Bank Failures and Wage Inequality *

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Abstract

Whether financial distress has an effect on inequality is an important question for which there is relatively scarce evidence. In this study, we use individual-level data to examine the local effects of bank failures on wage inequality. Exploiting geographical variation in bank failures across communities, we show that recent bank failures lead to widening wage gap between skilled and unskilled (skill premium) by around $ 1,000 annually. Additionally, we find that the type of capital employed in a sector determines the extent to which the effects of bank failures are transmitted to local labor markets. Especially for sectors that use knowledge-dependent capital, which cannot be pledged as collateral and therefore has to be financed internally, skill premium induced by bank failures is differentially exacerbated. These results can unlikely be explained by other confounding factors and are consistent with knowledge-dependent capital being financed through forgone earnings of unskilled workers when total financing capacity shrinks.

Keywords: Bank Failures, Financial Crisis, Wage Inequality, Skill Premium

JEL Classification: G21, G33, J23, J31

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1 Introduction

A notable feature of the recent financial crisis was the spike in local bank failures in US, with the share of failing depository institutions approximating to the levels seen towards the end of the savings and loan crisis in the 1990s. Although there is a growing consensus that local bank failures lead to disruptions in credit provision, resulting in a decline in economic growth (Gilbert and Kochin, 1989; Ashcraft, 2007; and Ziebarth, 2013), it is still unclear whether the credit shocks induced by bank failures affect the whole population equally, or whether it disproportionately affects the rich or poor. This paper attempts to fill this gap by analyzing the effect of local bank failures on the wage differential between skilled and unskilled workers; namely, the skill premium.

Bank failures can influence both aggregate production and the allocation of credit, which may alter the demand for low and high skilled workers with concomitant ramifications on the wage differentials between skilled and unskilled (Townsend and Ueda, 2006). In episodes of lacking financing induced by bank failures, an average firm may have to scale down operation and reduce labor demand. In doing so, it may tend to protect more educated workers due to higher firing and future re-recruitment costs, leading to relatively lower demand for unskilled vis-a-vis skilled workers (Lopez and Oliviella, 2013).

Also, effects of bank failures on wage inequality may not be homogeneous across all sectors of the economy. Heterogeneity may arise from the differential exposures of sectors to credit shocks. In particular, sectors may structurally differ in their dependence on bank credit and their technological ability to pledge collateral to alleviate the negative effects of bank failures. There may also be technological differences across sectors in terms of the degree of complementarity/substitutability of skilled versus unskilled workers with the type of capital employed in production.

We argue that tangible capital increases the ability of a firms to alleviate the negative effects of credit shocks induced by local bank failures. Conversely, firms that use more intangible capital as opposed to tangible capital would be relatively more affected by bank failures. We also argue that intangible capital is knowledge intensive and, therefore, relatively more complementary with skilled labor than unskilled labor. Hence, affected firms - the ones which cannot pledge enough collateral - are the ones which are likely to demand less of unskilled labor in episodes of bank failures.

Empirical testing of these hypotheses faces a major endogeneity problem [1]: Bank failures do not happen randomly. Underlying economic conditions (demographics, corporate and household leverage, creditworthiness of the community members) which vary over time may cause both the incidence of financial distress (Mian and Sufi, 2013) and widening inequality (Kumhof, 2015). Similarly, regulatory institutions

[1] See Demirguc-Kunt and Levine (2009) for an overarching description of the endogenous relationship between financial distress and inequality.

could “forbear” failing certain banks based on community-level economic trajectories [2] that may coincide with factors affecting wage differentials between skilled and unskilled.

We address this challenge by following two-fold empirical strategy. At first, we identify the location of failed bank branches in each Public Use Micro-data Area[3] (PUMA). Following Ashcraft (2007) and Kandrac (2014), we classify PUMAs with at least one failed bank branch as affected areas. We, then, estimate a Mincerian skill-wage equation to test if the wage gap between skilled and unskilled workers are higher in affected PUMAs. Importantly, we enrich our regressions with several multi-way fixed effects that control for all time-varying community, sector as well as community and sector differences that capture underlying economic conditions across each sector within a PUMA. Conditional on all these time varying and sector as well as community specific characteristics, we argue that failure of thrift and depository institutions are exogenous to individual workers. Hence, a multi-way fixed effects approach enables us to abstract from the above-mentioned endogeneity concerns.

Our findings indicate that local bank failures indeed widened the wage gap between skilled and unskilled during 2007 - 2009 recession. These findings are statistically and economically significant and suggest that average annual wage gap between skilled and unskilled workers are higher by around $1000 in PUMAs witnessing bank failures than the ones without bank failures. Following Popov and Rocholl (2016), we consider the effect of bank failures not only on wages but also on labor hours. Simultaneous consideration of wages (price) and labor hours (quantity) in a reduced form model enables us to conclude that the effect is demand-driven. A demand-driven increase in wage inequality indicates that bank failures indirectly affect individual workers through their firms.This indirect link reassures the exogeneity of bank failures to individual workers.

We further substantiate the demand channel by exploiting the variation of knowledge intensity across sectors. The idea is the following: If credit shocks induced by bank failures indeed increase the skill premium, it should do more so in sectors for which skilled workers are indispensable for production,or put it differently, sectors that are knowledge intensive. Following the definition of knowledge intensity by Cleassens and Ueda (2008) [4], we indeed show that effect of bank failures on skill premium positively depends on the knowledge intensity of the sectors. The economic significance of the results suggest that moving from the sector at $25^t h$ percentile of knowledge intensity to the sector at $75^t h$ percentile of the knowledge intensity, skill premium induced by bank failures increase by around %1, which evaluated at the average, translates into an annual increase of $450.

[2] See Dinc and Kraig (2011).

[3] PUMAs are geographical units used by the US Census for providing statistical and demographic information. Next section provides an extensive description of PUMAs.

[4] The ratio of research and development (R&D) expenditures to sales is the measure proposed by Cleassens and Ueda (2008).

In the next step, continuing with the sectoral approach, we identify a unique channel for the observed demand-driven wage inequality. In particular, we by exploit sectoral heterogeneity across the usage of tangible and intangible capital to test if one observes higher wage inequality in more affected firms - the ones that use more intangible capital and less tangible capital. In particular, we show that the effect of bank failures on wage inequality is differentially exacerbated for sectors that rely more on intangible capital relative to tangible capital. We attribute this finding to the fact that the type of capital firms use matters for the transmission of local credit shocks to the labor market. These results are consistent with knowledge-dependent capital being financed through forgone earnings of unskilled workers when total financing capacity shrinks.

Being the first to study the effects of local bank failures on wage inequality, this paper contributes to several strands of the literature. Firstly, Gilbert and Kochin (1989), Ashcraft (2007) and Ziebarth (2013) found that local bank failures cause decline in economic growth. Also, Chodorow-Reich (2013), Berg (2016) and Popov and Rocholl (2016) show the employment effects of negative credit shocks on affected firms' employment. We complement this literature by showing the distributional effects of credit shocks, in general and bank failures, in particular. Secondly, we contribute to small but growing literature on how finance affects inequality. Beck et al. (2010) shows that branch deregulation decreases income inequality, whereas Jerzmanowski and Nabar (2013) found the effect of branch deregulation as increasing the wage inequality. Larrain (2015) showed that financial liberalization following capital account opening by several eastern European states increased relative wages of skilled to unskilled. Our findings also complement this literature by establishing the channel of bank failures as a determinant of wage inequality.

The remainder of this paper is organized as follows: Section 2 explains how banks failures affect wage inequality. Section 3 describes te data. Section 4 presents empirical methodology employed in the study and presents the baseline results. Section 5 establishes the channel through which bank failures widen the wage gap between skilled and unskilled. Section 6 presents the additional robustness tests and, finally, section 7 concludes.

2 How do bank failures affect wage inequality?

Previous literature shows that in episodes of financial distress, when firms have to cut down the production and input costs, they may have skill-specific labor demand (Lopez and Oliviella, 2013). In particular, firms may tend to protect more educated workers due to higher firing and future re-recruitment costs, leading to relatively lower demand for unskilled vis-a-vis skilled workers. In addition, employment protection legislation (EPL) could also create skill specific unemployment risks (Bennett 2016), which may favor skilled vis-a-vis unskilled, especially during the times of financial distress when firms have to cut down production. These lead us to form our first hypothesis:

Hypothesis 1: *Local bank failures will increase wage inequality between skilled and unskilled workers (skill premium) by, in relative terms, inducing firms to demand more skilled vis-a-vis unskilled labor, widening the wage gap between two types of workers.*

It should be noted that Hypothesis 1 does not necessarily state that firms will demand more of skilled labor and less of unskilled a bank a result of bank failures. It rather argues that although there can be decline in the labor demand overall, reduction in the demand for unskilled labor will be relatively more severe than that if skilled labor, which ultimately widens the wage gap between skilled and unskilled.

Moreover, observed effects of banks failures on wage inequality may be heterogenous across sectors of economy. First, it can be argued that how firms would be affected by bank-failure-induced credit shocks is very much dependent on how much firms rely on external finance as opposed to internal finance. Rajan and Zingales (1998) in their seminal contribution, show that for technological reasons, sectors are heterogenous in terms of their need for external finance. It is therefore plausible to claim that, holding all else constant, sectors that rely more on external finance are likely more affected by bank failures. Therefore, to the extent that externally dependent sectors demand more of skilled labor vis-a-vis unskilled labor, bank failures may widen the wage gap between skilled and unskilled.

Second, the heterogeneity in firms exposure to credit shocks induced by bank failures can also stem from the heterogeneity in firms ability to pledge collateral. It has been widely documented that during recessions and financial crises, financial factors, such as collateral constraints and debt overhang, exacerbate the financial constraints faced by firms. Put it differently, in financial distress situations, in which information asymmetries are exacerbated, a firms ability to be able to pledge collateral could be vital for accessing scarce credit. Thus, if firms that are less able to pledge collateral happen to be the firms that demand more skilled as opposed to unskilled labor, financial distress situation can indeed increase the wage inequality between skilled and unskilled.

The following question then arises: What is the linkage between a firms exposure to credit shocks and its relative demand for skilled versus unskilled labor?

The type of labor a firm demands for is very much dependent on the type of capital a firm employs. At the same time, the type of capital a firm employs can also determine how much a firm would be exposed to contraction in credit induced by local bank failures. Intangible capital which is arguably more knowledge intensive than tangible capital, complements skilled labor more than unskilled labor (Hall 2000, 2001). Firms that have relatively more intangible capital naturally demand unskilled labor to a lesser degree than firms that operate with more tangible capital. However, as outlined by previous literature (Almeida and

Campello, 2008; Rampini and Viswanathan 2010), tangible capital has a comparative advantage in terms of serving as collateral vis-a-vis intangible capital. Assets that are more tangible sustain more external financing because such assets mitigate contractibility problems: Especially during the episodes of financial distress such as bank failures in which information asymmetries and contractibility problems are exacerbated, possession of tangible capital that can be pledged as collateral is arguably vital to alleviate the negative effects of credit contractions.

Hence, in episodes of bank failures, firms that relatively rely more on intangible capital would be more affected by credit contraction. These are the firms that demand more skilled labor as opposed to unskilled. In a way, the affected firms - firms which cannot pledge enough collateral are the ones which are likely to demand less of unskilled labor in episodes of bank failures. In other words, when bank failures hit local economy and lead firms to decrease input costs, relatively affected sectors are the ones that rely more on skill labor for sustaining the production and that can give up employing unskilled labor relatively easier.

It should also be noted that the extent to which firms would be affected by bank failures does not only depend on the share of tangible capital in overall capital. It also depends on to what extent firms are dependent on external finance. In fact, for the firms that depend on external finance to a lesser degree or do not depend at all the effects of bank failures would only be very indirect and minimal. These lead us to form our second hypothesis:

Hypothesis 2: *Holding external dependence constant, effects of bank failures on skill premium will be differentially exacerbated in sectors that rely more on intangible capital vis-a-vis tangible capital.*

It is important to note that the hypotheses we explain in this section need not be the only explanations for why and how bank failures may affect wage inequality. One important explanation, among others, could be that bank failures may alter the supply of credit and how it is allocated in an economy, which in turn can have repercussions in the labor market. Due to data limitations, we are unable to systematically analyze if and how allocation of credit changes in the economy. What we are able to do, however, is to control for all factors that are changing at community, sector and time through multi-way fixed effects so as to abstract from the explanations we cannot observe to confound the tests of above-mentioned hypothesis, which is explained in detail in the next section.

3 Data

To measure the effects of bank and thrift failure on local economic conditions, we begin by taking each PUMA[5] in the 50 U.S. states as a separate observation. PUMAs are geographic units used by the US Census for providing statistical and demographic information. The state governments draw PUMA boundaries to allow reporting of detailed data for all areas. There are a total of 2,071 PUMAs in the 2000 Census. Each PUMA contains at least 100,000 people. They do not overlap, and are contained within a single state.Figure 3 shows PUMA boundaries as of Census 2000.

[Figure 3 here]

We proceed by (1) identifying PUMAs affected by the failure of a financial institution within each PUMA for a given date, and (2) measuring subsequent wage differentials between skilled and unskilled in that PUMA. Although the purview of an individual branch may extend beyond PUMA borders, we only consider the effects in the PUMAs in which failed banks operated (Ashcraft, 2007; Kandrac 2014). Previous studies suggest that physical proximity to a bank is a highly important determinant in the establishment of a bank-customer relationship (Whitehead, 1982; Hannan, 1991; Laderman, 2008). Moreover, to detect a PUMA-level effect, it is not a requirement that the banking market for an individual branch is confined to a single PUMA, but only that a bank is most heavily engaged with the community in which it operates. In either case, the incidence of any potential negative credit shocks as a result of bank failure would fall most heavily on the area nearest the bank (though the disruption would be stronger in the former case, leading us to at least estimating a lower bound of the actual effect).

First, we identify the location of each bank branch nationwide for 2007-2009. The FDIC's Summary of Deposits provides latitude and longitude information of each bank branch, enabling us to determine the exact point of a bank branch on a physical map. We, then, draw 2071 polygons on a physical US Map by using data on PUMA borders' geo-coordinates as of Census 2000 from Missouri Census Data Center. By applying a point-to-polygon matching we identify the PUMAs within which each bank branch precisely lies. Merging this data with the FDICs Failed Bank List, we are able to identify the number of failed banks in each PUMA for each year.

Our analysis covers the period of 2007 - 2010. As Figure 2 shows, although number of failed banks quite high for 2011 and also onwards, we are unable to study post 2010 period due to PUMA borders being changed following census 2010.

[Figure 2 here]

[5]The reason for us to focus on PUMA classification as opposed to county or ZIP-code is that the most granular geographic classification American Community Survey - from which we obtain American workforce information - provides is PUMA classification.

Second, we collect individual-level information for each PUMA from American Community Survey(ACS). ACS is an ongoing survey by the U.S. Census Bureau. It regularly gathers information previously contained only in the long form of the decennial census, such as ancestry, educational attainment, income, language proficiency, migration, disability, employment, and housing characteristics. These data are used by many public-sector, private-sector, and not-for-profit stakeholders to allocate funding, track shifting demographics, plan for emergencies, and learn about local communities. Sent to approximately 295,000 addresses monthly (or 3.5 million per year), it is the largest household survey that the Census Bureau administers. The number of observations are kept large to ensure that the survey is always representative at PUMA-level.

By using ACS, we obtain annual wages, number of hours worked, sector in which an individual works, demographic information, educational attainment for over 3 million individuals annually, summing up to more than 12 Million observations. Due to its immense size and limitations on computing power, and we **randomly** sample 413 PUMAs (20% of 2071 PUMAs) from the entire data set and conduct our empirical analysis throughout. With this sampling we are still able to work with nearly 1.8 million observations in our analysis. Even though it is not feasible to conduct entire analysis with complete sample, we at least run the baseline regression with entire sample to make sure that our findings are confirmed [6].

Our sample only includes individuals who are of working age and who are in and out of the labor force. To this end, individuals who are below 15 and who are older than 65 are excluded from our sample (Following Jerzmanowski and Nabar 2013).The variables used in the analysis are explained below in line with the summary statistics provided in Table 1:

[Table 1 here]

Wage: Our main dependent variable is annual wages. Table 1 indicates that mean annual wages are between $4,348 and $729,834 with an average of $45,0.25. Several studies (Lydall, 1959; Lillard and Willis, 1978) point out the skewed distribution of wages in Mincerian skill-wage set-ups. We also observe this feature in our data set. Figure 1 depicts this feature.

[Figure 1 here]

Panel (a) in Figure 1 shows that fractional histogram of annual wages are highly skewed to the right. For this reason, and also due to theoretical derivation of Mincerian skill-wage equation (Mincer, 1974), natural logarithm of wages are considered. Panel (b) of Figure 1 presents fractional histogram of the natural logarithm of annual wages. Taking the natural logarithm helps us penalize too big and too small observations as well as tightens up the distribution of wages.

[6] Baseline results with entire sample can be found in section 5.

Hours: Another dependent variable that we utilize throughout the paper is the number of hours an individual works in a given year. ACS provides information on number of weeks worked in a given year as well as 6 ranges within which the weekly hourse worked lies. In order to make this information compatible with annual wages we observe, we take the mean of the ranges and multiply by it by the number of weeks worked in a given year. This enables us to construct an arguably good proxy for the unobserved number of hours an individual works in a given year. Table 1 indicates that our proxy for yearly hours lie between 7.5 hours and 5049 hours with an average of 1759 hours.

Labor Force: Another dependent variable that we take into account is the external margin of the labor supply, i.e., labor force participation status of individuals. This is an indicator variable that takes the value one for individuals who are in the labor force and zero otherwise. As Table 1 shows, around %62 of the individuals are in the labor force in our data.

FAILED: Our treatment variable, FAILED, is, as explained above, an indicator variable that takes the value one for PUMAs in which a failed bank branch is located and zero elsewhere. As Table 1 indicates, around %21 of observations are attributed to a PUMA in which at least one bank failure occurred during the period 2007 - 2009.

EDUC: Following Jerzmanowski and Nabar (2013), we consider a binary classification for the level skill an individual has. We classify individuals as skilled if they have undergraduate or above degree and unskilled otherwise. In lieu of this, EDUC is a dummy variable that takes the value one for the individuals with undergraduate or above degree and zero otherwise. As Table 1 shows nearly half of the workers are considered as skilled in our analysis.

EDUC*FAILED Our identification comes from estimating average wage differentials between skilled and unskilled workers in PUMAs where bank failures happen vs. in PUMAs where no bank failures happen. In this regard, our variable of interest is the interaction of EDUC and FAILED. Table 1 shows that nearly %12 of the observations are skilled individuals who reside in PUMAs in which at least a bank failure was experienced.

Our regressions are also enriched by several control covariates in the form of continuous, categorical and dummy variables as shown in Table 1. In particular we have standard Mincerian skill-wage control variables such as experience and experience square (measuring the decreasing returns to experience) as well as additional control variables such as age, age squared, race, sex, marital status, maternity or paternity status, being born in a foreign country and interactions of these variables.

4 Method and Results

Following Jerzmanowski and Nabar (2013), we at first estimate a standard Mincerian earnings equation of the following form:

$$log(wage)_{ipt} = \beta_0 + \beta_1 * EDUC_{ipt} + \beta_2 * FAILED_{pt-1} + \beta_3 * EDUC_{ipt} * FAILED_{pt-1} + \alpha_p + \alpha_t \tag{1}$$

where, i stands for individual, p stands for PUMA and t stands for year. $Falied$ takes the value one for the year that comes after the bank failure and zero otherwise. The reason for not extending the effect for the second or the third year is that the bank resolution regime applied by the FDIC, namely the Purchase and Agreement Assumption enabled that there was almost always an acquiring bank of the failed bank, which prevents the long term disruptions in credit to local economies. Following Ashcraft (2007) and Kandrac (2014), we include $Falied$ with one year lag to lessen the concerns regarding reverse causality. $EDUC$ is a dummy variable that takes the value one for the individuals with high school degree or less and zero for the ones who have some college or above degrees of education.

PUMAs can be significantly different from each other. Based on the discussion in section 1, there may be PUMA-level time-varying omitted factors that may lead to overestimation. To address this concern, we enrich the model above by including several multi-way fixed effects:

$$log(wage)_{ipt} = \beta_0 + \beta_1 * EDUC_{ipt} + \beta_3 * EDUC_{ipt} * FAILED_{pt-1} + \alpha_{pt} \tag{2}$$

$$log(wage)_{ispkt} = \beta_0 + \beta_1 * EDUC_{ipt} + \beta_2 * FAILED_{pt-1} + \beta_3 * EDUC_{ipt} * FAILED_{pt-1} + \alpha_{spk} + \alpha_{pkt} \tag{3}$$

$$log(wage)_{ispkt} = \beta_0 + \beta_1 * EDUC_{ipt} + \beta_3 * EDUC_{ipt} * FAILED_{pt-1} + \alpha_{spkt} \tag{4}$$

where, s stands for sector (based on 3 digit SIC classification) and k stands for age cohort. In equations (2) and (4) we are unable to estimate the effect of $Falied$ on $log(wage)$ since the multi-way fixed effects capture the entire variation that is changing at least at PUMA-year level.

Sector fixed effects control for any potential wage difference attributable to the differences in sectors. Following the seminal contribution of Polachek (2007), we also include fixed effects for different age cohorts. Inclusion of age-cohort dummies enables us to abstract from any life-cycle effects that may potentially widen the wage gap between skilled and unskilled. Moreover, our data set is repeated cross-section with a panel dimension at the PUMA-level. That is, although we can observe the same PUMAs over time, we are unable to observe individuals over time. Despite this, by including age-cohort fixed effects, we are at least able to observe the same age cohort over year within a PUMA.

In Table 2, we present the estimation results arising from these equations.

[Table 2 here]

Columns(1) and (3) of Table 2 shows that although average annual wages decline more in PUMAs that witnessed bank failure, average wage gap between the skilled and unskilled widens; i. e., skill premium is significantly higher in PUMAs having witnessed bank failures in the previous year. In columns (2) and (4), we repeat the same exercise by controlling for all characteristics that change in PUMA and year by including PUMA-Year and PUMA-Ind-Age-Year fixed effects. Although we are unable to estimate the average effect of bank failures on overall decline in wages (as PUMA-year fixed effects capture the entire variation in these dimensions), we are still able to estimate the interaction term. Overall, the estimation results in columns (2) and (4) verify the findings in columns (1) and (3). Therefore, findings presented in Table 2, columns (1) to (4) suggest a very strong positive relationship between bank failures and wage gap between skilled and unskilled, with the direction of impact going from bank failures to skill premium. In other words, bank failures result in widening wage inequality between skilled and unskilled.

Moreover, these findings are also economically significant: Bank failures are associated with roughly 5%[7] increase in the skill premium in the most conservative specification.

Regression estimations in Table 2 columns (1) to (4) use several control variables which are used as standard controls in estimating Mincerian earnings functions. Following Jerzmanowski and Nabar (2013), we include following additional control variables, Age, $Age{-}squared$, $married$ $married{-}child$ $female{-}child$ to ensure that the results in Table 2 are not driven by age [8], marriage, maternity (paternity) status and any interaction of last two. We present these results with extra control variables in columns (5) to (8) of Table 2 and confirm the robustness of previous results to these additions.

All in all, in this section, we establish that bank failures widen the wage gap between skilled and unskilled and; hence; are associated with higher wage inequality.

4.1 Supply versus Demand

Although previous results confirm that bank failures are associated with higher wage inequality, they are inconclusive as to whether this relationship is associated with demand-side or supply-side explanations. That is, it is still unclear if the observed effect is driven by a negative credit shock making employees (firms) demand relatively less unskilled workers or if unskilled individuals increase the supply of labor during times of financial distress, driving down their average wages. However, the Mincerian earnings

[7] According to Halvoren and Palmquist (1980), the effect of dummy variables in semi-logarithmic equations is $(exp(\beta_3){-}1)$. Kennedy proposes a variance correction for this interpretation, which has negligible impact here.

[8] Whenever we include age-cohort fixed effects, we are unable to estimate the marginal effect of Age and $Age - squared$

equation of the above does not exclude the fact that the effect could be supply-driven. In what follows, in order to disentangle demand and supply, we consider labor supply-demand conditions both in external and intensive margins.

4.1.1 Extensive Margin of Labor Supply

Extensive margin of the labor supply is attributed to binary decision of workers to supply labor or not. This binary decision is congruent to being in or out of the labor force.

The results in Table 2 indicate that bank failures are associated with an increase in the wage gap between skilled and unskilled. One could imagine that bank failures could affect the skill premium if it affected the relative supplies of skilled and unskilled labor. In particular, if the labor force participation of less skilled workers increased relative to the labor force participation of skilled workers after bank failures, the increase in the relative supply of less skilled workers could drive down their wages relative to the wages of skilled workers.

In Table 3, we study the impact of bank failures on labor force participation and the supply of different types of different types of workers. Namely, we run the following linear probability models with a dependent binary variable, D of labor force participation status, one being in the labor force and zero otherwise.

$$D_{ispkt} = \delta_0 + \delta_1 * EDUC_{ipt} + \delta_2 * FAILED_{pt-1} + \delta_3 * EDUC_{ipt} * FAILED_{pt-1} + \mu_{spk} + \mu_{pkt} \tag{5}$$

$$D_{ispkt} = \delta_0 + \delta_1 * EDUC_{ipt} + \delta_3 * EDUC_{ipt} * Failed_{pt-1} + \mu_{spkt} \tag{6}$$

[Table 3 here]

Insignificance of the coefficients of $FAILED$ as well as $EDUC*FAILED$ in Table 3 indicates bank failures neither change local labor force participation, nor do they increase the probability of unskilled to supply labor more at the extensive margin more than unskilled [9].

4.1.2 Intensive Margin of Labor Supply

Next we consider the labor hours to check the intensive margin of the labor supply. In particular, we consider here if there is a differential change in annual hours worked by skilled versus unskilled workers. To this end, we run the following regressions, which are analogous to previous baseline equations:

[9] Though not presented here, we also run the analogous logit regressions and reassure these findings.

$$log(hours)_{ipt} = \gamma_0 + \gamma_1 * EDUC_{ipt} + \gamma_2 * FAILED_{pt-1} + \gamma_3 * EDUC_{ipt} * FAILED_{pt-1} + \mu_p + \mu_t \tag{7}$$

$$log(hours)_{ipt} = \gamma_0 + \gamma_1 * EDUC_{ipt} + \gamma_3 * EDUC_{ipt} * FAILED_{pt-1} + \mu_{pt} \tag{8}$$

$$log(hours)_{ispkt} = \gamma_0 + \gamma_1 * EDUC_{ipt} + \gamma_2 * FAILED_{pt-1} + \gamma_3 * EDUC_{ipt} * FAILED_{pt-1} + \mu_{spk} + \mu_{pkt} \tag{9}$$

$$log(hours)_{ispkt} = \gamma_0 + \gamma_1 * EDUC_{ipt} + \gamma_3 * EDUC_{ipt} * FAILED_{pt-1} + \mu_{spkt} \tag{10}$$

which is the analog of the wage equations presented formerly. In a reduced form model, in which the wage equation is a "price" equation and the hours equation is a "quantity" equation, one can conclude if the observed effects are supply- or demand-driven. For this purpose, we expect both β_3 (from equations 1 - 4) and γ_3 to be negative. Observing that both of these coefficients are negative and significant, one can conclude that the observed effects are demand-driven (Popov and Rocholl, 2016). The idea behind that is that in a simple supply-demand frame work, a simultaneous decline in the price and the quantity can only be attributed to a downward shift in the demand. Table 4 columns (1) to (4) show the baseline results whereas columns (5) to (8) indicate the results with additional controls (being on par with Table 2, respectively.)

[Table 4 here]

Table 4 indicate that not just the skill premium but also the differences in annual working hours between skilled and unskilled are exacerbated after bank failures. Since both the estimated β_3 and γ_3 are positive and significant in all specifications in Table 2 and 4, we conclude that the observed increase in skill-premium after bank failures is a demand-driven effect.

4.2 Results with stable sample

So far, number of observations used in the analysis conducted in Table 2, 3 and 4 vary significantly. There is a big drop in sample size when we make specifications more conservative each time by including multi-way fixed effects. In the most conservative specification in which we focus on the variation across wages within an age cohort, in a sector, in a PUMA at given point in time, we sometimes lack enough observations to ensure the convergence of the estimates to population parameters. In order to ensure that results are not driven by different samples used through out the tables, we conduct the entire analysis with a stable sample. The key results with a stable sample are presented in Table 5.

[Table 5 here]

The findings presented in Table 5 verify the findings demonstrated in Table 2 and 4 that observed increase in skill-premium after bank failures is demand-driven and they are not driven by differential samples and sample sizes.

4.3 More evidence on demand effects: Knowledge intensity

Previous sections show a robust evidence on a demand-driven increase in skill premium, which is differentially higher in PUMAs that experienced a bank failure. To further substantiate this evidence, we exploit the variation across sectors in terms of knowledge intensity. The underlying idea is the following: Sector which are, for technological reasons, more dependent on knowledge intensive capital are expected to have relatively more inelastic labor demand for skilled labor and more elastic demand for unskilled labor Claessens and Ueda (2008). Therefore, assuming that knowledge intensive capital and skilled labor are rather complementary and knowledge dependent firms have an elastic demand for unskilled labor, it can be expected that firms that depend more on knowledge intensive capital will have a differentially lower demand for unskilled labor during the time of financial distress. Therefore, the effect of negative credit shocks on the wage gap between skilled and unskilled is expected to be much higher in more knowledge intensive sectors.

Following Claessens and Ueda (2008), we calculate knowledge intensity as te ratio of R&D expenditures to sales, which we encode as *R&D* in the tables. So as to ensure that knowledge intensity measure is not itself affected by bank failures we take the average this ratio for 1987 - 2005 and conduct the analysis with a time invariant sector specific knowledge intensity for 2 digits Standard Industry Classification (SIC) classification. Appendix shows the data for *R&D* for 2 digit sectoral classification. Although we use 2-digit classification in our analysis, we nevertheless present mean R&D ratio higher level sector classification in panel (a) of Figure 4. As expected, service, transportation and non-classifiable sectors have higher *R&D* ratios than sectors such as mining and agriculture.

[Figure 4 here]

To test if the effect of bank failures on skill premium is differentially higher in relatively more knowledge intensive sectors, we interact our variable of interest, $Failed * Education$ with *R&D*. That is, this triple interaction term captures the effect of bank failures on wage premium depending on knowledge intensity. The estimation results of this triple interaction model is demonstrated in Table 6.

[Table 6 here]

The positive and significant estimated coefficient of this triple interaction term indicates that sectors there is a differentially higher skill premium across sectors, which increases as knowledge intensity increases.

In order to get a sense of the economic significance of this term, we calculate the differentials in the effect of bank failures on skill premium on par with the analysis by Rajan and Zingales (1998) and Friedrich et al. (2013). That is, we consider two sectors at the $25^t h$ and 75^{th} percentile of the knowledge intensity. Then we test the null hypothesis of the effect of bank failures on skill premium moving from a sectors at the $25^t h$ percentile to a sector at the 75^{th} percentile of knowledge intensity is statistically zero. Table 7 illustrates this.

[Table 7 here]

Each column of the Table 7 conducts the test of above mentioned null hypothesis utilizing regression results presented in the respective columns of Table 6. Table 7 indeed shows that the null hypothesis can be rejected and the size of the effect bank failures on skill premium moving from a sectors at the $25^t h$ percentile to a sector at the 75^{th} percentile of knowledge intensity is comparable to the size of the effect found in Table 2 (nearly 1% of annual wages, which, calculated at the average, amounts to nearly $ 450 per year).

5 Transmission channels of the effect of bank failures to labor market

The results presented in Tables 1 to 7 strongly verify Hypothesis 1 introduced in Section 2. In this section, we try to understand the channel through which the effects of bank failures are transmitted to the labor market, ultimately widening the wage gap between skilled and unskilled. In doing so, we turn our attention to testing Hypothesis 2.

As discussed in section 2, the type of capital employed by the sectors of the economy can play an important role in transmitting the credit market shocks to labor markets. In episodes of bank failures, sectors that relatively rely more on intangible capital as opposed to tangible capital would be more affected by credit contraction (Almeida and Campello, 2008). These are also the firms that demand more skilled labor as opposed to unskilled as we plausibly assume that intangible capital and skilled labor are complementary inputs (Hall 2000, 2001). In a way, the affected firms - firms which cannot pledge enough collateral are the ones which are likely to demand less of unskilled labor in episodes of bank failures. In other words, when bank failures hit local economy and leads firms to decrease input costs, relatively affected sectors are the ones that rely more on skill labor for sustaining the production and that can give up employing unskilled labor relatively easier. Therefore, fixing the level of external dependence, effects of bank failures on skill premium will be differentially exacerbated in sectors that rely more on intangible capital vis-a-vis tangible capital.

As in the previous section and following Rajan and Zingales (1998), Friedrich et al. (2013) and Larrain (2015), we focus on time-invariant sector-variant measures of capital tangibility and intangibility to test this hypothesis. That is, we classify sectors in two dimensions: asset tangibility (tangible assets/total assets) and asset intangibility (intangible assets/total assets). The following matrix explains our methodology:

	Low intangibility	**High intangibility**
Low tangibility	$\frac{\text{intangible assets}}{\text{total assets}}$ low, $\frac{\text{tangible assets}}{\text{total assets}}$ low	$\frac{\text{intangible assets}}{\text{total assets}}$ high, $\frac{\text{tangible assets}}{\text{total assets}}$ low $\Longrightarrow$ $\frac{\text{intangible assets}}{\text{tangible assets}}$ high
High tangibility	$\frac{\text{intangible assets}}{\text{total assets}}$ low, $\frac{\text{tangible assets}}{\text{total assets}}$ high $\Longrightarrow$ $\frac{\text{intangible assets}}{\text{tangible assets}}$ low	$\frac{\text{intangible assets}}{\text{total assets}}$ high, $\frac{\text{tangible assets}}{\text{total assets}}$ high

Sectors which fall into first row are the ones which are treated as relatively highly affected by bank failures due to binding collateral constraints and sectors that fall into second row less affected by bank failures due to non binding collateral constraints. By a similar token, sectors that fall into first column are the ones for which skilled labor is relatively less indispensable for production whereas sectors that fall into second column are the ones for which skilled labor is relatively more indispensable for production. Our identification comes from comparing the effect of bank failures on skill premium across sectors that fall into cell with low intangibility - high tangibility (unaffected and for which skilled labor is less important) versus high intangibility - low tangibility (affected and for which skilled labor is important). Put it differently, comparison of sectors with high (intangible/tangible) and low (intangible/tangible) enables us to test the hypothesis of whether effect of bank failures is differentially exacerbated in sectors that are more affected by bank failures and for which the skill labor is more important fort he production [10].

Following Claessens and Ueda (2008), we calculate the ratio of intangibles to tangibles as the ratio of intangible assets as given in Compustat to net property plant equipment (or tangible assets). As before, in order to ensure that knowledge intensity measure is not itself affected by bank failures we take the average this ratio for 1987 - 2005 and conduct the analysis with a time invariant sector specific knowledge intensity for 2 digits Standard Industry Classification (SIC) classification. We encode this variable as "KNOWDEP" through out the analysis. Appendix shows the data for $KNOWDEP$ for 2 digit sectoral classification. Although we use 2-digit classification in our analysis, we nevertheless present mean of this ratio for higher level sector classification in panel (d) of Figure 4. Panels (b) and (c) also presents the means of the ratios intangible assets to total assets and net property plant equipment to total assets.

To test if effects of bank failures on skill premium will be differentially exacerbated in sectors that rely

[10] At high and low levels of intangibility/tangibility, the interpretation of $KNOWDEP$ is clear. However, one is unable to interpret the cases of what would happen if both intangibility and tangibility was high or low. In order to provide a robustness check, that in principle also capture these affects in further specifications, we also introduce both of these measures separately to the regressions.

more on intangible capital vis-a-vis tangible capital, we interact our variable of interest, $Failed * Education$ with $KNOWDEP$. That is, this triple interaction term captures the effect of bank failures on wage premium depending on knowledge intensity. The estimation results of this triple interaction model is demonstrated in Table 8.

The positive and significant estimated coefficient of this triple interaction term in all columns of Table 8 verifies Hypothesis 2: effects of bank failures on skill premium depends on the use of intangible capital relative to tangible capital in a sector. Note that our most reliable estimates are presented in columns 3 and 4 where we include industry-year fixed effects to fix level effect of industries and hold external dependence differentials across industries constant as required by Hypothesis 2.

As before, so as to get a sense of the economic significance of this triple interaction term, we calculate the differentials in the effect of bank failures on skill premium on par with the analysis by Rajan and Zingales (1998) and Friedrich et al. (2013). That is, we consider two sectors at the $25^t h$ and $75^t h$ percentile of $KNOWDEP$. We then test the null hypothesis of the effect of bank failures on skill premium moving from a sectors at the $25^t h$ percentile to a sector at the 75^{th} percentile of $KNOWDEP$ is statistically zero. Table 9 illustrates this.

[Table 9 here]

Each column of the Table 9 conducts the test of above mentioned null hypothesis utilizing regression results presented in the respective columns of Table 8. Table 9 indeed shows that the null hypothesis can be rejected and the size of the effect bank failures on skill premium moving from a sectors at the $25^t h$ percentile to a sector at the 75^{th} percentile of $KNOWDEP$ is comparable to the size of the effect found in Table 2 (nearly 5% of annual wages).

To further unveil the heterogeneity across sector stemming from relative intangibility to tangibility, we plot the marginal effect of bank failures on skill premium, depending on relative intangibility to tangibility in Figure 5.

[Figure 5 here]

Figure 5 refers to specification(4) of Table 8 and shows the marginal effects of sectoral $KNOWDEP$ on bank-failures-induced wage inequality (skill premium). 95% confidence bands from PUMA-level clustering of standard errors are shown with blue. The dashed vertical lines indicated with red show 25, 50 and 75 percentiles of knowledge dependence. This figure clearly highlights how relative use of intangible to tangible assets may create an heterogeneity in transmitting credit market shocks to labor market. At very low levels of intangibility/tangibility (i.e. unaffected, less skilled labor dependent) ($25^t h$ percentile of $KNOWDEP$), the skill premium even declines after bank failures. Only at high levels of intangibility/tangibility (i.e. affected, more skilled labor dependent) (75^{th} percentile of $KNOWDEP$), we observe an increase in skill premium after bank failures.

Although at high and low levels of intangibility/tangibility, the interpretation of $KNOWDEP$ is clear, one is unable to interpret the cases of what would happen if both intangibility and tangibility was high or low. In order to provide a robustness check, that in principle also capture these affects, we would need to present an empirical model that includes the interaction of $EDUC * FAILED$, $intangibles/assets$, $tangibles/assets$, in which we end up with a quadruple interaction term, which makes coefficient interpretations highly complicated. We are in a trade-off between being more precise and concise. Nevertheless, we still run the following empirical model with quadruple interaction with PUMA-industry-age-year fixed effects. Figure 6 shows the plot of the marginal effect of $intangibles/assets$, when we move from a sector at 75^{th} percentile of $tangibles/assets$ (sectors unaffected by bank failures) to $25^{t}h$ percentile of $tangibles/assets$ (sectors affected by bank failures).

[Figure 6 here]

Plot in the figure 6 shows that when sectors become more prone to credit shocks, bank failures will widen the wage gap more in the sectors whose share of intangible capital is higher as opposed t sectors whose share of intangible capital is lower. This reassures the finding presented in Figure 5.

The analysis provided in this section shows that type of capital used in production is a clear determinant of if and how much the shocks in credit markets would be transmitted to labor markets and affect wage inequality.

6 Additional Robustness Tests

6.1 Migration

Section 2 argues that to detect a PUMA-level effect, it is not a requirement that the banking market for an individual branch is confined to a single PUMA, but only that a bank is most heavily engaged with the community in which it operates. In either case, the incidence of any potential negative credit shocks as a result of bank failure would fall most heavily on the area nearest the bank (though the disruption would be stronger in the former case, leading us to at least estimating a lower bound of the actual effect). Here the underlying assumption is that individuals are stable within a PUMA. However, migration between PUMAs could lead to overestimation of the results if for an endogenous reason, high skilled individuals systematically migrate to PUMAs that experience bank failures.

Although our data neither shows a systematic migration pattern, nor does it show a mass migration to the extend that it could contaminate results, we still provide a robustness test against this concern. Our data set allows us to track individuals' location for the last 12 months. In particular, we run the regressions only with individuals who have been living in the same PUMA for at least 12 months. Results of these estimations are shown in Table 10

[Table 10 here]

Table 10 confirms our results in the sense that even only with a sample of non movers, we are able to show statistically and economically significant effect of bank failures on the wage inequality between skilled and unskilled as well as heterogeneity of the effect of bank failures on skill premium depending on $KNOWDEP$.

6.2 Occupation types

One issue that has not been addressed so far is how different occupation types are affected by bank failures. In particular, the link between education and wages may not be strong in certain occupation types. That is, despite obtaining little education certain job types may provide high earnings. To the extent that low skilled people with high earnings leave the labor market whereas low skilled people with low earnings stay, we may still observe an increase in the skill premium which is independent of bank failures.

So far we use several multi way fixed effects including a component for sector fixed effects, which can imperfectly control for the differences across occupation types to the extent that workers in the same sector are working in similar types of occupations. However, this is rather unrealistic to assume. In order to control for differences in occupation types, we repeat our baseline regressions by replacing industry components of multi-way fixed effects with occupation types. American Community Survey provides information on occupation types consisting of 539 specific occupational categories for employed people, including 4 military codes, arranged into 23 major occupational groups. This classification was developed based on the Standard Occupational Classification (SOC) Manual: 2010, published by the Executive Office of the President, Office of Management and Budget (OMB).

Table 11 presents the baselines results provided in Table 2 with occupation type fixed effects.

[Table 11 here]

Table 11 confirms our previous findings. Controlling for all factors that may change across occupation types, time and communities, our results still suggest that bank failures lead to a widening wage gap between skilled and unskilled workers.

6.3 Entire sample

So far we present the results only for a sample of randomly drawn PUMAs due to lack of computing power to estimate regressions over 2 million fixed effects. However, we at least run the baseline regressions with the entire sample, with 2069 PUMAs to show the robustness of our baseline findings. Although not reported here (available upon request), we indeed verify that results are similar. This also ensures us to conclude that the findings are not only valid for the randomly selected sample of PUMAs but valid for the entire US.

7 Conclusion

Bank failures affects both economic growth and income inequality. While economists have thoroughly studied the effects of bank failures on growth, the potentially enormous impact of such an event on inequality has been under appreciated. The three volumes of the Handbook of Income Distribution, for example, do not mention any possible connections between inequality and bank failures.

In this paper, we provide robust evidence that bank failures increase wage inequality in a big sample of Americans from US PUMAs for 2007-2009 economics recession, which is associated with large number of bank failures.

We conduct a two-fold empirical strategy. First, we identify the location of failed bank branches in each PUMA; classify PUMAs with at least one failed bank branch as affected areas. We, then, estimate a Mincerian skill-wage equation to test if the wage gap between skilled and unskilled workers are higher in affected PUMAs. We estimate various fixed effects specifications, in many of which we control for time-varying PUMA specific characteristics to control for all static and dynamic regional economic conditions.

We find that bank failures lead to an increase in wage gap between between skilled and unskilled by around 5% and the found effect is demand-driven. We also show that the effect of bank failures on wage inequality is differentially exacerbated for sectors that are knowledge intensive, which further substantiates the observed demand effects.

We also show, for the first time in the literature, that the type of capital employed in sectors of an economy is an important channel through which the effects of bank failures are transmitted to local labor markets. In particular, we show that the effect of bank failures on wage inequality is differentially exacerbated for sectors that rely more on intangible capital relative to tangible capital. We attribute this finding to the fact that the type of capital firms use matters for the transmission of local credit shocks to the labor market. These results are consistent with knowledge-dependent capital being financed through forgone earnings of unskilled workers when total financing capacity shrinks.

Our findings can be extended in several directions. First, it would be interesting to conduct this analysis with rich data set in which researcher can observe the matched bank-firm and employee to be able to be able to gain a deeper understanding on the relationship between firm and bank characteristics and the evolution of wages under financial distress. Secondly, a theoretical framework can be built to improve our understanding of the exact mechanisms that could play a role beyond the one that we present here. Thirdly, we believe that our findings open up a space for policy debate through which whether regulators avoid bank failures or whether banking system should be altered in such a way that despite banks may come and go, a stable level of credit is always supplied can be elaborated from *distributional* perspective.

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Appendix

Variable descriptions

- **Wage** (Monetary value) Individual-level annual wages.
- **Hours** (Absolute number) Individual-level proxy for work hours calculated as the mean of the range of weekly hours worked and multiply by it by the number of weeks worked in a given year.
- **Labor Force** (Dummy variable) Individual-level binary variable taking the value 1 if an individual participates in the labor force and zero otherwise.
- **FAILED** (Dummy variable) PUMA-level binary variable taking the value 1 if at least a bank failure occurs in a PUMA and zero otherwise.
- **EDUC** (Dummy variable) Individual-level binary variable taking the value 1 if an individual has university degree or more and zero otherwise.
- **EDUC*FAILED** (Dummy variable) Interaction of EDUC and FAILED.
- **Experience** (Categorical variable) Individual-level variable comprising of integer scores from 1 to 15, 1 being the highest and 15 being the lowest experience scores.
- **Experience^2** (Categorical variable) Square of Experience variable.
- **Foreign Born** (Dummy variable) Individual-level binary variable taking the value 1 if an individual was born outside of the US and zero otherwise.
- **Race** (Categorical variable) Individual level variable comprising of integer scores from 1 to 7, each score being attributed to a different race.
- **Female** (Dummy variable) Individual-level binary variable taking the value 1 if an individual is female and zero otherwise.
- **EDUC*Experience** (Categorical variable) Interaction of EDUC and Experience.
- **EDUC*Experience^2** (Categorical variable) Interaction of EDUC and Experience^2.
- **Age** (Absolute number) Individual-level variable indicating the age of a selected individual.
- **Age^2** (Absolute number) Square of Age.
- **Married** (Dummy variable) Individual-level binary variable taking the value 1 if an individual is married and zero otherwise.
- **Married*Child** (Dummy variable) Individual-level binary variable taking the value 1 if an individual is married and has children, and zero otherwise.

- **Female*Child** (Dummy variable) Individual-level binary variable taking the value 1 if an individual is female and has children, and zero otherwise.

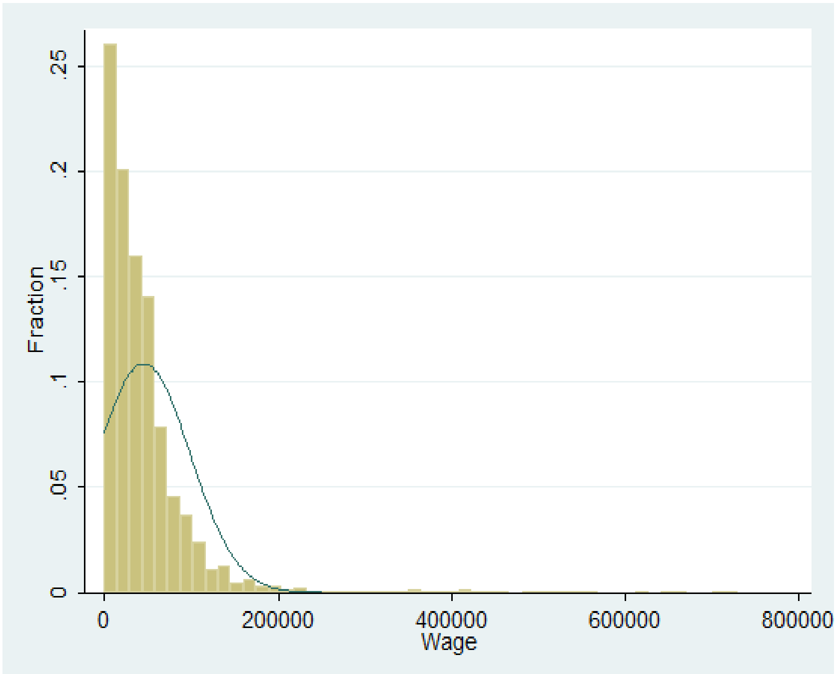
Share of Intangible assets and collateralizable assets as separate variables

Mean sector variables by 2-Digit SIC (Standard Industrial Classification)

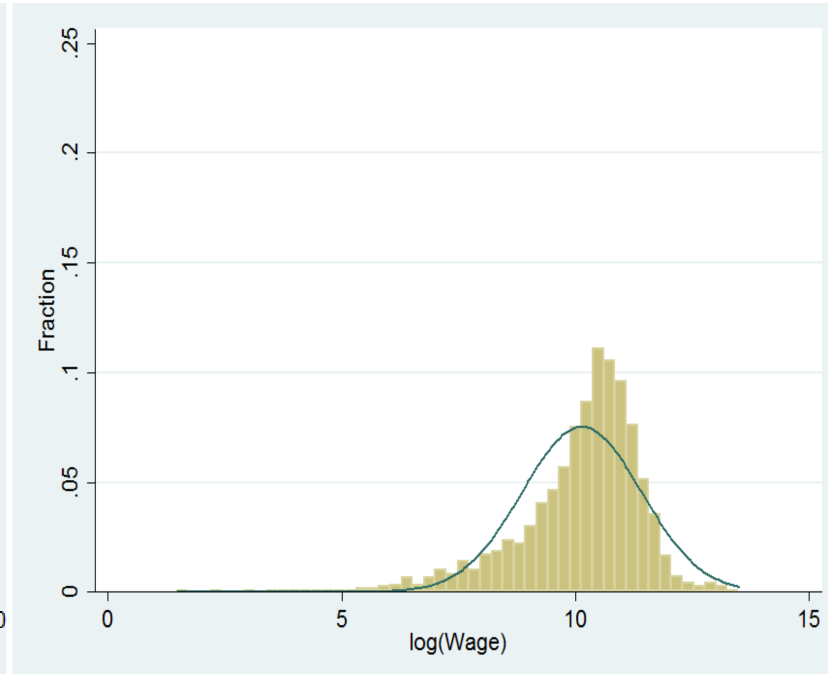
2-Digit SIC Name	Intangibles/assets	Tangibles/assets	KNOWDEP	R&D
Agricultural Production Crops	0.059427	0.594479	0.151305	0.455389
Agricultural Production Livestock	0.004192	0.703093	0.024139	0.747403
Agricultural Services	0.134598	0.618243	0.747803	0.063762
Forestry	0.031325	0.681796	0.424498	0.068386
Fishing, Hunting, & Trapping	0.000095	1.005946	0.000078	
Metal, Mining	0.007763	0.963913	0.056904	0.171905
Coal Mining	0.020083	0.939759	0.112496	0.013471
Oil & Gas Extraction	0.012783	1.432468	0.030783	0.459748
Nonmetallic Minerals, Except Fuels	0.029293	0.922543	0.03562	0.069991
General Building Contractors	0.014043	0.188525	0.3938	0.105417
Heavy Construction, Except Building	0.060185	0.573223	0.21374	0.422241
Special Trade Contractors	0.096189	0.400392	0.621499	0.071641
Food & Kindred Products	0.097052	0.644603	0.506252	0.095748
Tobacco Products	0.146438	0.362788	0.943541	0.013387
Textile Mill Products	0.045749	0.653015	0.164822	0.014023
Apparel & Other Textile Products	0.074176	0.300974	0.535394	0.010608
Lumber & Wood Products	0.032077	0.58503	0.127942	0.22049
Furniture & Fixtures	0.07021	0.54244	0.400687	0.013242
Paper & Allied Products	0.062602	0.821591	0.154391	0.054201
Printing & Publishing	0.151341	0.492898	5.346832	0.123747
Chemical & Allied Products	0.077122	0.502117	0.978517	9.774382
Petroleum & Coal Products	0.030938	0.881926	0.711745	0.393832
Rubber & Miscellaneous Plastics Products	0.076852	0.638611	4.494277	0.305464
Leather & Leather Products	0.033225	0.312095	0.267476	0.011096
Stone, Clay, & Glass Products	0.041183	0.818295	0.263211	0.062714
Primary Metal Industries	0.041067	0.775496	0.094593	0.055454
Fabricated Metal Products	0.062535	0.578087	0.215784	0.050036
Industrial Machinery & Equipment	0.059606	0.428448	0.398471	0.682878
Electronic & Other Electric Equipment	0.055085	0.480293	0.402781	0.560331
Transportation Equipment	0.072584	0.52185	0.261344	0.343355
Instruments & Related Products	0.07487	0.415944	0.52175	1.262835
Miscellaneous Manufacturing Industries	0.089641	0.433554	0.602253	0.079654
Railroad Transportation	0.007479	1.054491	0.017133	0
Local & Interurban Passenger Transit	0.221026	0.630114	0.930721	
Trucking & Warehousing	0.059915	0.901791	0.222955	0.022067
Water Transportation	0.031193	0.933722	0.374183	0.711787
Transportation by Air	0.039994	1.044497	0.114993	0.049092
Pipelines, Except Natural Gas	0.006324	0.961937	0.008413	0.004112
Transportation Services	0.095888	0.508835	1.339969	0.392274
Communications	0.174043	0.750878	1.437204	1.675165
Electric, Gas, & Sanitary Services	0.021906	1.017693	0.629692	0.854205
Wholesale Trade Durable Goods	0.066073	0.298551	0.565646	0.072783
Wholesale Trade Nondurable Goods	0.07366	0.452229	1.002055	0.043932
Building Materials & Gardening Supplies	0.040487	0.472629	0.119269	0.000188
General Merchandise Stores	0.026232	0.494069	0.076489	1.13E-05
Food Stores	0.065927	0.740634	0.147964	0.000645
Automative Dealers & Service Stations	0.07059	0.455622	0.630495	0.001201
Apparel & Accessory Stores	0.043245	0.505526	0.154629	9.82E-06
Furniture & Homefurnishings Stores	0.040823	0.393476	0.255776	0.152175
Eating & Drinking Places	0.089878	0.931654	0.185981	0.000734
Miscellaneous Retail	0.095479	0.377572	0.783622	0.049566
Security & Commodity Brokers	0.069881	0.1901	1.338647	0.140124
Insurance Carriers	0.044209	0.100358	0.937069	0.022122
Insurance Agents, Brokers, & Service	0.134933	0.322552	1.274459	0.373106
Real Estate	0.024043	0.608607	0.228173	0.128294
Holding & Other Investment Offices	0.027469	0.291771	1.44803	0.430532
Hotels & Other Lodging Places	0.028295	0.890658	0.345758	0.000168
Personal Services	0.148433	0.527805	0.744147	0.018285
Business Services	0.105535	0.393198	1.107481	1.369059
Auto Repair, Services, & Parking	0.065621	0.832469	0.246146	0.558569
Miscellaneous Repair Services	0.14338	0.43632	0.730276	0.705867
Motion Pictures	0.072575	1.175083	2.3072	12.25975
Amusement & Recreation Services	0.066808	0.886573	0.523658	0.07265
Health Services	0.176342	0.469644	1.377628	5.688106
Legal Services	0.070771	0.21923	0.526684	
Educational Services	0.160887	0.529874	1.248616	0.084439
Social Services	0.082075	0.628686	0.283365	0.00336
Museums, Botanical, Zoological Gardens	0	0.996176	0	0.001696
Membership Organizations	0.308923	0.311719	0.765212	0.255741
Engineering & Management Services	0.101832	1.03145	0.764601	3.369467
Services, Not Elsewhere Classified	0.090426	0.340929	1.173497	0.114815
Non-Classifiable Establishments	0.059234	0.50888	1.816929	2.240335

Figure 1: Fractional histogram of wages versus log(wages)

(**a**) Annual wages

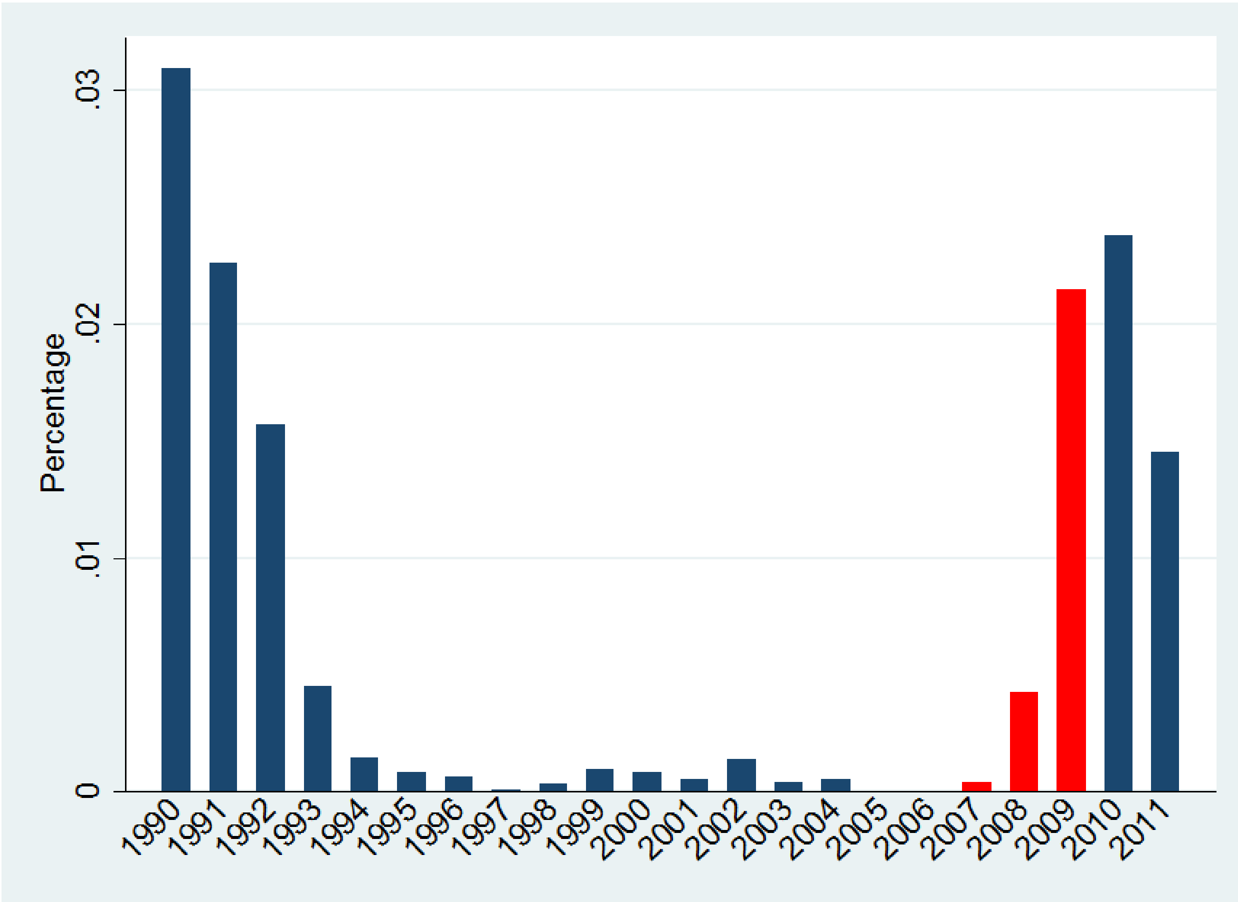


(**b**) Logarithm of annual wages



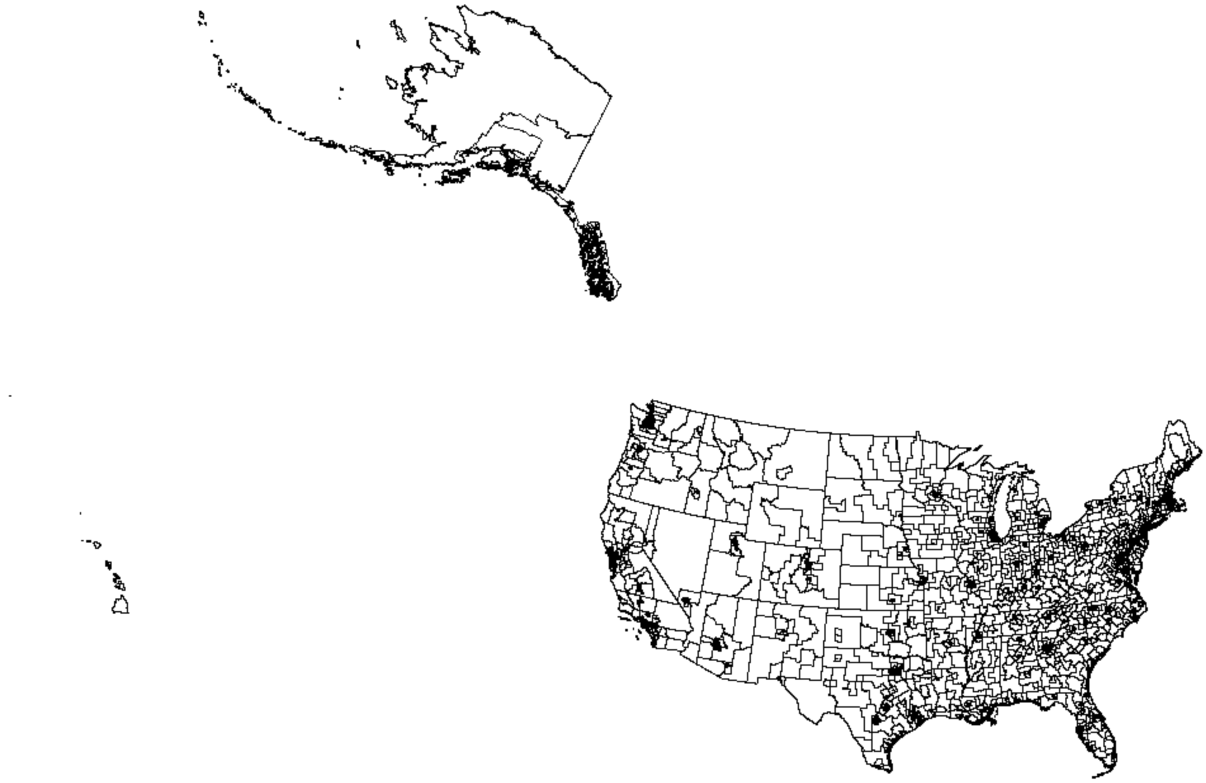
Notes: Data is obtained from American Community Survey, for the period 2008-2010. Panel (a) depicts the fractional histogram of annual wages whereas Panel (b) depicts the factional histogram of annual natural logarithm of wages. In order to make panels comparable to one another, heights of the bars are scaled so that the sum of heights equals 1 in both panels.

Figure 2: Share of commercial bank failures



Notes: Data is obtained from Federal Deposit Insurance Corporation (FDIC), Failed Bank List. The figure shows the percentage of failed commercial banks as a share of the total commercial banks in the US for the time period 1990-2011. Years whose bars are indicated with red demonstrates the time frame considered in this paper.

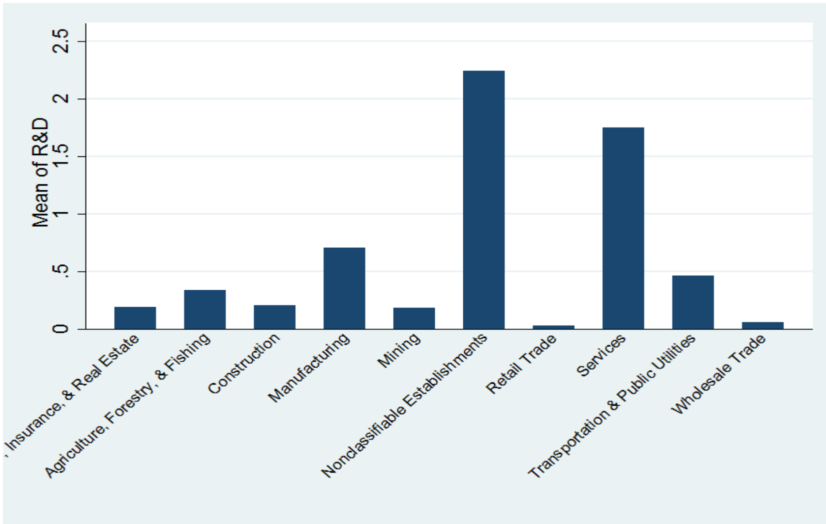
Figure 3: Public Use Microdata Area (PUMA) borders



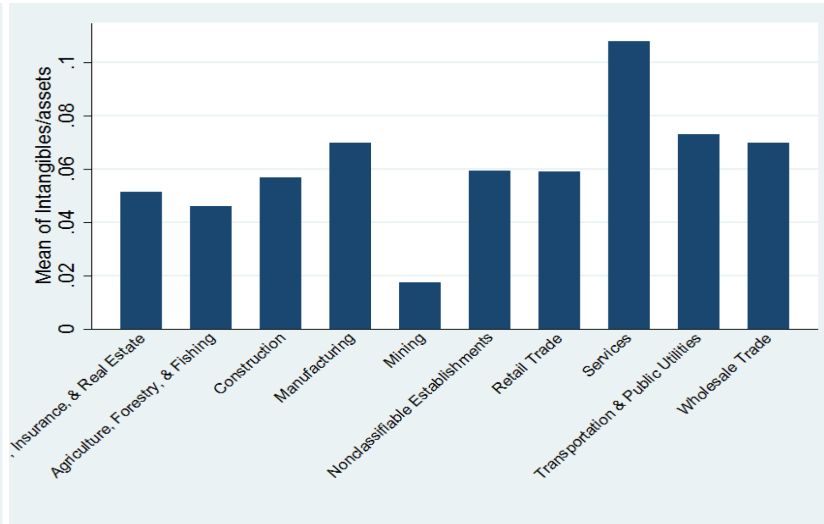
Notes: Geo-code data of PUMA borders are obtained from Missouri Census Data Center. This figure highlights PUMA borders as of Census 2000. PUMA borders changed substantially with Census 2010.

Figure 4: Industry characteristics by high level ISIC classification

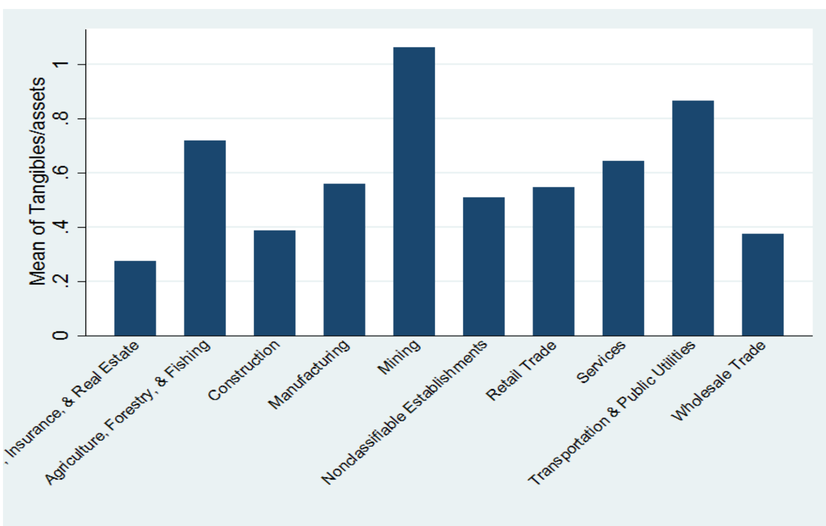
(**a**) R&D



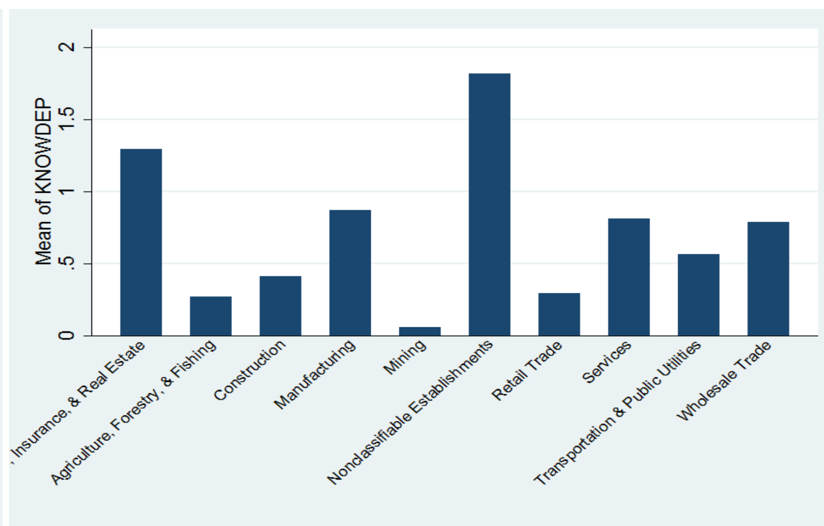
(**b**) Intangibles/assets



(**c**) Tangibles/assets

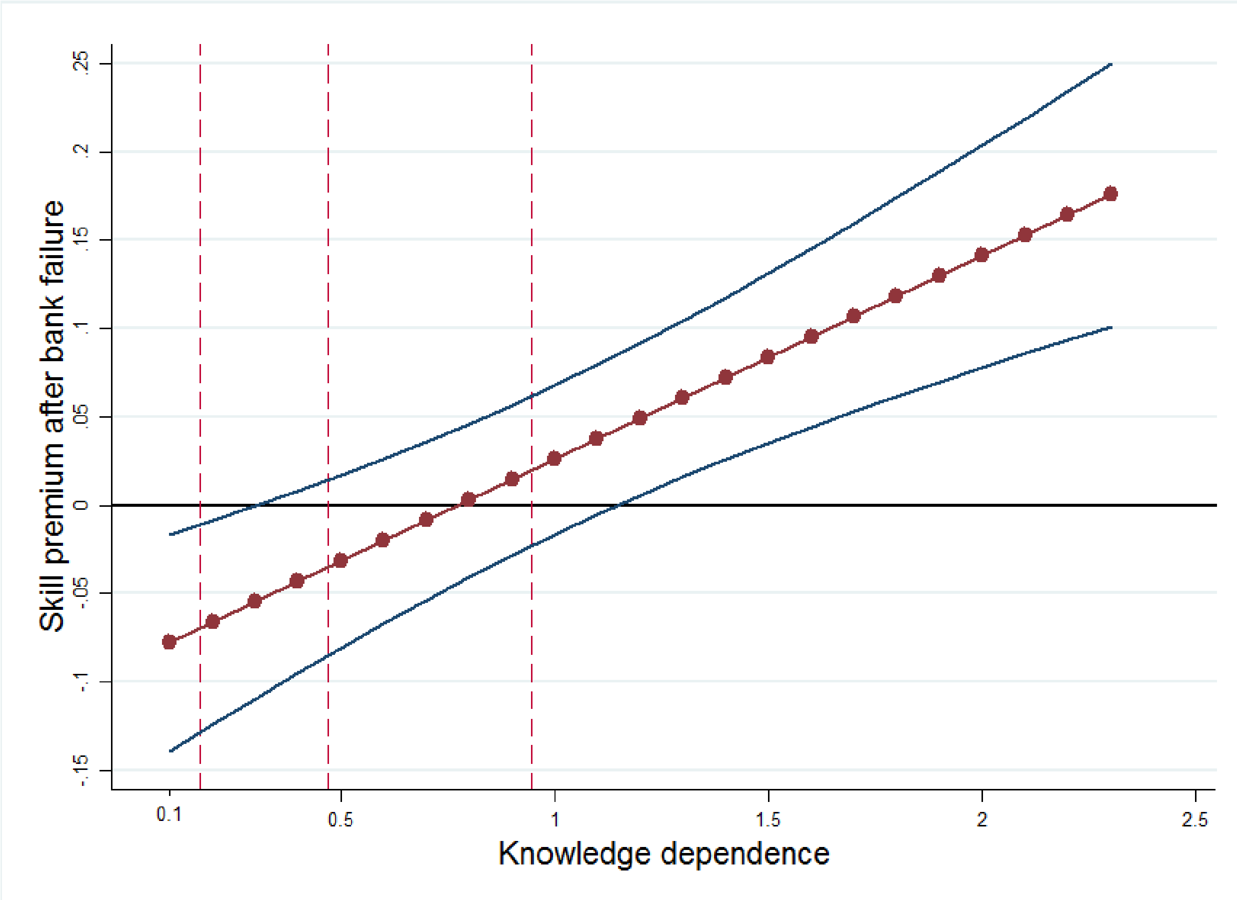


(**d**) Knowledge dependence



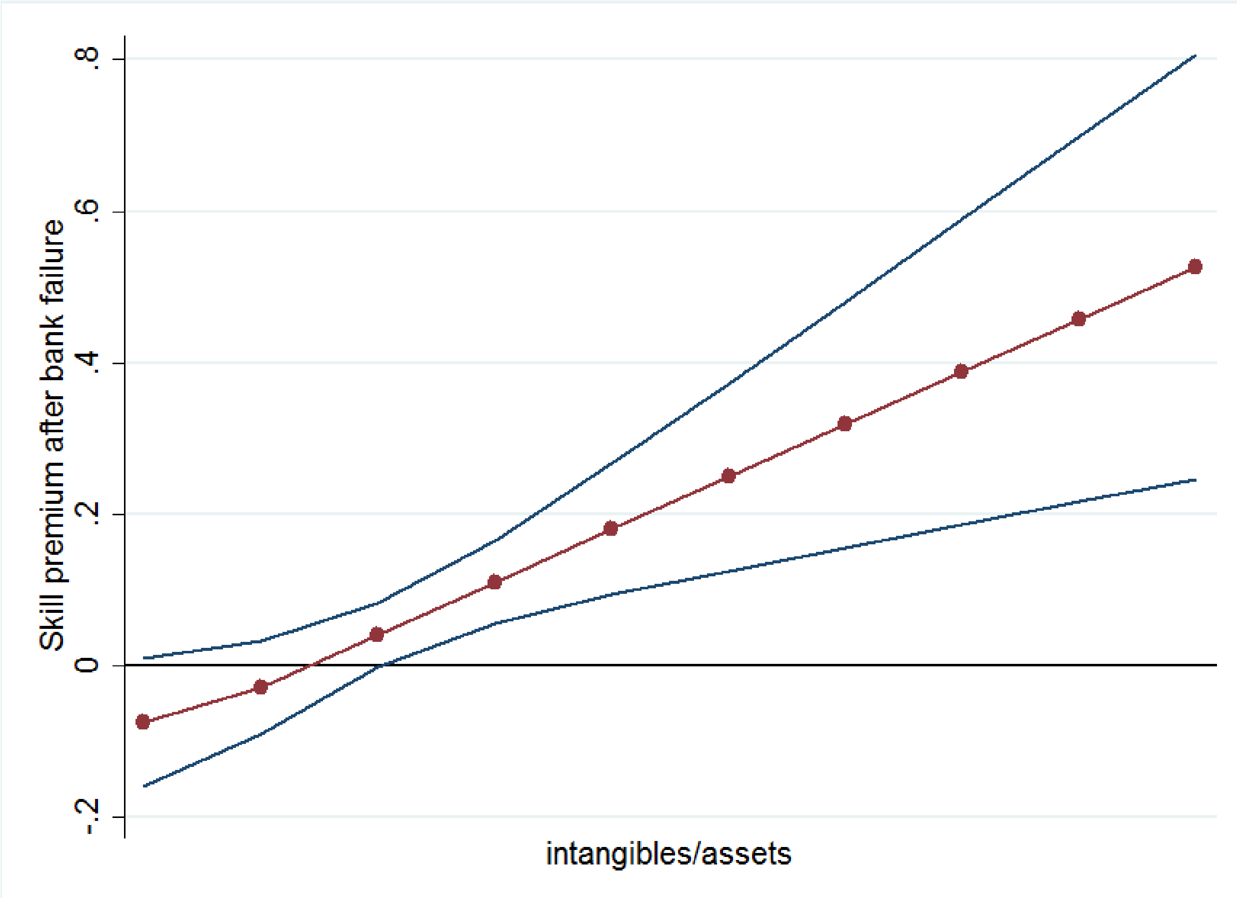
Notes: Data is obtained from Compustat, for the period 1987-2005.

Figure 5: Marginal effects of sectoral knowledge dependence on skill premium



Notes: The figure refers to specification(4) of Table 6 and shows the marginal effects of sectoral knowledge dependence on bank-failures-induced wage inequality (skill premium). 95% confidence bands from PUMA-level clustering of standard errors are shown with blue. The dashed vertical lines indicated with red show 25, 50 and 75 percentiles of knowledge dependence.

Figure 6: Marginal effects of intangibles/assets on skill premium when sectors prone to credit shocks more



Notes: The figure refers to a specification with quadruple interaction of $EDUC * FAILED$, $intangibles/assets$ and $tangibles/assets$ with PUMA-industry-age-year fixed effects. It shows the marginal effects of $intangibles/assets$ on bank-failures-induced wage inequality (skill premium) when moving from a sector at $75^{t}h$ percentile of $tangibles/assets$ (sectors unaffected by bank failures) to $25^{t}h$ percentile of $tangibles/assets$ (sectors affected by bank failures). 95% confidence bands from PUMA-level clustering of standard errors are shown with blue.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Wage	45025.164	53641.319	4.348	729834	1143681
Hours	1759.665	812.025	7.5	5049	1222378
Labor Force	0.621	0.485	0	1	1883442
FAILED	0.212	0.409	0	1	1880454
EDUC	0.538	0.499	0	1	1883442
EDUC*FAILED	0.119	0.324	0	1	1880454
Experience	5.935	4.531	1	15	1454709
Experience^2	55.748	67.882	1	225	1454709
Foreign Born	0.125	0.331	0	1	1883442
Race	1.845	1.677	1	7	1883442
Female	0.519	0.5	0	1	1883442
EDUC*Experience	2.772	4.066	0	15	1454709
EDUC*Experience^2	24.219	50.768	0	225	1454709
Age	47.583	18.923	16	95	1883442
Age^2	2622.218	1911.461	256	9025	1883442
Married	0.545	0.498	0	1	1883442
Married*Child	0.231	0.421	0	1	1814114
Female*Child	0.201	0.401	0	1	1814114

Notes: The exact definition of all variables are given in the text and the Appendix.

Table 2: Baseline results: Effects of bank failures on skill premium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Wage)	log(Wage)	log(Wage)	log(Wage)	log(Wage)	log(Wage)	log(Wage)	log(Wage)
FAILED	-0.0351***		-0.0428***		-0.0425***		-0.0420***	
	(0.00935)		(0.0108)		(0.00750)		(0.0107)	
EDUC	0.789***	0.789***	0.396***	0.407***	0.568***	0.568***	0.393***	0.403***
	(0.0134)	(0.0134)	(0.0108)	(0.0149)	(0.00831)	(0.00831)	(0.0109)	(0.0150)
EDUC*FAILED	0.0454***	0.0489***	0.0426***	0.0466***	0.0566***	0.0594***	0.0415***	0.0456***
	(0.0117)	(0.0121)	(0.0115)	(0.0172)	(0.00807)	(0.00830)	(0.0114)	(0.0172)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extra Controls	No	No	No	No	Yes	Yes	Yes	Yes
PUMA FE	Yes	No	No	No	Yes	No	No	No
Year FE	Yes	No	No	No	Yes	No	No	No
PUMA -Year FE	No	Yes	No	No	No	Yes	No	No
PUMA -Ind-Age FE	No	No	Yes	No	No	No	Yes	No
Ind-Age-Year FE	No	No	Yes	No	No	No	Yes	No
PUMA -Ind-Age-Year FE	No	No	No	Yes	No	No	No	Yes
Observations	911368	911368	654517	571112	911368	911368	654517	571112
R^2	0.168	0.170	0.818	0.885	0.375	0.376	0.819	0.885

Notes: The sample period is 2008 - 2010. Dependent variable is the natural logarithm of annual wages. Columns (1) and (5), (2) and (6), (3) and (7), (4) and (8) show the estimation results of equations (1), (2), (3) and (4) respectively. EDUC is dummy variable taking the value 1 for individuals with a degree of undergraduate or above and zero otherwise. FAILED is a dummy variable taking the value 1 for individuals residing in PUMAs that experience at least one bank failure during the sample period and zero otherwise. In line with equations (1), (2), (3) and (4), each columns include one- or multi-way fixed effects. Controls include the following variables: Experience, Experience^2 Foreign born, Race, Female, EDUC*Experience and EDUC*Experience^2. Extra controls include the following variables: Age, Age^2, Married, Married*Child, Female*Child. Whenever Age fixed effects are included, Age and Age^2 are dropped from the regressions. Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Linear probability model: Effect of bank failures on labor force participation

	(1) Labor Force	(2) Labor Force	(3) Labor Force	(4) Labor Force
FAILED	0.000886		0.000449	
	(0.00334)		(0.00331)	
EDUC	0.0440***	0.0493***	0.0464***	0.0518***
	(0.00332)	(0.00473)	(0.00329)	(0.00471)
EDUC*FAILED	-0.00383	-0.00253	-0.00330	-0.00191
	(0.00354)	(0.00490)	(0.00351)	(0.00489)
Controls	Yes	Yes	Yes	Yes
Extra Controls	No	No	Yes	Yes
PUMA FE	No	No	No	No
Year FE	No	No	No	No
PUMA-Year FE	No	No	No	No
PUMA-Ind-Age FE	Yes	No	Yes	No
Ind-Age-Year FE	Yes	No	Yes	No
PUMA-Ind-Age-Year	No	Yes	No	Yes
Observations	802483	698436	802483	698436
R^2	0.695	0.803	0.697	0.804

Notes: The sample period is 2008 - 2010. Dependent variable is Labor Force, which is a dummy variable taking the value one for individuals in the labor force and zero otherwise. Columns (1) and (3), (2) and (4) show the estimation results of equations (5) and (6) respectively. EDUC is dummy variable taking the value 1 for individuals with a degree of undergraduate or above and zero otherwise. FAILED is a dummy variable taking the value 1 for individuals residing in PUMAs that experience at least one bank failure during the sample period and zero otherwise. Each column includes one- or multi-way fixed effects. Controls include the following variables: Experience, Experience^2 Foreign born, Race, Female, EDUC*Experience and EDUC*Experience^2. Extra controls include the following variables: Age, Age^2, Married, Married*Child, Female*Child. Whenever Age fixed effects are included, Age and Age^2 are dropped from the regressions. Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Effects of bank failures on work hours

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Hours)	log(Hours)	log(Hours)	log(Hours)	log(Hours)	log(Hours)	log(Hours)	log(Hours)
FAILED	-0.0143**		-0.0201**		-0.0179***		-0.0198**	
	(0.00578)		(0.00864)		(0.00529)		(0.00865)	
EDUC	0.360***	0.360***	0.128***	0.130***	0.236***	0.236***	0.128***	0.129***
	(0.00845)	(0.00849)	(0.00793)	(0.0117)	(0.00548)	(0.00551)	(0.00798)	(0.0118)
EDUC*FAILED	0.0147**	0.0146**	0.0143*	0.0265**	0.0196***	0.0193***	0.0139*	0.0263**
	(0.00688)	(0.00708)	(0.00834)	(0.0121)	(0.00516)	(0.00534)	(0.00833)	(0.0122)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extra Controls	No	No	No	No	Yes	Yes	Yes	Yes
PUMA FE	Yes	No	No	No	Yes	No	No	No
Year FE	Yes	No	No	No	Yes	No	No	No
PUMA -Year FE	No	Yes	No	No	No	Yes	No	No
PUMA -Ind-Age FE	No	No	Yes	No	No	No	Yes	No
Ind-Age-Year FE	No	No	Yes	No	No	No	Yes	No
PUMA -Ind-Age-Year FE	No	No	No	Yes	No	No	No	Yes
Observations	911368	911368	654517	571112	911368	911368	654517	571112
R^2	0.168	0.170	0.818	0.885	0.375	0.376	0.819	0.885

Notes: The sample period is 2008 - 2010. Dependent variable is the natural logarithm of annual work hours. Columns (1) and (5), (2) and (6), (3) and (7), (4) and (8) show the estimation results of equations (7), (8), (9) and (10) respectively. EDUC is dummy variable taking the value 1 for individuals with a degree of undergraduate or above and zero otherwise. FAILED is a dummy variable taking the value 1 for individuals residing in PUMAs that experience at least one bank failure during the sample period and zero otherwise. Each column includes one- or multi-way fixed effects. Controls include the following variables: Experience, Experience^2 Foreign born, Race, Female, EDUC*Experience and EDUC*Experience^2. Extra controls include the following variables: Age, Age^2, Married, Married*Child, Female*Child. Whenever Age fixed effects are included, Age and Age^2 are dropped from the regressions. Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Stable sample: Effects of bank failures on skill premium and work hours

	(1) log(Wage)	(2) log(Wage)	(3) log(Wage)	(4) log(Wage)	(5) log(Hours)	(6) log(Hours)	(7) log(Hours)	(8) log(Hours)
FAILED	-0.0734***		-0.0323**		-0.0232**		-0.00718	
	(0.0125)		(0.0159)		(0.00942)		(0.0133)	
EDUC	0.579***	0.578***	0.408***	0.403***	0.243***	0.243***	0.142***	0.137***
	(0.00975)	(0.00975)	(0.0132)	(0.0150)	(0.00674)	(0.00674)	(0.0105)	(0.0121)
EDUC*FAILED	0.0976***	0.0964***	0.0505***	0.0456***	0.0383***	0.0362***	0.0256**	0.0287**
	(0.0139)	(0.0144)	(0.0154)	(0.0172)	(0.00978)	(0.0101)	(0.0118)	(0.0124)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extra Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PUMA FE	Yes	No	No	No	Yes	No	No	No
Year FE	Yes	No	No	No	Yes	No	No	No
PUMA -Year FE	No	Yes	No	No	No	Yes	No	No
PUMA -Ind-Age FE	No	No	Yes	No	No	No	Yes	No
Ind-Age-Year FE	No	No	Yes	No	No	No	Yes	No
PUMA -Ind-Age-Year FE	No	No	No	Yes	No	No	No	Yes
Observations	571112	571112	571112	571112	571112	571112	571112	571112
R^2	0.397	0.399	0.861	0.885	0.256	0.258	0.815	0.847

Notes: The sample period is 2008 - 2010. Dependent variable in columns (1) to (4) the natural logarithm of annual wages whereas dependent variable in columns (5) to (8) is the natural logarithm of annual work hours. Columns (1) and (3), (2) and (4), (5) and (7), (6) and (8) show the estimation results of equations (3), (4), (9) and (10) respectively. EDUC is dummy variable taking the value 1 for individuals with a degree of undergraduate or above and zero otherwise. FAILED is a dummy variable taking the value 1 for individuals residing in PUMAs that experience at least one bank failure during the sample period and zero otherwise. Each column includes one- or multi-way fixed effects. Controls include the following variables: Experience, Experience^2 Foreign born, Race, Female, EDUC*Experience and EDUC*Experience^2. Extra controls include the following variables: Age, Age^2, Married, Married*Child, Female*Child. Whenever Age fixed effects are included, Age and Age^2 are dropped from the regressions. Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

Table 6: Sectoral heterogeneity: Effect of bank failures on skill premium depending on knowledge intensity

	(1) log(Wage)	(2) log(Wage)	(3) log(Wage)	(4) log(Wage)
FAILED	-0.0616***		-0.0610***	
	(0.0154)		(0.0155)	
EDUC	0.464***	0.472***	0.461***	0.468***
	(0.0148)	(0.0203)	(0.0150)	(0.0205)
EDUC*FAILED	-0.0246	-0.0611**	-0.0253	-0.0632**
	(0.0176)	(0.0265)	(0.0175)	(0.0265)
EDUC*FAILED*R&D	0.0141***	0.0264***	0.0141***	0.0267***
	(0.00188)	(0.00383)	(0.00188)	(0.00382)
Controls	Yes	Yes	Yes	Yes
Extra Controls	No	No	Yes	Yes
PUMA FE	No	No	No	No
Year FE	No	No	No	No
PUMA-Year FE	No	No	No	No
PUMA-Ind-Age FE	Yes	No	Yes	No
Ind-Age-Year FE	Yes	No	Yes	No
PUMA-Ind-Age-Year	No	Yes	No	Yes
Observations	431235	379054	431235	379054
R^2	0.821	0.886	0.821	0.886

Notes: The sample period is 2008 - 2010. Dependent variable in all columns is the natural logarithm of annual wages. EDUC is dummy variable taking the value 1 for individuals with a degree of undergraduate or above and zero otherwise. FAILED is a dummy variable taking the value 1 for individuals residing in PUMAs that experience at least one bank failure during the sample period and zero otherwise. R&D is sector-level time invariant variable. Each column includes one- or multi-way fixed effects. Controls include the following variables: Experience, Experience^2 Foreign born, Race, Female, EDUC*Experience and EDUC*Experience^2. Extra controls include the following variables: Age, Age^2, Married, Married*Child, Female*Child. Whenever Age fixed effects are included, Age and Age^2 are dropped from the regressions. Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

Table 7: Economic significance of the effect of bank failures on skill premium depending on knowledge intensity

	(1) R&D	(2) R&D	(3) R&D	(4) R&D
H_0: δ (75th pctl - 25th pctl) = 0	0.0058*** (0.0007)	0.0108*** (0.0015)	0.0057*** (0.0007)	0.0110*** (0.0015)
25th pctl	0.018	0.018	0.018	0.018
75th pctl	0.430	0.430	0.430	0.430
75th pctl - 25th pctl	0.412	0.412	0.412	0.412

Notes: Columns refer to the respective specifications in Table 7. The sample period is 2008 - 2010. Dependent variable in all columns is the natural logarithm of annual wages. Columns (1) to (4) uses R&D KNOWDEP variable as sectoral knowledge intensity. 25^{th} and 75^{th} percentiles refer to respective percentiles of R&D in columns (1) to (4). Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Sectoral heterogeneity: Effect of bank failures on skill premium depending on *KNOWDEP*

	(1) log(Wage)	(2) log(Wage)	(3) log(Wage)	(4) log(Wage)
FAILED	-0.0460***		-0.0452***	
	(0.0142)		(0.0143)	
EDUC	0.469***	0.476***	0.466***	0.472***
	(0.0134)	(0.0185)	(0.0135)	(0.0186)
EDUC*FAILED	-0.0276	-0.0865***	-0.0287	-0.0896***
	(0.0192)	(0.0330)	(0.0193)	(0.0329)
EDUC*FAILED*KNOWDEP	0.0578***	0.113***	0.0578***	0.115***
	(0.0121)	(0.0244)	(0.0121)	(0.0244)
Controls	Yes	Yes	Yes	Yes
Extra Controls	No	No	Yes	Yes
PUMA FE	No	No	No	No
Year FE	No	No	No	No
PUMA-Year FE	No	No	No	No
PUMA-Ind-Age FE	Yes	No	Yes	No
Ind-Age-Year FE	Yes	No	Yes	No
PUMA-Ind-Age-Year	No	Yes	No	Yes
Observations	481413	420886	481413	420886
R^2	0.817	0.883	0.817	0.884

Notes: The sample period is 2008 - 2010. Dependent variable in all columns is the natural logarithm of annual wages. EDUC is dummy variable taking the value 1 for individuals with a degree of undergraduate or above and zero otherwise. FAILED is a dummy variable taking the value 1 for individuals residing in PUMAs that experience at least one bank failure during the sample period and zero otherwise. KNOWDEP is a sector-level time invariant variable. Each column includes one- or multi-way fixed effects. Controls include the following variables: Experience, Experience^2 Foreign born, Race, Female, EDUC*Experience and EDUC*Experience^2. Extra controls include the following variables: Age, Age^2, Married, Married*Child, Female*Child. Whenever Age fixed effects are included, Age and Age^2 are dropped from the regressions. Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

Table 9: Economic significance of the effect of bank failures on skill premium depending on knowledge dependence

	(1) KNOWDEP	(2) KNOWDEP	(3) KNOWDEP	(4) KNOWDEP
	(4)			
H_0: δ (75th pctl - 25th pctl) = 0	0.0446*** (0.009)	0.0876*** (0.018)	0.0446*** (0.009)	0.0890*** (0.018)
25th pctl	0.164	0.164	0.164	0.164
75th pctl	0.937	0.937	0.937	0.937
75th pctl - 25th pctl	0.773	0.773	0.773	0.773

Notes: Columns refer to the respective specifications in Table 8. The sample period is 2008 - 2010. Dependent variable in all columns is the natural logarithm of annual wages. Columns (1) to (4) uses KNOWDEP variable as sectoral knowledge dependence. 25^{th} and 75^{th} percentiles refer to respective percentiles of KNOWDEP in columns (1) to (4). Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Key results with a sample of non-movers

	(1) log(Wage)	(2) log(Wage)	(3) log(Wage)	(4) log(Wage)	(5) log(Wage)	(6) log(Wage)	(7) log(Wage)	(8) log(Wage)
FAILED	-0.0300**		-0.0291**		-0.0335**		-0.0329**	
	(0.0118)		(0.0118)		(0.0150)		(0.0151)	
EDUC	0.397***	0.409***	0.395***	0.405***	0.474***	0.485***	0.473***	0.483***
	(0.0115)	(0.0152)	(0.0116)	(0.0153)	(0.0140)	(0.0189)	(0.0141)	(0.0189)
EDUC*FAILED	0.0330***	0.0354*	0.0317**	0.0344*	-0.0509**	-0.115***	-0.0520**	-0.117***
	(0.0125)	(0.0181)	(0.0125)	(0.0181)	(0.0203)	(0.0337)	(0.0204)	(0.0337)
EDUC*FAILED*KNOWDEP					0.0639***	0.123***	0.0637***	0.123***
					(0.0127)	(0.0251)	(0.0127)	(0.0250)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extra Controls	No	No	Yes	Yes	No	No	Yes	Yes
PUMA FE	No	No	No	No	No	No	No	No
Year FE	No	No	No	No	No	No	No	No
PUMA-Year FE	No	No	No	No	No	No	No	No
PUMA-Ind-Age FE	Yes	No	Yes	No	Yes	No	Yes	No
Ind-Age-Year FE	Yes	No	Yes	No	Yes	No	Yes	No
PUMA-Ind-Age-Year	No	Yes	No	Yes	No	Yes	No	Yes
Observations	573163	501266	573163	501266	421466	369545	421466	369545
R^2	0.831	0.894	0.831	0.894	0.829	0.893	0.829	0.893

Notes: The sample period is 2008 - 2010. Dependent variable in all columns is the natural logarithm of annual wages. EDUC is dummy variable taking the value 1 for individuals with a degree of undergraduate or above and zero otherwise. FAILED is a dummy variable taking the value 1 for individuals residing in PUMAs that experience at least one bank failure during the sample period and zero otherwise. KNOWDEP and R&D are sector-level time invariant variables. Each column includes one- or multi-way fixed effects. Controls include the following variables: Experience, Experience^2 Foreign born, Race, Female, EDUC*Experience and EDUC*Experience^2. Extra controls include the following variables: Age, Age^2, Married, Married*Child, Female*Child. Whenever Age fixed effects are included, Age and Age^2 are dropped from the regressions. Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

Table 11: Key results with occupation fixed effects

	(1) log_wage	(2) log_wage	(3) log_wage	(4) log_wage
FAILED	-0.0339*		-0.0344*	
	(0.0140)		(0.0140)	
EDUC	0.146***	0.163***	0.145***	0.161***
	(0.0138)	(0.0206)	(0.0138)	(0.0205)
EDUC*FAILED	0.0347*	0.0593*	0.0348*	0.0592*
	(0.0142)	(0.0233)	(0.0142)	(0.0233)
Controls	Yes	Yes	Yes	Yes
Extra controls	No	No	Yes	Yes
Puma FE	No	No	No	No
Year FE	No	No	No	No
Puma-Year FE	No	No	No	No
Puma-Occp-Age FE	Yes	No	Yes	No
Occp-Age-Year FE	Yes	No	Yes	No
Puma-Occp-Age-Year FE	No	Yes	No	Yes
N	592444	523621	592444	523621
R^2	0.885	0.934	0.885	0.934

Notes: The sample period is 2008 - 2010. Dependent variable in all columns is the natural logarithm of annual wages. EDUC is dummy variable taking the value 1 for individuals with a degree of undergraduate or above and zero otherwise. FAILED is a dummy variable taking the value 1 for individuals residing in PUMAs that experience at least one bank failure during the sample period and zero otherwise. KNOWDEP and R&D are sector-level time invariant variables. Each column includes one- or multi-way fixed effects. Controls include the following variables: Experience, Experience^2 Foreign born, Race, Female, EDUC*Experience and EDUC*Experience^2. Extra controls include the following variables: Age, Age^2, Married, Married*Child, Female*Child. Whenever Age fixed effects are included, Age and Age^2 are dropped from the regressions. Standard errors are shown in parentheses and are clustered by PUMAs. *, **, *** indicate significance at the 10%, 5%, and 1% levels.