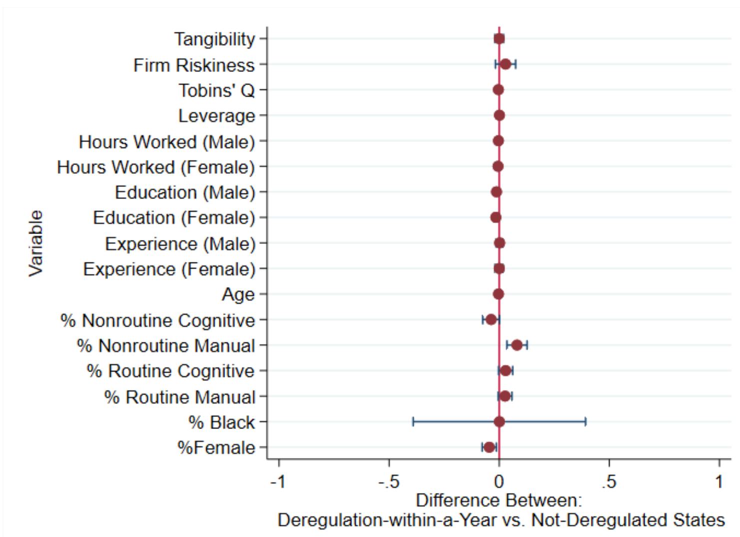
Appendix Figures and Tables

Figure B.1 Balance in Covariates between Nonderegulated and Deregulated (within a year) States

Panel A: Intrastate Deregulation



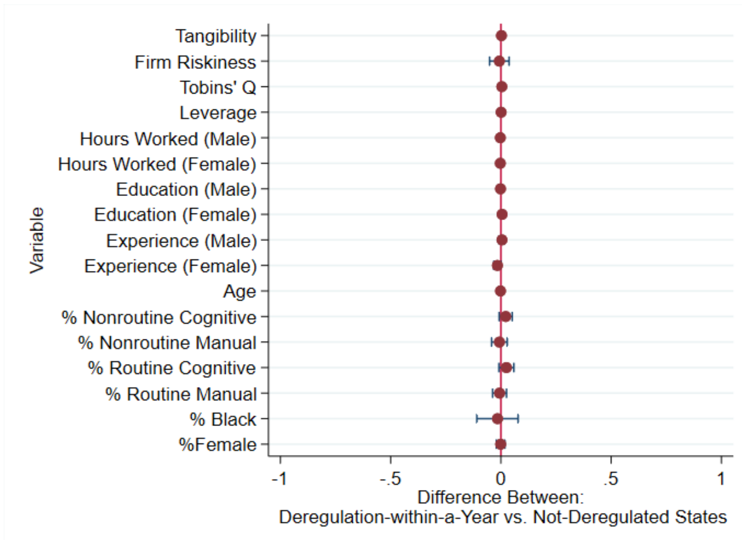
Panel B: Interstate Deregulation



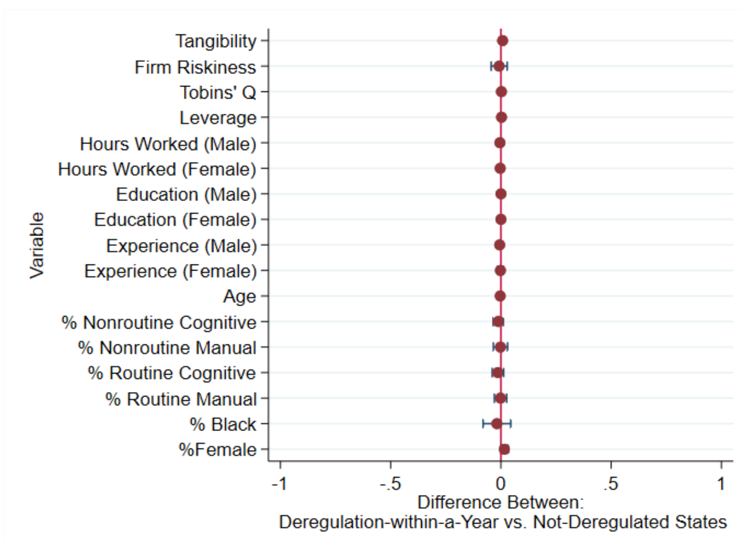
NOTES: This figure shows balance in covariates between states that have been deregulated (just before the passing of deregulation) and states that have not been deregulated. Normalized differences are computed by subtracting the average of each characteristic by deregulation status and then combining the averages. Tangibility, firm riskiness (volatility of firm earnings), Tobins' q, and leverage are obtained from Compustat at the industry level and are averaged by worker. Thus, they should be interpreted as workers' exposure to those industry characteristics. Data on usual hours worked, education, age, experience (proxied), % black, and % female are from the CPS. Occupation classifications by routine/nonroutine and cognitive/manual are from O*NET. Data cover the years 1976–2014.

Figure B.2 Balance in Covariates' Trends between Nonderegulated and Deregulated (within a year) States

Panel A: Intrastate Deregulation



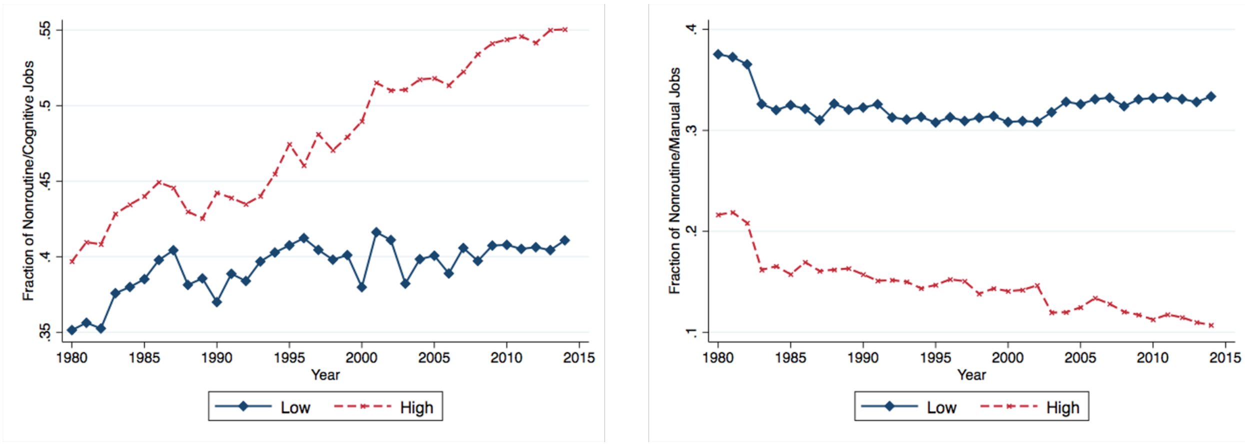
Panel B: Interstate Deregulation



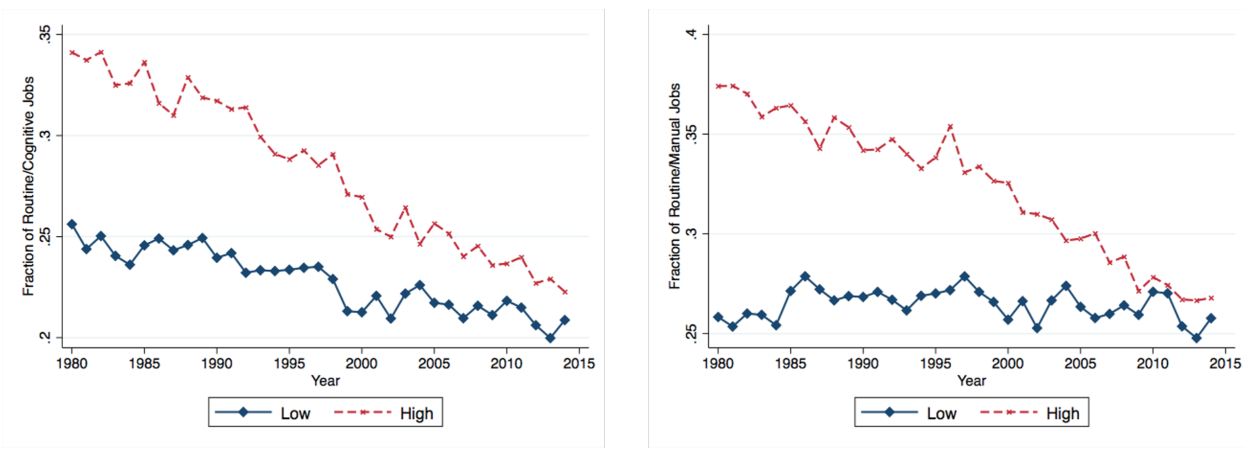
Notes: This figure shows balance in covariates between states that have been deregulated (just before the passing of deregulation) and states that have not been deregulated. Normalized differences are computed by subtracting the average of each characteristic by deregulation status and then combining the averages. Tangibility, firm riskiness (volatility of firm earnings), Tobins' q, and leverage are obtained from Compustat at the industry level and averaged by worker. Thus, they should be interpreted as workers' exposure to those industry characteristics. Data on usual hours worked, education, age, experience (proxied), % black, and % female are from the CPS. Occupation classifications by routine/nonroutine and cognitive/manual are from O*NET. Data cover the years 1976–2014.

Figure C.3 Nonroutine/routine and Cognitive/Manual Task in Low and High-Pay-Gap Industries

Panel A: Nonroutine Cognitive/Manual Task



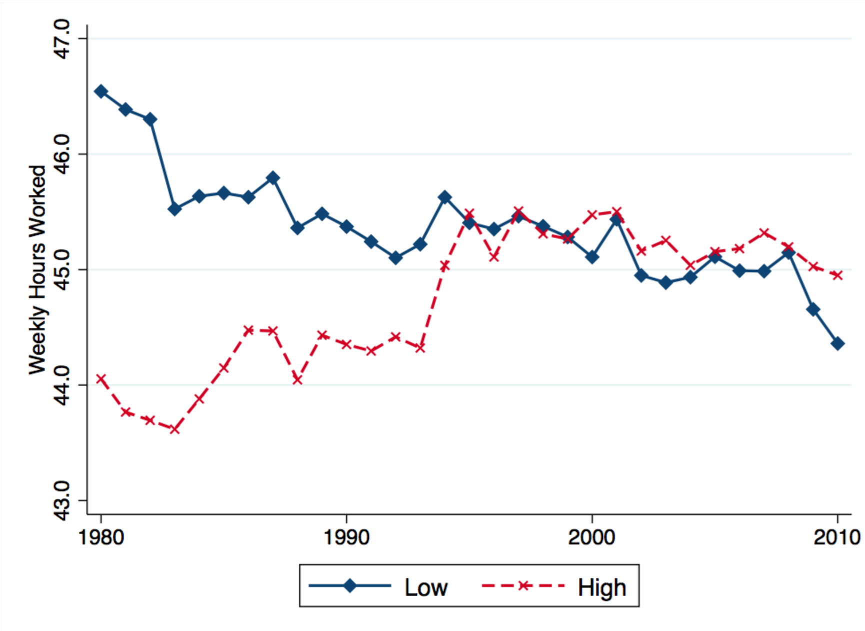
Panel B: Routine Cognitive/Manual Task



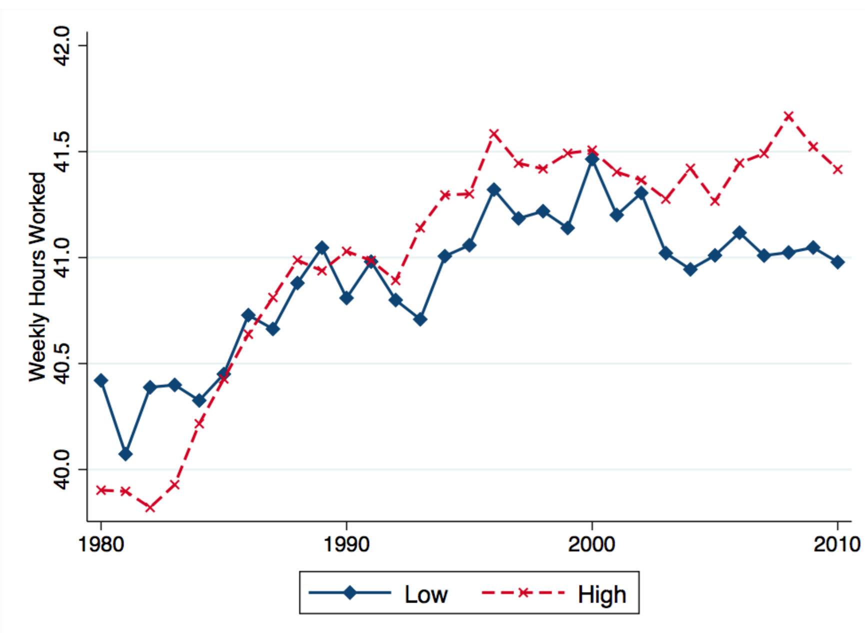
Notes: This figure plots the share of workers performing nonroutine/routine and cognitive/manual tasks computed using the DOT measures developed and defined by Autor, Levy, and Murnane 2003 and the CPS data from 1976-2014. The sample includes full time working-age adults. The sample excludes individuals working in the Finance, Insurance and Real Estate (FIRE) industries. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. For more details, see Section II.6.

Figure C.4 Working Hours by Gender

Panel A: Average Working Hours by Male Workers



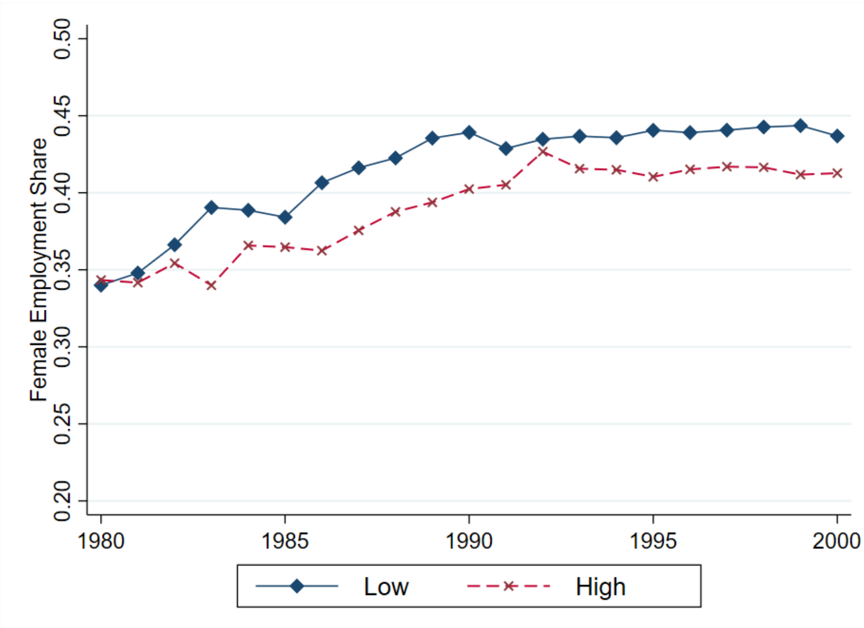
Panel B: Average Working Hours by Female Workers



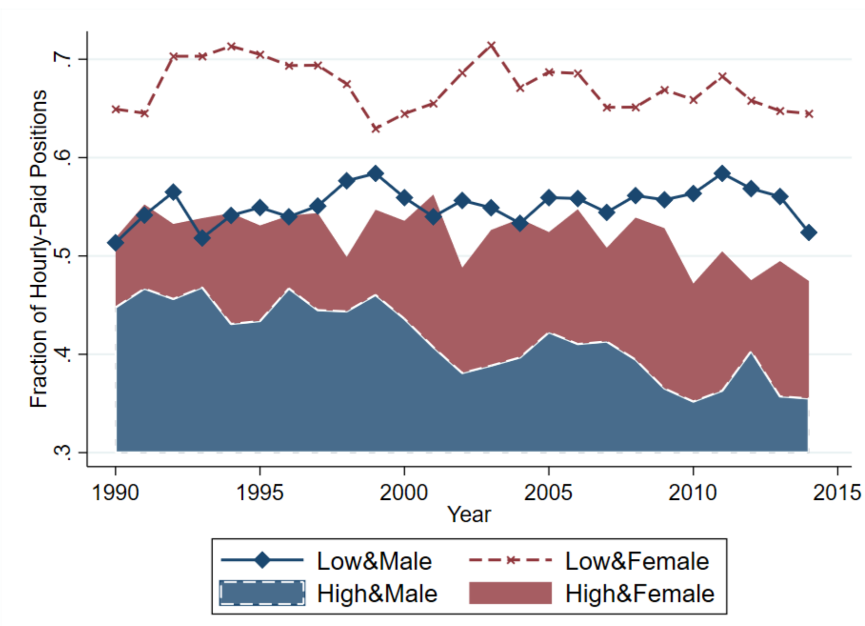
Notes: This figure plots the average weekly hours worked by gender and industry during 1980–2010 using the CPS data. The top panel plots the average weekly hours worked for full time working-age male employees in industries excluding Finance, Insurance, and Real Estate (FIRE) industries. The bottom panel plots the average weekly hours worked for female employees. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution.

Figure C.5 Employment Composition of Low and High-Pay-Gap Industries

Panel A: Female Share in Low and High-Pay-Gap Industries



Panel B: Share of Hourly-Paid Positions by Gender and Industry



Notes: This figure plots the fraction of hourly-paid positions between 1990 and 2014 using the CPS data from 1976-2014. The sample includes full time working-age adults. The sample excludes individuals working in the Finance, Insurance and Real Estate (FIRE) industries. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. For more details, see Section II.6.

Table D.1: Oaxaca Blinder Decomposition Pre- and Post-Deregulation

	Year Pre-Deregulation		Five Years Post-Deregulation		Difference	
	Log Points	Percentage	Log Points	Percentage	Log Points	Percentage
	(1)	(2)	(3)	(4)	(5)	(6)
Total Pay Gap	0.423	100.0%	0.312	100%	-0.111	100%
High Pay Gap Industry	0.034	8.0	0.022	7.0	-0.012	0.107
Low Pay Gap Industry	-0.013	-3.1	-0.039	-12.5	-0.026	0.237

NOTES: This table reports the Oaxaca-Blinder estimates of bank deregulation on the pay gap for full-time full-year workers, excluding the Finance, Insurance, and Real Estate (FIRE) industries. Columns (1)–(2) show estimates calculated for the year immediately preceding deregulation in the state. Columns (3)–(4) show estimates calculated five years following deregulation. Columns (5)–(6) show the difference. Wages in the wage regressions are the residual of a regression of log wages on Mincerian traits (education, experience, and experience squared) by year, and year and state fixed effects. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution.

Table E.2: Effects of Bank Mergers on Gender Pay Gap

	(1)	(2)	(3)	(4)
Merger × Female	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Merger × Female – Low PG Industry	-0.06***	-0.06***	-0.06***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Merger × Female – High PG Industry	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Merger	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Merger – Low PG Industry	0.02***	0.02***	0.02***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
Merger – High PG Industry	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Female – Low PG Industry	0.12***	0.12***	0.12***	0.12***
	(0.00)	(0.00)	(0.00)	(0.00)
Female – High PG Industry	-0.03***	-0.03***	-0.02***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Low PG Industry	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
High PG Industry	0.13***	0.12***	0.12***	0.12***
	(0.00)	(0.00)	(0.00)	(0.00)
N	477,550	477,550	477,550	477,550
County × Gender	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes
Age × Gender	No	Yes	Yes	Yes
Marital Status × Gender	No	No	Yes	No
Age × Gender	No	No	No	Yes

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

NOTES: This table reports the difference-in-differences estimates of the effects of bank merger on the gender pay gap when log(hourly wage) is regressed on a set of indicators and controls, as specified in Equation (2). Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. All specifications control for Mincerian traits×gender, and county×gender and year×gender fixed effects. Columns (2)–(4) and (6)–(8) additionally control for age×gender fixed effects. For details, see Section E. Errors are clustered at the county level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table F.3: Comparison of Industry Categorization using Alternative Sample — Excluding States Always-Treated for Intrastate Bank Deregulation

	# Industries in Subsample Original Categorization	# Industries Unchanged After Recategorization Excluding Always Treated	Match Rate(%)
	(1)	(2)	(3)
Panel A: All Industries			
	189	187	99%
Panel B: Low Pay Gap Industries			
	46	45	98%
Panel C: High Pay Gap Industries			
	51	51	100%

NOTES: The table reports the number of low and high-pay-gap industries within a subsample excluding the 17 states that deregulated prior to 1980. Column (1) shows the number of total, low-, and high-pay-gap industries categorized using the full sample. Column (2) shows the number of industries whose categories remain unchanged after they are recategorized into low-, medium-, and high-pay-gap industries using the subsample. Column (3) reports the match rate between the main and sub-sample. Two industries changed categories after re-categorization: *Electric light and power* (CPS ind1990 = 450) moved from the medium-pay-gap to the high-pay-gap category, while *Lumber and building material retailing* (CPS ind1990 = 580) moved from the low-pay-gap to the medium-pay-gap category.

Table F.4: Effects of Interstate Bank Deregulation on Gender Pay Gap — Excluding States Always-Treated for Intrastate Bank Deregulation

	(1)	(2)	(3)	(4)
Deregulation × Female	-0.02**	-0.02**	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – Low PG Industry	0.05***	0.05***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – High PG Industry	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – Low PG Industry	0.01*	0.01*	0.02**	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – High PG Industry	0.10***	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
Female – Low PG Industry	0.13***	0.13***	0.13***	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)
Female – High PG Industry	-0.03***	-0.03***	-0.03***	-0.03***
	(0.01)	(.01)	(.01)	(.01)
Low PG Industry	-0.19***	-.19***	-.19***	-.19***
	(0.01)	(.01)	(.01)	(.01)
High PG Industry	0.02**	0.02**	0.02***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
N	804,878	804,878	804,878	804,878
State × Gender	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes
Age × Gender	No	Yes	Yes	Yes
Marital Status × Gender	No	No	Yes	No
Race × Gender	No	No	No	Yes

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

NOTES: This table reports the difference-in-differences estimates of the effects of bank deregulation on the gender pay gap when log(hourly wage) is regressed on a set of indicators and controls, as specified in Equation (1), excluding states that deregulated prior to 1980. Columns (1)–(4) report the effects of intrastate deregulation, excluding the 17 states that deregulated prior to 1980. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. Columns (3)–(4) additionally control for age×gender fixed effects. For more details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table G.5: Effects of Intrastate Bank Deregulation on Gender Differences in Housing and Transportation

	Owns House (1)	Moved House (2)	Mortgage (3)	Owns Car (4)	Transportation Time (5)
Panel A: All Industries					
Deregulation × Female	-0.0024	-0.0006	-0.0014	-0.0015	0.0069
	(0.0068)	(0.0051)	(0.0024)	(0.0032)	(0.0063)
Deregulation	0.0171*	-0.0035	-0.0102	0.0153**	-0.0032
	(0.0092)	(0.0065)	(0.0082)	(0.0067)	(0.0147)
N	815,650	688,547	5,345,055	8,806,388	6,144,008
Panel B: Low Pay Gap Industries					
Deregulation × Female	-0.0088	0.0015	-0.0036	-0.0064	0.0072
	(0.0097)	(0.0093)	(0.0029)	(0.0042)	(0.0078)
Deregulation	0.0181**	-0.0052	-0.0085	0.0150**	-0.0063
	(0.0090)	(0.0085)	(0.0072)	(0.0064)	(0.0119)
N	207,486	179,480	1,139,255	1,972,398	1,412,705
Panel C: High Pay Gap Industries					
Deregulation × Female	0.0051	0.0041	-0.0000	-0.0003	-0.0015
	(0.0100)	(0.0107)	(0.0046)	(0.0027)	(0.0076)
Deregulation	0.0063	-0.0052	-0.0060	0.0152**	0.0099
	(0.0107)	(0.0084)	(0.0092)	(0.0063)	(0.0148)
N	205,400	172,006	1,279,888	2,058,252	1,421,266
County × Gender	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Data	CPS	CPS	Census	Census	Census

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

Notes: This table reports the difference-in-differences estimates of the effects of intrastate bank deregulation on differences in housing and transportation by gender using the CPS data from 1976–2014 and the Census data from 1980–2000. Both samples are restricted to working-age full-time full-year workers in the private sectors, excluding the FIRE industries. The dependent variables are ownership of dwelling for column (1), moving to a different house for column (2), holding a mortgage for column (3), car ownership for column (4), and transportation time for column (5). Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. For more details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table G.6: Effects of Interstate Bank Deregulation on Gender Differences in Housing and Transportation

	Owns House (1)	Moved House (2)	Mortgage (3)	Owns Car (4)	Transportation Time (5)
Panel A: All Industries					
Deregulation × Female	-0.0014	-0.0000	-0.0118	-0.0053	0.0053
	(0.0025)	(0.0030)	(0.0117)	(0.0072)	(0.0075)
Deregulation	-0.0014	0.0014	-0.0135	0.0114*	-0.0022
	(0.0067)	(0.0055)	(0.0139)	(0.0062)	(0.0048)
N	5,345,055	8,806,388	6,144,008	815,650	688,547
Panel B: Low Pay Gap Industries					
Deregulation × Female	-0.0074	-0.0034	-0.0064	-0.0187	-0.0053
	(0.0097)	(0.0049)	(0.0189)	(0.0180)	(0.0114)
Deregulation	-0.0079	-0.0011	-0.0070	0.0238**	-0.0071
	(0.0078)	(0.0072)	(0.0160)	(0.0093)	(0.0118)
N	1,139,255	1,972,398	1,412,705	207,486	179,480
Panel C: High Pay Gap Industries					
Deregulation × Female	-0.0015	-0.0029	-0.0155	-0.0169	0.0093
	(0.0041)	(0.0034)	(0.0112)	(0.0128)	(0.0146)
Deregulation	0.0012	0.0013	-0.0206***	0.0119	-0.0084
	(0.0083)	(0.0035)	(0.0040)	(0.0073)	(0.0063)
N	1,279,888	2,058,252	1,421,266	205,400	172,006
County × Gender	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Data	CPS	CPS	Census	Census	Census

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

Notes: This table reports the difference-in-differences estimates of the effects of interstate bank deregulation on differences in housing and transportation by gender using the CPS data from 1976–2014 and the Census data from 1980–2000. Both samples are restricted to working-age full-time full-year workers in the private sectors, excluding the FIRE industries. The dependent variables are ownership of dwelling for column (1), moving to a different house for column (2), holding a mortgage for column (3), car ownership for column (4), and transportation time for column (5). Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. For more details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table G.7: Effects of Bank Deregulation on Gender Differences in Self-Employment

	Self-Employed Incorporated			Self-Employed Unincorporated			Incorporated|Self-Employed		
	All	Low Pay Gap	High Pay Gap	All	Low Pay Gap	High Pay Gap	All	Low Pay Gap	High Pay Gap
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Intrastate Deregulation									
Deregulation × Female	0.0034	0.0029	0.0065	0.0001	0.0005	0.0004	0.0009	0.0091	-0.0096
	(0.0029)	(0.0035)	(0.0039)	(0.0006)	(0.0011)	(0.0012)	(0.0288)	(0.0443)	(0.0391)
Deregulation	-0.0012	-0.0005	-0.0027	-0.0002	-0.0003	-0.0014	-0.0041	-0.0033	-0.0052
	(0.0043)	(0.0042)	(0.0055)	(0.0009)	(0.0009)	(0.0018)	(0.0183)	(0.0223)	(0.0186)
N	1,214,036	290,286	270,618	1,214,036	290,286	270,618	51,643	11,219	17,367
Panel B: Interstate Deregulation									
Deregulation × Female	0.0069***	0.0104***	0.0081**	0.0004	0.0027**	-0.0004	0.0019	-0.0366	0.0315
	(0.0016)	(0.0025)	(0.0031)	(0.0004)	(0.0012)	(0.0010)	(0.0210)	(0.0501)	(0.0574)
Deregulation	-0.0068***	-0.0101***	-0.0056	0.0005	-0.0011	0.0012	-0.0226*	-0.0302	-0.0146
	(0.0024)	(0.0028)	(0.0044)	(0.0005)	(0.0012)	(0.0011)	(0.0125)	(0.0407)	(0.0161)
N	1,214,036	290,286	270,618	1,214,036	290,286	270,618	51,643	11,219	17,367
County × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Notes: This table reports difference-in-differences estimates of the effects of bank deregulation on the gender differences in self-employment following Equation (1) using Current Population Survey (CPS) from 1976–2014. We restrict to working-age full-time full-year workers and self-employed individuals in the private sector excluding FIRE industries. The dependent variable for columns (1)–(3) is an indicator variable for self-employed incorporated status; for columns (4)–(6) is an indicator variable for self-employed unincorporated status; and for columns (7)–(9) is an indicator variable for self-employed incorporated status conditional on self-employment. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. For additional details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table H.8: Effects of Bank Deregulation on Gender Pay Gap
— Additional Industry-Level Controls

	Intrastate Deregulation				Interstate Deregulation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deregulation × Female	-0.01	-0.01	-0.02*	-0.01	-0.02*	-0.01	-0.02*	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – Low PG Industry	0.05***	0.05***	0.06***	0.05***	0.04***	0.04***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – High PG Industry	-0.01	-0.01	-0.00	-0.01	-0.00	-0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation	-0.04***	-0.04***	-0.04***	-0.04***	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – Low PG Industry	0.02	0.01	0.01	0.01	0.04***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – High PG Industry	0.08***	0.08***	0.08***	0.08***	0.10***	0.10***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – Low PG Industry	0.09***	0.03**	0.10***	0.03**	0.10***	0.04***	0.11***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – High PG Industry	-0.04***	-0.05***	-0.04***	-0.06***	-0.05***	-0.06***	-0.04***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Low PG Industry	-0.19***	-0.17***	-0.18***	-0.18***	-0.20***	-0.18***	-0.19***	-0.20***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High PG Industry	0.01	0.02*	0.01	0.00	0.00	0.01	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female × Tobins' Q			-0.05**	0.08***			-0.04**	0.08***
			(0.02)	(0.02)			(0.02)	(0.02)
Female × Leverage		0.24***		0.23***		0.24***		0.23***
		(0.03)		(0.03)		(0.03)		(0.03)
Female × Earnings Volatility	0.00***			0.00***	0.00***			0.00***
	(0.00)			(0.00)	(0.00)			(0.00)
Tobins' Q			0.10***	0.11***			0.10***	0.11***
			(0.02)	(0.02)			(0.02)	(0.02)
Leverage		0.17***		0.23***		0.17***		0.23***
		(0.02)		(0.03)		(0.02)		(0.03)
Earnings Volatility	0.00***			0.00***	0.00***			0.00***
	(0.00)			(0.00)	(0.00)			(0.00)
N	711,241	711,241	711,241	711,241	711,241	711,241	711,241	711,241
County × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age × Gender	Yes	Yes	Yes	No	No	Yes	Yes	Yes

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

NOTES: This table reports difference-in-differences estimates of the effects of bank deregulation on gender pay gap when log(hourly wage) is regressed on the set of indicators and controls specified in Equation (1) and industry-level controls are included. Columns (1)–(4) report the effects of intrastate deregulation as a treatment, and columns(5)–(8) report the effects of interstate deregulation as a treatment. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. For additional details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table I.9: Effects of Bank Deregulation on Gender Pay Gap — Industries Categorized based on Pay Gaps from 1968 to 1972

	Intrastate Deregulation				Interstate Deregulation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deregulation × Female	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – Low PG Industry	0.06***	0.06***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – High PG Industry	0.01	0.01	0.01	0.01	0.02**	0.02**	0.01*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation	-0.02	-0.02	-0.02	-0.02	-0.04***	-0.04***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – Low PG Industry	-0.04***	-0.04***	-0.04***	-0.04***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – High PG Industry	0.05***	0.05***	0.05***	0.05***	0.06***	0.06***	0.06***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – Low PG Industry	0.06***	0.06***	0.06***	0.07***	0.07***	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – High PG Industry	-0.02**	-0.02**	-0.02**	-0.02**	-0.03***	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Low PG Industry	-0.11***	-0.11***	-0.11***	-0.11***	-0.12***	-0.12***	-0.12***	-0.12***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
High PG Industry	0.07***	0.07***	0.07***	0.07***	0.07***	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black				-0.12***				-0.12***
				(0.01)				(0.01)
Married			0.16***				0.16***	
			(0.00)				(0.00)	
N	774,186	774,186	774,186	774,186	774,186	774,186	774,186	774,186
County × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age × Gender	No	Yes	Yes	Yes	No	Yes	Yes	Yes

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

NOTES: This table reports the difference-in-differences estimates of the effects of bank deregulation on gender pay gap when log(hourly wage) is regressed on the set of indicators and controls specified in Equation (1) and industries are categorized based on the gender pay gap during the years 1968–1972 instead of 1976–1980. Columns (1)–(4) reports the impact of intrastate deregulation as a treatment, and columns(5)–(8) reports the impact of interstate deregulation as a treatment. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1968-1972. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. Columns (2)–(4) and (6)–(8) additionally control for age×gender fixed effects. For details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table I.10: Effects of Bank Deregulation on Gender Pay Gap,
— Industries Categorized by Asset Tangibility

	Intrastate Deregulation				Interstate Deregulation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deregulation × Female	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation × Female – High Tangibility	0.07***	0.07***	0.07***	0.07***	0.03*	0.03*	0.03*	0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Deregulation × Female – Low Tangibility	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation	-0.01	-0.01	-0.02	-0.02	-0.02*	-0.02*	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – High Tangibility Industry	-0.05***	-0.05***	-0.05**	-0.06***	-0.04***	-0.04***	-0.03**	-0.04***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Deregulation – Low Tangibility Industry	0.07***	0.07***	0.07***	0.06***	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – High Tangibility Industry	-0.09***	-0.09***	-0.09***	-0.08***	-0.05**	-0.05**	-0.05**	-0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Female – Low Tangibility Industry	0.02	0.02	0.01	0.01	0.00	0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High Tangibility Industry	-0.14***	-0.14***	-0.14***	-0.14***	-0.16***	-0.16***	-0.15***	-0.16***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Low Tangibility Industry	-0.10***	-0.10***	-0.09***	-0.09***	-0.08***	-0.08***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black				-0.14***				-0.14***
				(0.01)				(0.01)
Married			0.16***				0.16***	
			(0.00)				(0.00)	
N	867,993	867,993	867,993	867,993	867,993	867,993	867,993	867,993
County × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age × Gender	No	Yes	Yes	Yes	No	Yes	Yes	Yes

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

Notes: This table reports the difference-in-differences estimates of the effects of bank deregulation on the gender pay gap when log(hourly wage) is regressed on a set of indicators and controls specified, as in Equation (1), and industries are categorized by their level of asset tangibility. Columns (1)–(4) report the effects of intrastate deregulation as a treatment, and columns(5)–(8) report the effects of interstate deregulation as a treatment. Industries are categorized into low asset tangibility and high asset tangibility based on the difference in the mean asset tangibility share in each industry during 1976–1980. The high-asset-tangibility industries refer to industries that belong to the top 25% of the asset tangibility distribution, and the low-asset-tangibility industries refer to those in the bottom 25% of the asset tangibility distribution. High tangibility is a dummy variable that takes the value one for the high-asset-tangibility industries and 0 otherwise. Low tangibility is a dummy variable that takes the value one for the low-asset-tangibility industries and 0 otherwise. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. Columns (2)–(4) and (6)–(8) additionally control for age×gender fixed effects. For more details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table J.11: Effects of Deregulation on Firm Borrowing
— Industries Categorized by Asset Tangibility

	Debt Ratio			Debt Growth			Long Term Debt Growth		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intrastate – Low Tangibility	-0.10	-0.08	-0.06	-0.00	-0.00	-0.01	0.01	0.01	0.01
	(0.09)	(0.09)	(0.09)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Intrastate – High Tangibility	0.14***	0.18***	0.18***	0.05**	0.03	0.03	0.05***	0.03	0.04*
	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Intrastate	0.01	0.00	0.00	0.03	0.00	0.00	0.02	0.00	0.00
	(0.03)	(0.)	(0.)	(0.02)	(0.)	(0.)	(0.02)	(0.)	(0.)
Total Assets	0.11***	0.11***	0.11***	0.22***	0.22***	0.22***	0.18***	0.18***	0.19***
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tobin's Q			-0.00			-0.00			0.01
			(0.04)			(0.02)			(0.01)
Book Leverage									
N	61,612	61,553	60,551	61,574	61,515	60,515	61,621	61,562	60,547
Interstate – Low Tangibility	-0.07	-0.04	-0.04	0.00	0.01	0.01	0.01	0.02	0.02
	(0.06)	(0.06)	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Interstate – High Tangibility	0.12***	0.15***	0.14***	0.03	0.02	0.02	0.04	0.02	0.02
	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Interstate	0.02	0.00	0.00	0.04*	0.00	0.00	0.04	0.00	0.00
	(0.03)	(0.)	(0.)	(0.02)	(0.)	(0.)	(0.03)	(0.)	(0.)
Total Assets	0.11***	0.11***	0.11***	0.22***	0.22***	0.22***	0.18***	0.18***	0.19***
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tobin's Q			-0.00			-0.00			0.01
			(0.04)			(0.02)			(0.01)
Book Leverage									
N	61,612	61,553	60,551	61,574	61,515	60,515	61,621	61,562	60,547
Firm FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FX	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

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

NOTES: This table reports estimates of the effects of bank deregulation on firm debt. The dependent variable is debt ratio in columns (1)–(3), debt growth in columns (4)–(6), long-term debt growth columns (7)–(9). Industries are categorized into low asset tangibility and high asset tangibility based on the difference in the mean asset tangibility share in each industry during 1976–1980. The high-asset-tangibility industries refer to industries that belong to the top 25% of the asset tangibility distribution, and the low-asset-tangibility industries refer to those in the bottom 25% of the asset tangibility distribution. High tangibility is a dummy variable that takes the value one for the high-asset-tangibility industries and 0 otherwise. Low tangibility is a dummy variable that takes the value one for the low-asset-tangibility industries and 0 otherwise. All specifications control for firms, state, and year fixed effects. Columns (2), (5), (8), and (11) additionally control for state×year fixed effects. For details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table J.12: Effects of Deregulation on Firm Percentage of Tangible Assets

	% Tangible			R&D Spending		
	(1)	(2)	(3)	(4)	(5)	(6)
Intrastate – High PG Industry	-0.00	-0.01	-0.01	0.31***	0.32***	0.32***
	(0.00)	(0.01)	(0.00)	(0.06)	(0.05)	(0.03)
Intrastate – Low PG Industry	0.02***	0.02***	0.02***	-0.09	0.01	0.09
	(0.01)	(0.01)	(0.01)	(0.08)	(0.09)	(0.07)
Intrastate	-0.00			-0.29***		
	(0.01)			(0.06)		
N	68,407	68,355	60,593	41,535	41,387	36,541
Interstate – High PG Industry	-0.01**	-0.01**	-0.01***	0.35***	0.33***	0.29***
	(0.00)	(0.00)	(0.00)	(0.05)	(0.04)	(0.03)
Interstate – Low PG Industry	0.02***	0.02***	0.01***	-0.12*	-0.07	0.01
	(0.00)	(0.01)	(0.01)	(0.07)	(0.08)	(0.06)
Interstate	-0.00			-0.22***		
	(0.00)			(0.04)		
N	68,407	68,355	60,593	41,535	41,387	36,541
Firm FX	Yes	Yes	Yes	Yes	Yes	Yes
Year FX	Yes	Yes	Yes	Yes	Yes	Yes
State FX	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FX	No	Yes	Yes	No	Yes	Yes
Firm Controls	No	No	Yes	No	No	Yes

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

Notes: This table reports estimates of the effects of bank deregulation on tangible asset share (columns 1–3) and R&D (columns 4–6). Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. The high-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. High PG is a dummy variable that takes the value one for high-pay-gap industries and 0 otherwise. Low PG is a dummy variable that takes the value one for low-pay-gap industries and 0 otherwise. All specifications control for firms, state, and year fixed effects. Columns (2), (5), (8), and (11) additionally control for state×year fixed effects. Deregulation equals one if intrastate branching is deregulated and zero otherwise. For details, see Section II.4. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table K.13: "Unstaggered" DiD Estimates of Deregulation on Gender Pay Gap

	Intrastate			Interstate		
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year BW	3-year BW	5-year BW	1-year BW	3-year BW	5-year BW
Deregulation × Female	-0.01	-0.01	-0.01	-0.03**	-0.03**	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Deregulation × Female – Low PG Industry	0.04***	0.03**	0.03**	0.05***	0.07***	0.07***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Deregulation × Female – High PG Industry	-0.01	-0.01	-0.01	0.01	0.03**	0.04**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Deregulation	-0.02**	-0.02	-0.02	-0.03*	-0.02	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Deregulation – Low PG Industry	-0.03*	-0.02	-0.02	-0.03	-0.02*	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Deregulation – High PG Industry	0.03***	0.04***	0.03***	0.03***	0.04***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – Low PG Industry	0.11***	0.13***	0.13***	0.11***	0.10***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female – High PG Industry	-0.03***	-0.03**	-0.03**	-0.05***	-0.05***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Low PG Industry	-0.18***	-0.19***	-0.19***	-0.18***	-0.18***	-0.18***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
High PG Industry	0.04***	0.04***	0.04***	0.05***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1,890,824	3,544,025	4,645,609	1,798,185	2,027,712	1,422,063
County × Gender	Yes	Yes	Yes	Yes	Yes	Yes
Year × Gender	Yes	Yes	Yes	Yes	Yes	Yes

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

NOTES: This table reports the difference-in-differences estimates of the effects of bank deregulation on gender pay gap when we regress log(hourly wage) on the set of indicators and controls specified in Equation (1) and align events by event-time instead of calender-time ("unstaggered" DiD design) similar to Cengiz et al. (2019). Columns (1)–(3) report the effects of intrastate deregulation as a treatment, and columns(5)–(8) report the effects of interstate deregulation as a treatment. Industries are categorized into low pay gap and high pay gap based on the difference in the mean log wage between male and female employees in each industry during 1976–1980. High-pay-gap industries refer to industries that belong to the top 25% of the pay gap distribution, and the low-pay-gap industries refer to those in the bottom 25% of the pay gap distribution. High PG is a dummy variable that takes the value one for high-pay-gap industries and 0 otherwise. Low PG is a dummy variable that takes the value one for low-pay-gap industries and 0 otherwise. All specifications control for Mincerian traits×gender, and state×gender and year×gender fixed effects. Columns (1) and (4), (2) and (5), and (3) and (6) use a bandwith (years around deregulation event) of 1, 3, and 5 years, respectively. For additional details, see Section K. Errors are clustered at the state level and reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.