Regulatory Risk Perception and Small Business Lending

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Abstract

We study how Small Business Administration (SBA) employees respond to salient defaults. Using novel data to identify employees transferring across SBA offices, we find that defaults on SBA loans in their previous workplace reduce SBA loans in their current workplace. The effect is independent of local risk conditions and the informational content of the non-local defaults, consistent with a mechanical (rather than rational) updating of risk perceptions among local SBA employees. Moreover, the local SBA loan market becomes geographically clustered and concentrated among fewer borrowers and lenders, especially those who have prior relationships with the SBA, suggesting higher barriers for participation.

JEL Classification: D02, D73, G28, G41

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1 Introduction

The Small Business Administration (SBA), a federal agency, helps small businesses get access to finance. Through its flagship 7(a) loan program, the focus of this paper, the SBA guarantees loans made by private lenders to small businesses who are unable to obtain credit elsewhere. The SBA's staff plays a key role in the process, for example by training and monitoring private lenders and guiding businesses through SBA-sponsored financing opportunities. While a growing literature explores the consequences of the agency's activities, we know surprisingly little on what influences SBA employees during the allocation of SBA-backed capital. In this paper we highlight one such factor: salient default risk.

Salient events could increase the perception of risk (Tversky and Kahneman 1973; Dessaint and Matray 2017). Therefore, when an SBA employee experiences salient defaults by small businesses, her perception of default risk will increase. An open question, though, is how does the potential change in risk perception affect SBA lending. It could raise awareness to the SBA's budget constraints (which depend on Congressional approval) and to reputational costs from engaging with risky businesses, leading to fewer SBA loans. On the other hand, SBA employees are not personally liable for defaulting loans and thus the perceived risk might not play a dominant role in their decision-making process. Moreover, the SBA's strategic goal is to support small businesses and its budgetary requests are typically fulfilled. Ultimately, it becomes an empirical question which we test using novel data on SBA employees. Our main finding is that salient defaults reduce SBA loans, consistent with the former hypothesis. Subsequent tests show that the effect is driven by a mechanical updating of risk perception, rather than rational learning or changes in actual default risk.

Our notion of salience is based on past and present job locations. To illustrate the idea, imagine an SBA employee stationed in Minneapolis. From her perspective, defaults on SBA loans in Minneapolis are salient. Now suppose she moves from Minneapolis to Boston. While she no longer works in Minneapolis, she likely retains social connections

there and keeps abreast of major developments (Bailey et al. 2018). Therefore, we consider defaults in both Boston and Minneapolis to be salient.[1] To track job transitions across the country, we source a unique data set which covers the entire SBA workforce from 1996 till 2019, including each employee's name and work location.[2] We merge it with loan-level data set on 7(a) loans, which includes the SBA office responsible for the loan and whether the loan has defaulted. We calculate risk salience for each employee, depending on their past and present workplaces, and our final measure is the average risk salience across employees within the office. It varies within-office across industries, as a function of industry defaults across SBA regions, and the subjective importance employees attach to each region based on their personal job histories. Using the previous example, in the eyes of the Boston office, defaults by Minneapolis retailers become salient after an ex-Minneapolis employee transfers into Boston.

Preliminary evidence shows a significant negative correlation between risk salience and SBA loans: the probability of receiving any SBA-guaranteed loan declines, and so does the quantity of loans and their dollar value. It suggests that SBA employees are inclined to back industries which they perceive as less risky. The challenge, though, is to separate risk salience from confounding factors which also affect SBA lending. In the above example, suppose Boston retailers receive a negative productivity shock. Their defaults would rise and hence their risk salience in the eyes of the Boston office. But their actual risk also increases, and their demand for SBA lending likely decreases as well, leading to fewer SBA loans for Boston retailers. Therefore, the decline in Boston-retail lending could be driven by their risk salience but also by changes in demand and actual risk due to an unobserved productivity shock.

To isolate the impact of salient risk, we construct an instrument based *only* on distant SBA regions located at least $1,000$ miles away from the current workplace (similar in spirit to Bailey et al. 2018). Continuing with the above example, we instrument for the risk salience of Boston-retail using only default rates in Minneapolis-retail.[3] In the second

[1] Formally, we define the salience of default risk as a weighted average of current defaults across past and present workplaces. The results are robust to several weighting schemes.

[2] The data set is available on our website (here).

[3] $1,000$ miles is the median distance between a pair of SBA local offices. The instrument has high

stage, our estimates are identified only by variation in risk salience which is based on personal job histories but is plausibly orthogonal to local industry conditions. We add year×office, office×industry, and year×industry fixed effects, focusing on within-office variation across industries net of national industry trends. We further control for the number of workers and the number of defaults by the borrowing industry, to proxy for credit demand and actual risk, respectively. Across all specifications, risk salience has a negative impact on lending. The effect is statistically significant and economically large, close in magnitude to the effect of our proxies for demand and actual risk. Using the example above, if there are ex-Minneapolis employees in Boston, and Minneapolis retailers default on their SBA loans, then SBA lending to Boston retailers declines. This effect is independent of retailers' national performance and of the size, risk, and average SBA lending for Boston retailers. However, if no ex-Minneapolis employees work in Boston, then SBA lending in Boston is unaffected by what happens in Minneapolis.

The results are robust to various permutations of the risk salience measure, are not driven by outlier offices or industries, and remain similar when we measure the dollar value of loans rather than their number. In a separate test, we focus on a subset of borrowers who have the capacity to match to different SBA offices, and exploit *within-borrower* variation in risk salience across offices (similar to Khwaja and Mian 2008). This specification absorbs all local conditions, including actual risk and demand, and uses only the variation in risk salience across offices. Again, we find a significant negative effect of risk salience on SBA lending: a one-standard-deviation increase in risk salience reduces loan probability by 5.6 percentage point, which is 25% of the unconditional probability within this (small) subsample.

Our results indicate that salient defaults affect SBA lending through changes in risk perception. This channel is rooted in the extensive literature on risk salience and risk perception, but it is important to note that we do not observe risk perception explicitly. To substantiate the link between risk salience and risk perception, we focus on ex-post loan performance and find that risk salience reduces future defaults, on the extensive and

F-statistic in the first stage, since the endogenous variable (defaults in Minneapolis and Boston) directly builds on the instrument (defaults in Minneapolis alone).

intensive margins. We interpret that as indirect evidence for changes in risk perception: salient defaults raise the perception of risk, reducing the overall number of loans while increasing the fraction of "safe" loans. A subsequent question is whether the changes in risk perception reflect rational learning. This could happen if distant defaults reflect unobserved industry trends which will eventually reach the local industries, and thus provide valuable information for the local SBA office. However, several tests seem to suggest otherwise. For example, we split the sample into five groups based on how predictive the risk salience is of future employment growth in the region ("do default rates in Minneapolis-retail predict slower employment growth of Boston-retail?"). We find no evidence that the effect of risk salience increases with the informativeness of the salient events. This test and others point away from a rational learning explanation, being more consistent with the idea that SBA employees mechanically update their perception of risk due to signals they receive from past workplaces (Akerlof and Shiller 2010; Barberis and Thaler 2005).

Finally, we highlight three mechanisms through which risk salience reduces SBA lending. We document a decline in the entrance of new lenders and an increase in the concentration of SBA loans among the remaining ones. This suggests that risk salience raises the barriers for lender participation in the SBA loan market, perhaps due to more intense monitoring by SBA staff whose perception of risk has been raised. We also find a decline in the fraction of new borrowers and a rising concentration of loans among few borrowers. It indicates that risk salience reduces the access to finance for businesses who lack prior relationships with the SBA, perhaps due to reallocation of outreach effort toward industries which are perceived as safer. We also exploit a major reform, completed in 2007, which transferred the bulk of screening duties from district offices to central locations. The effect of risk salience in the earlier period was nearly twice as high, indicating that risk salience raises risk perception which leads to a more thorough screening of loan applications by SBA employees.

Our work contributes to several strands in the literature. First, we document a novel driver of SBA-backed lending: salience of default risk among SBA staff. Several

studies explore the impact of SBA guarantees on productivity (Krishnan et al. 2015), hiring (Brown and Earle 2017), and credit supply (Bachas et al. 2021). The launch of the Paycheck Protection Program during the COVID-19 epidemic triggered a renewed interest in those questions (Granja et al. 2020; Hubbard and Strain 2020; Humphries et al. 2020; Bartik et al. 2020; Lutz et al. 2020; Barrios et al. 2020; Cororaton and Rosen 2020). However, the role of individual SBA employees is often overlooked. Our work begins to fill the gap, by documenting the impact of employee-specific risk salience on the allocation of capital for small businesses.

Second, we add to the literature on personal experiences in finance (Malmendier 2021). Studies show that personal experiences affect trust in financial institutions (Guiso et al. 2004; Guiso et al. 2008; Alesina and Fuchs-Schündeln 2007; Osili and Paulson 2008), stock market participation (Malmendier and Nagel 2011), managerial style (Malmendier and Nagel 2011; Schoar and Zuo 2017), and cash holdings (Dessaint and Matray 2017). We expand the analysis to the realm of the federal government and focus on the personal job histories of SBA employees: employees who transfer across distant regions remain sensitive to conditions in their previous workplace and develop a unique perception of risk with real economic consequences. We also find that SBA employees are affected by *past* defaults in their previous workplaces, a result very much aligned with the literature on experience effects in finance.

Third, an emerging economic literature explores factors which affect the performance of state bureaucracy. Studies highlight the role of intrinsic motivation (Besley and Ghatak 2005; Bénabou and Tirole 2006), starting salaries (Dal Bó et al. 2013), special rewards (Ashraf et al. 2014), outside career opportunities (Bond and Glode 2014; Lucca et al. 2014), promotion incentives (Kalmenovitz 2020), and the organizational design of regulatory agencies (Kisin and Manela 2018; Gopalan et al. 2017; Eisenbach et al. 2016; Hirtle et al. 2019; Kalmenovitz et al. 2021). Our work sheds light on a different factor: personal experiences and job histories of public sector employees. Since the career paths of Federal employees in the United States are fairly transparent, future research can explore how their experiences affect other aspects of the economy which are subject to intense

government intervention.

2 Background and hypotheses

2.1 Institutional setting

The paper is centered upon 7(a) loans, the flagship loan guarantee program of the Small Business Administration (SBA). This program is designed to help small businesses that are creditworthy but face challenges getting approved for financing. The loans are made and administered by banks and other lending institutions, and the SBA offers a government guarantee for a portion of the loan. The guarantee assures the lender that if the borrower does not repay the loan, the SBA will reimburse the lender for the pre-specified portion of its loss.

Generally, the process begins when the borrower selects a lender and submits a loan application. The borrower must meet certain eligibility criteria, and demonstrate an ability to repay the loan and inability to access credit elsewhere. Lenders should consider the strength of the business and various factors such as character, reputation, and credit history.[4] The lender reviews the application and makes an initial decision on whether to approve the loan. The lender then submits the application to the SBA which conducts its own analysis before making a final decision. The degree of scrutiny by the SBA varies, depending on the sub-category of the 7(a) loan; we will explore those differences in our empirical analysis (Section 5). If the decision is favorable, an SBA loan authorization is prepared which outlines the conditions under which the SBA will guarantee the loan. The guarantee rate ranges from 50% to 90%, depending on loan size and other factors. The lender completes the loan underwriting, disburses the loan proceeds, and services the loan until it is paid in full.

A key component of our analysis is charge-offs, that is, the dollars spent to cover SBA-guaranteed loans which defaulted. A 7(a) loan becomes a charge-off after all efforts to

[4]See Code of Federal Regulations (13 CFR §120.150) and the SBA's Standard Operating Procedure ("SOP 50 10, Lender and Development Company Loan Programs," last updated: October 1, 2020).

recover the delinquent balance have been exhausted. Charge-offs reflect the agency's and the taxpayers' liabilities from operating the 7(a) program, and are therefore prominently featured in the agency's annual financial reports. Moreover, one of the agency's strategic objectives is to mitigate the risk to taxpayers and specifically the credit risk. For instance, in its strategic plan for 2011-2016 the agency announces plans to improve its loan program risk management systems, increase the transparency of its portfolio performance, and implement "best practices" for lender oversight.

Finally, our analysis takes advantage of the SBA's organizational structure and its reliance on local offices. The agency is organized by ten regions (see Figure 1). Each region maintains a regional headquarters and serves the adjacent states and territories through multiple branch and district offices.[5] For example, Region 5 serves Illinois, Minnesota, Wisconsin, Indiana, Ohio, and Michigan. The regional headquarters is in Chicago, and additional local offices are based in Springfield (Illinois), Minneapolis, Madison, Indianapolis, Cincinnati, Cleveland, Columbus, and Detroit. The district offices are responsible for the delivery of the SBA's many programs and services throughout the country. They provide counseling and training services to individuals or businesses related to the formation and financing of a small business. District offices provide information on and promote SBA products to lending partners, the small business community, and groups such as chambers of commerce and trade associations.[6] Finally, district offices play a key role in screening and training lenders who participate in the 7(a) loan program. We add further details below (Section 5).

2.2 Hypotheses

When a private lender fails to recover the delinquent loan, the SBA must purchase the loan, up to the guaranteed amount. It is no surprise, then, that the SBA puts great

[5]Larger offices are labeled as "district" and smaller ones as "branch." For the main analysis we do not distinguish between the two, and refer to both as "district office" or "local office" interchangeably.

[6]For example, the district office for Eastern Pennsylvania lists among its responsibilities "Educating small business owners and the general public about the programs and services available through SBA," "Providing one-on-one counseling to existing and perspective business owners on starting and/or expanding their businesses," and "Educating and assisting bank and non-bank lenders on securing SBA loans for their small business customers" (see here).

effort into managing the default risk and tracking its progress. Our focus is on variation in risk salience across employees and industries. Put differently, the aggregate default risk is experienced differently by individual SBA employees. Below we elaborate on the empirical approach we develop to capture the differences in risk salience. In this section, we discuss how the salience of default risk could affect SBA lending.

A rich literature in psychology and behavioral economics shows that salient events distort the process of risk assessment, by increasing the perception of risk (Tversky and Kahneman 1973; Kahneman and Tversky 2013; Bordalo et al. 2012; Bordalo et al. 2013). The intuition is that people rely on salient experiences to judge the probability of an event, even though the actual probabilities did not change.[7] Empirical studies document this mechanism in various settings. For example, homeowners rely on a recent flood to overestimate the probability of a future flood (Kunreuther et al. 1978). Following a hurricane, managers express more concerns about hurricane risk even though the actual risk remains unchanged (Dessaint and Matray 2017). Following an aviation disaster, implied volatility of stock prices (perceived risk) increases without an increase in actual volatility (actual risk) (Kaplanski and Levy 2010).

In our context, salient defaults could increase the perception of default risk. However, even if true, it is not clear how the elevated risk perception would affect SBA lending. On one hand, defaults constrain the SBA's ability to guarantee new loans until additional budget is secured. This may lead employees to reallocate effort toward industries which they perceive as more safe. Reputational concerns could also be at play, as employees prefer to engage industries which they perceive as less likely to fail. Either way, when choosing between two enterprises, then - all else equal - the SBA would support the one with the lowest perceived risk. The alternative hypothesis argues that, even if salient defaults increase the perceived default risk (which is difficult to prove since risk perception is largely unobservable), that should not reduce SBA lending. The SBA's strategic goal is to enhance job creation and Congress typically provides the requested budget. Moreover, employees are not personally liable to SBA loans. In fact, employees may be willing to

[7] Salience, availability, and attention bias are all closely related concepts, and for our purpose we do not distinguish between the three.

engage with industries which they perceive as more risky, in order to support a more robust employment growth in the long run.

To study the contradicting predictions, we proceed in the following way. First, we propose a methodology to estimate risk salience based on a novel employee-level data set (Section 3.2). Next, we discuss various empirical strategies linking risk salience to SBA lending (Section 3.3). Finally, we present the results (Section 4) and evaluate potential mechanisms (Section 5).

3 Data, variables, and empirical strategy

3.1 Data sources

Our pivotal data set covers the entire SBA workforce. We obtained it through multiple Freedom of Information Act requests submitted to various federal entities. It contains comprehensive information on any employee who worked at the SBA at any point between 1996 and 2019. The data set includes each employee's full name, occupation, and date of accession. It also provides annual information on location (state, county, city), salary, pay plan and pay grade, tenure, and bonus. To the best of our knowledge, the data set is free of selection bias and includes the universe of SBA employees from that period.

We match the employee-level data set to public loan-level data on the 7(a) program. The latter data set includes information about the borrower and lender (name, address, and industry), loan characteristics (loan amount, jobs supported, guarantee rate, interest rate), and ex-post loan performance and charge offs. Crucially for our analysis, we observe the SBA office which approved the guarantee and the approval date. We match the loan-level data to industry-level information, gathered from the Quarterly Census of Employment and Wages (QCEW) of the Bureau of Labor Statistics. It reports employment and wages by county-industry based on all establishments in the region, using NAICS classification.

3.2 Measuring risk salience

As mentioned above, we focus on the salience of default risk. We first construct an employee×industry measure of risk salience, and then aggregate it into an office×industry measure of risk salience. Let $L_{j,t}$ denote the set of locations where employee j worked up until year t, which we identify using the granular SBA employment records. The risk salience of industry i at time t, in the eyes of employee j, is:

$$RiskSal_{j,i,t} = \sum_{l \in L_{j,t}} \omega_{l,t} Default_{l,i,t}, \tag{1}$$

where $Default_{l,i,t}$ is the number of SBA loans, guaranteed by office l to industry i and charged-off at time t. It reflects the realized risk, when the lenders turned to the SBA and the agency was required to write off the defaulting loans. We scale $Default_{l,i,t}$ by the number of loans guaranteed by office l for industry i at time t. If no loans were approved at time t, we use the amount of loans from the previously available period.[8] Industries are defined based on 3-digit NAICS codes. Note that there are several sources of variation in Equation 1: default rates ($Default_{l,i,t}$) vary both across and within-industry, while their relative importance ($\omega_{l,t}$) varies both across and within-employee. Put differently, each employee picks a different subset of the SBA's regions and assigns a unique set of weights within that subset.

Past locations may be less salient, and we capture that with the weight $\omega_{l,t}$. We provide here a brief description and the precise methodology is outlined in the Internet Appendix. Intuitively, the weight decreases with the number of years which have passed since working in that location. Formally, let $\tau_{l,t}$ denote the time that have passed since working at location l, as of time t. For example, in the current location l, $\tau_{l,t} = 0$ for all

[8] The "mismatch" could happen since a loan defaulting at time t was most likely approved prior to time t. Those observations account for 4.9% of the sample, and excluding them from the analysis does not affect the results. Conditional on being charged-off, the median loan was charged-off 50 months after being approved.

t. The weight of location l as of time t is then defined as:

$$\omega_{l,t} = \frac{\frac{1}{1+\tau_{l,t}}}{\sum_i \frac{1}{1+\tau_{i,t}}}. \tag{2}$$

This weighting scheme has several desirable properties. In any given year, the sum of annual weights within employee×industry ($\sum_l \omega_{l,t}$) equals one, meaning that the industry's risk salience the average default rates of that industry across a selected subset of SBA regions. Defaults in the current location are assigned the greatest weight, since these are likely to be the most salient. The longer the employee stays at his current location, the greater that weight becomes, while the weights on past locations gradually decrease.

In the second step, we average across employees to obtain an office×industry measure of risk salience:

$$RiskSal_{o,i,t} = \frac{1}{N} \sum_{j \in E_{o,t}} RiskSal_{j,i,t}, \tag{3}$$

where $E_{o,t}$ is the set of employees who work at office o at time t, N is the number of employees who work at office o at time t, and $RiskSal_{j,i,t}$ is employee×industry risk salience from Equation 1. Note that if no employee transferred from another office, then $RiskSal_{j,i,t} = RiskSal_{o,i,t}$ for all employees and it is simply the realized default rate around the office.

3.3 Impact of risk salience on lending

Having constructed a measure of salient risk, we turn to study its impact on SBA lending. Earlier we presented two competing hypotheses. One argues that risk salience reduces SBA lending by increasing the perception of default risk. The alternative argues that perceived default risk is not a dominant consideration, for the SBA as a whole and even less so for individual SBA employees. To evaluate the competing predictions, we estimate the following regression:

$$y_{o,i,t+l} = \alpha + \beta \cdot RiskSal_{o,i,t} + \overrightarrow{X} + \epsilon \tag{4}$$

We aggregate the loan-level data into office×industry pairs, that is, we combine all the loans approved by SBA office o to industry i at time t. We set the loan year on the federal government's fiscal year basis (October 1 through September 30), since the QCEW and the employee-level data are also based on the government's fiscal year. The dependent variable is loans guaranteed by SBA office o to industry i at time t, as a share of all loans guaranteed by SBA office o at time t. Equivalently, we consider the dollar amount of the approved guarantees as a share of total dollar guarantees. We exclude office×industry pairs which have no lending relations throughout the entire period ($y_{o,i,t} = 0$ for all t). The latter condition applies when the industry has no presence in counties adjacent to the particular SBA office. The baseline specification is in contemporary values ($l = 0$) but the results are qualitatively similar when we use one-period lag. We standardize continuous variables to facilitate the interpretation, and double-cluster standard errors at the office and year level to account for serial correlation.

$RiskSal_{o,i,t}$, as discussed earlier, is the average default rates by industry i across a subset of SBA offices. It reflects the salience of defaults by industry i at time t, in the eyes of office o. We predict that $\hat{\beta} < 0$: salient defaults increase the perception of default risk, which leads the SBA office to reduce its exposure to that industry. The challenge is that $RiskSal_{o,i,t}$ is not randomly assigned. Specifically, default rates in various SBA regions could be negatively correlated with the local demand for SBA lending, and/or positively correlated with local actual risk. For example, imagine that a negative productivity shock affects the retail industry in Boston. That shock triggers salient defaults among retail businesses in Boston (higher $RiskSal_{o,i,t}$). It also increases the actual risk of retail companies in Boston and perhaps also lowers their demand for SBA lending, leading in equilibrium to fewer SBA guarantees for Boston-based retail companies. In this scenario, the negative correlation between $RiskSal_{o,i,t}$ and $y_{o,i,t+l}$ is driven by the contemporaneous productivity shock, which affect the outcome through lower demand and/or greater actual risk, not just through risk salience.

To handle these challenges, our first strategy is based on explicit controls and saturated fixed effects specifications. We add year×office and office×industry fixed effects, focusing

on within-office variation across industries in lending and risk salience. In a tighter specification we add year×industry fixed effects, to address the possibility that national industry trends drive both defaults rates and new SBA loans. We restrict the analysis to non-local borrowers, who are based in a different county than the SBA's district office, and are therefore less likely exposed to correlated demand and risk shocks.[9] We further control for the number of workers in the borrowing industry, as a proxy for its demand for SBA loans,[10] and for the number of defaults by the borrowing industry, as a proxy for its actual risk.[11] Continuing with the example above, we seek to explain SBA guarantees from the Boston office to non-Boston retail stores, controlling for the national condition of the retail industry, the size and risk of the non-Boston retailers, and their average relation to the Boston office, as a function of default rates by retail stores in Minneapolis where some of the Boston employees used to work.

Our second strategy exploits variation in risk salience which is plausibly orthogonal to local demand and risk. It is similar in spirit to Bailey et al. 2018. Specifically, we instrument for $RiskSal_{o,i,t}$ with the component of risk salience that is based *only* on distant offices. In the above example, we instrument for Boston retailers' risk salience, as viewed by the Boston office, using only the default rates of retailers in Minneapolis. We construct the instrument using a cutoff of $1,000$ miles, which is the median distance between a pair of SBA district offices, and an alternative cutoff based on out-of-state offices yields similar results. The first and second stages of this IV regression, respectively, are given by:

$$RiskSal_{o,i,t} = \beta^{FS} RiskSal^{far}_{o,i,t} + \overrightarrow{X} \tag{5}$$

and:

$$y_{o,i,t+l} = \beta^{IV} \widehat{RiskSal}_{o,i,t} + \overrightarrow{X}. \tag{6}$$

The instrument, $RiskSal^{far}_{o,i,t}$, has high F-statistics across all first-stage regressions. The reason is that the instrumented variable directly builds on the instrument. For

[9] We obtain similar results when focusing on borrowers located at least 500 miles away.

[10] The results do not change when we replace workers with establishments, or use growth rates instead of levels.

[11] Those defaults are a component of the endogenous variable, *RiskSal* (correlation: 0.32).

example, suppose the Boston office has two employees, one of them previously worked in Minneapolis and the other stayed in Boston his entire career. In that case, $RiskSal_{o,i,t}$ would account for defaults in both Minneapolis and Boston, while $RiskSal^{far}_{o,i,t}$ would account only for defaults in Minneapolis. In the second-stage, our estimates of β^{IV} are identified only by variation in $RiskSal_{o,i,t}$ that is driven by Minneapolis defaults, independent of the variation in Boston defaults.[12]

Our third strategy exploits within-borrower variation in risk salience, similar to Khwaja and Mian 2008. We aggregate the loan-level data into office×industry×county triplets, that is, we group together all loans approved by SBA office from county o to industry i in county c. We then estimate a similar regression to Equation 4:

$$y_{o,i,c,t+l} = \alpha + \beta \cdot RiskSal_{o,i,t} + \overrightarrow{X} + \epsilon, \tag{7}$$

where the difference is that variables are measured at the triplet level. For example, the dependent variable is the number of loans guaranteed by SBA office o to industry i in county c at time t, as a share of all loans guaranteed by SBA office o to county c at time t. As before, we exclude office×industry×county triplets which have no lending relations throughout the entire period. The advantage of this specification is that we can control explicitly for the borrower's conditions (demand and risk) by including year×county×industry fixed effects. This specification represents a special case where a local industry switches from one SBA office to another. We thus compare the behavior of two different SBA offices with respect to the same borrowing industry, absorbing all the variation coming from the average risk and demand of that industry, and plausibly exploiting only the variation in risk salience across offices.

[12] A threat to the identification arises if a shock affects *new* SBA guarantees in the local office's area, and also moves equilibrium default rates on *past* SBA-guaranteed loans in geographically distant counties from which the local office "imported" employees.

3.4 Summary statistics

The sample consists of 80 district and branch offices between 1998 and 2019. Combined with 3-digit NAICS industries, they yield nearly 190,000 office×industry observations. However, we exclude observations that answer to any of the following criteria: pair with no lending relations throughout the entire sample period, the industry did not obtain any SBA loan in a particular year, and/or the office did not have any loan in a particular year. The final sample includes 6,965 unique office×industry pairs and 98,246 pair-year observations.

Panel A in Table 1 reports descriptive statistics. The unconditional probability of receiving any SBA-guaranteed loan is 85%. Conditional on any loan, the average industry secured 9.5 loans worth \$1.85 million in total, and captured 1.9% of the office's portfolio. The unconditional probability of default is 43%, and conditional on any default, the average industry defaulted on 3.8 loans worth \$369,000 combined. Our main independent variable, $RiskSal$, ranges from 0 to 2.01. It reflects the weighted average of office×industry defaults across a subset of SBA regions, where the subset includes all past workplaces of the local SBA employees.[13] The corresponding instrument, $RiskSal^{far}$, uses only the subset of regions which are located at least 1,000 miles away.[14]

Panel B describe the SBA's workforce. The underlying data set starts in 1996, and since we wish to exploit job transitions, we focus on the sample of employees starting from 1998. It includes 18,740 unique employees and 96,535 employee-year observations.[15] The unconditional probability of relocation in a given year is 1.8%. Conditional on having relocated at least once, the average employee has served in 2.2 locations (including the current one). At the office level, 15% of each office's workforce have relocated from a different office.

In Table 2, we provide additional descriptive evidence on employee movement across

[13]Defaults are scaled by number of loans, and since the defaulting loans are from an earlier vintage than the current loans, the rate could be greater than one.

[14]The equivalent table in the Internet Appendix reports statistics for the subsample of 53,454 observations with non-missing instrument values, which are similar to those in the full sample.

[15]We removed from the sample observations with undisclosed place of unemployment or undisclosed names, as well as observations with duplicate names.

the SBA's 80 offices. For a given focal office, employees could move into the focal from peer offices ("inbound") or from the focal to peer offices ("outbound"). We define office turnover as the sum of the inbound and outbound employees, scaled by the number of employees in the office at the beginning of the year. The average turnover in an SBA office is 4.7% and with an average of 54.3 employees per office, this implies that the average office would see a turnover of 2.5 employees per year. Table 2 lists the top ten (Panel A) and bottom ten (Panel B) offices by average turnover over our sample period. We restrict ourselves only to offices with more than ten employees on average in order to prevent our listing being biased by small branch offices which often see more employee turnover. In Panel A, we see that the Richmond District Office has the highest turnover at almost 15%, and that offices with high turnover are spread all over the country. Similarly, in Panel B, the offices with the lowest turnover are geographically dispersed.

In order to further explore employee movement to and from SBA offices, we take the Dallas-Fort Worth District Office as a case study and visually depict employee turnover at the office in Figure 2. We chose this office since it is the second largest one, after Washington DC. The map in Panel A depicts outbound transfers, that is, peer offices to which employees transferred *from* the Dallas office. The darker the shade, the more outbound transfers from Dallas to that location. The map in Panel B depicts inbound transfers, that is, the original offices from which employees transferred into the Dallas office. Both maps tell a consistent story: there is significant turnover at SBA offices, and employee movement is not concentrated regionally but takes place all over the country. The corresponding table in the Internet Appendix reports the top ten locations of outbound and inbound employees, with respect to the Dallas office. Both panels confirm the dispersed nature of employee movement, with 40% of the locations being over $1,000$ miles away from Dallas.

4 Results

4.1 Main result

To obtain a visual impression, Figure 3 plots the non-parametric relation between risk salience and loan activity. We plot both the number of loans and the dollar volume, as a share of total loans and total dollar volume. Both margins exhibit a negative relation with risk salience. It is consistent with the idea that salient defaults raise the perception of risk among SBA employees, which are consequently inclined to reallocate resources toward other industries perceived as more safe.

We formally test this relation in Table 3. Panel A reports the OLS results (Equation 4), where we rule out alternative explanations using saturated fixed effects specification. Panel B reports the results from the second stage of the IV strategy (Equation 6). Here, we keep the fixed effects as in Panel A, and in addition focus on the variation in risk salience driven only by external default rates. In the first column, we include year and office×industry fixed effects, focusing on within-pair variation in SBA lending. Next, we replace year with year×office FE. This specification removes office-specific time trends, such as budget considerations and managerial style, and focuses on the allocation of SBA guarantees within the same office across different industries. In the third column, we apply year×office×NAICS2 fixed effects. Here, we compare two industries from the same 2-digit NAICS sector who are supervised by the same SBA district office at the same time, ruling out regional industry trends (2-digit level). Finally, in the fourth column we add year×NAICS3 fixed effects, thus controlling for national industry trends (3-digit level). For instance, if the hotel industry is in decline nationally, that could affect default rates in distant regions as well as local SBA lending. With the addition of year×NAICS3 fixed effects we further narrow down the identifying variation, and focus on regional deviation off the industry's national average. All specifications include proxies for demand and risk at the borrowing industry's location, using the number of employees in the borrowing industry and its default rates.

Across all specifications and strategies, the effect of risk salience on SBA lending is negative and statistically significant at the 1% level. The magnitude is relatively stable and economically large: all variables are divided by their cross-sectional standard deviations, which implies that the negative impact of risk salience on SBA guarantees is at least as large (in absolute value) as the proxies for local demand and local risk. The IV coefficients are somewhat smaller than the OLS coefficients, consistent with our explanation above: the omitted variable reflects unobserved local credit risk and/or local demand for SBA loans, either one likely contributes to a downward bias in the estimated effect (that is, inflates the absolute value of the effect). Using distant default rates as the only source of variation removes the impact of local shocks, and consequently the coefficients obtained using IV strategy are attenuated toward zero. However, the differences between the OLS and the IV results are not statistically significant, and they all point to a substantial negative impact on SBA lending. We obtain similar results when the dependent variable is based on the dollar volume of loans, rather than pure counting of the loans. The estimated coefficient is smaller, indicating that risk salience particularly affects the allocation of smaller SBA-guaranteed loans.

Finally, Panel C focuses on the office×industry×county sample, for example: SBA-guaranteed loans from the SBA office in Boston to construction companies in Worcester. The dependent variables are the probability of receiving a loan, as well as number of loans and their dollar value (out of total SBA loans to the office×county). We report two specifications. The first includes year×office×NAICS2 fixed effects as well year×NAICS3 fixed effects, essentially repeating the tightest specification from Panels A and B and ruling out national industry trends (3-digit) and local industry trends (2-digit). We find a substantial negative impact of salient defaults on SBA lending, on the extensive and intensive margin, and the magnitude is similar to the one reported in the previous two panels. In the second specification we use year×county×NAICS3 fixed effects. Here, we focus on the subsample of borrowers that have the capacity to borrow from multiple SBA regions (industry×county observations who borrow from two SBA regions in the same year, at least once during the sample period). Effectively, we compare the behavior of

two different SBA offices with respect to the same borrowing industry, absorbing all the variation coming from the risk and demand of that industry, and using only the variation in risk salience across offices (as in Khwaja and Mian 2008). We find a significant negative effect of risk salience on SBA lending. For example, one-standard-deviation increase in risk salience reduces loan probability by 5.6 percentage point, which is 25% of the unconditional probability within this subsample.

4.2 Robustness and persistence

Several tests verify the robustness of our main results and their persistence across subsamples. For brevity, some are reported in the Internet Appendix and the remainder are available upon request.

First, we winsorize all variables at the 1%, 5%, and 10% levels. We choose different methods to cluster standard errors, accounting for various possibilities of serial correlation: by office×industry-county, by county, by year, by SBA office, and by industry. We define industry at the 2-digit or 4-digit NAICS code, as opposed to 3-digit in the baseline specification. The more granular definition helps to rule out industry-specific shocks, but on the other hand the measurement error in the employment variables increases with granularity. We estimate the regressions in contemporaneous and lagged values, and add the lagged dependent variable as a control (since lending relations are persistent).

Returning to the first step, we consider several permutations of our baseline measure of $RiskSal$. In the baseline version, past locations are weighted by the number of years passed. Alternatively, we assign equal weights to all locations, or focus on the most recent past location and assign zero weight to locations from the distant past. To aggregate employee-level to office-level, in the baseline regression we took a simple average across all employees. Alternatively, we attach weights based on the employee's salary. Here, the intuition is that higher-paid employees have greater influence on the decision-making process in the office, and therefore their risk salience matter more. We replace $Default$ in Equation 1 with the dollar volume of defaulting loans scaled by the dollar volume of loans, and alternatively with the dollar value of the guarantee (the SBA's loss) scaled

by the dollar volume of the guaranteed loans. None of these permutations changes the results.

We estimate a reduced-form regression of Equation 4 which replaces $RiskSal_{o,i,t}$ with $RiskSal^{far}_{o,i,t}$ and otherwise keeps the same structure. The magnitude of β in the reduced-form specification is similar to the magnitude of β^{IV}, scaled by the average share of employees with past experiences. These reduced-form estimates capture the average effect of risk saliences, based only on the non-local trends, on the outcome of interest. We also estimate Equation 4 iteratively, each time excluding one industry or one state from the sample. The obtained coefficients are virtually identical across the subsamples, reassuring us that the results are not driven by an outlier industry or state. In a separate test we estimate Equation 7 for counties that are at least d miles away from the SBA's office, where d ranges from 0 (the baseline) to 500. The coefficients remain stable and significant, indicating that the effect of risk salience on SBA lending propagates across counties and is not limited to neighboring counties. Finally, we interact $RiskSal$ with the characteristics of the SBA office: average tenure, average salary, and number of employees. The negative effect is slightly stronger among small offices, and we find no statistically significant marginal impact of the employees' pay or tenure.

4.3 Lifetime experience

Suppose an employee transferred from San Francisco to Philadelphia. In our baseline measure, we treat the current default rates in San Francisco as salient. In this section, we consider an alternative (non-mutually exclusive) idea: *past* default rates in San Francisco, which occurred during the employee's spell in that office, are also salient in the employee's experience. It relies on the rich literature which documents how lifetime experiences affect the decision-making process (Nisbett and Ross 1980; Weber et al. 1993; Hertwig et al. 2004). For example, trust in financial institutions is shaped by distant childhood experiences (Guiso et al. 2004; Guiso et al. 2008; Alesina and Fuchs-Schündeln 2007; Osili and Paulson 2008), and recently experienced stock market returns affect the individual's willingness to assume financial risk (Malmendier and Nagel 2011). Similarly, the CEO's

managerial style relates to her life experience, such as military service (Malmendier and Nagel 2011) and past career milestones (Schoar and Zuo 2017).

Formally, we define lifetime experience of employee j with respect to industry i in time t as:

$$RiskLifetime_{j,i,t} = \sum_{\tau \leq t} \omega_{\tau,t} \cdot Default_{l_\tau,i,\tau}, \tag{8}$$

where l_τ denotes the location in which the employee worked at time τ, and τ is limited to the time frame when the employee worked at office l. In this definition, $Default_{l_\tau,i,\tau}$ is the number of SBA loans to industry i in region l_τ defaulting at time τ. Previous years may be less salient, and we capture that with the weight $\omega_{\tau,t}$. Intuitively, the weight decreases with the number of years which have passed since the defaults. We provide here a brief description and the precise methodology is outlined in the Internet Appendix. The weighting scheme has several desirable properties. The sum of weights within employee-year equals one, and the current year is always assigned the greatest weight. The more years of experience, the lesser the weight on the current year (although it is still the largest).

Since our interest in this section is about the salience of past defaults, we restrict the sample only to those employees who appear in our employee data set for at least six years. This excludes a quarter of the SBA workforce. For this sample of employees, we construct the lifetime experience measure as in Equation 8. As with our baseline risk salience analysis, endogeneity is a concern while analyzing the effects of lifetime experience. In addition to the concerns laid out in Section 3.3, reverse causality is a concern in this scenario. SBA employees may specialize in an industry and might move as the industry prospects change. For instance, an employee specializing in chemicals might move from San Francisco to Philadelphia when that industry's prospects improve in Philadelphia relative to San Francisco. This might correlate with increased lending to chemicals out of the Philadelphia office compared to San Francisco.

To alleviate this concern, we employ an instrumental variable strategy similar to the one in the main section. The instrument we employ, plausibly orthogonal to local demand and risk, is based on employee experiences in the distant past. Specifically, we

instrument for $RiskLifetime_{o,i,t}$ with the component of life experience that is based *only* on experiences more than five years in the past. This instrument can be thought of as the temporal analog of the spatial instrument we use in our main results. The first and second stages of this IV regression, respectively, are given by:

$$RiskLifetime_{o,i,t} = \beta^{FS} RiskLifetime^{past}_{o,i,t} + \overrightarrow{X} \tag{9}$$

and:

$$y_{o,i,t+l} = \beta^{IV} \widehat{RiskLifetime}_{o,i,t} + \overrightarrow{X}. \tag{10}$$

The results from our 2SLS estimation are presented in Table 4. The set of fixed effects and controls are the same that we employ for our main results in Table 3, with the specifications ensuring narrower comparisons as we move from column (1) to column (4). We find that life experience of defaults has a negative and statistically significant effect on both the industry share of loan count and dollar volume. The magnitude of the effect is comparable to the effects of risk salience that we saw in earlier sections. We consider our life experience proxy to be complementary to our risk salience proxy, in that they capture different elements of how individuals perceive risk: one temporal, and the other spatial. Across both, the effect of heightened risk salience leads to a decline in new lending.

5 Mechanisms

In the previous section, we documented a causal relationship between risk salience and SBA lending. In this section we explore in greater detail potential mechanisms. First, we provide additional evidence that the results are driven by changes in risk perception. Next, we ask why does risk salience affect risk perception, and specifically if it reflects rational learning or mechanic belief formation ("why"). Finally, we discuss how risk salience affects various aspects of the SBA's workflow, eventually leading to the significant reduction in SBA-backed lending ("how").

5.1 Risk perception

Our interpretation for the baseline results is centered upon risk perception. We argue that salient defaults increase the perception of default risk, reducing the attractiveness of industries which are now perceived as risky. Risk perception is largely unobservable, and we do not have direct evidence linking salient defaults to the perception of default risk. However, our findings are consistent with the extensive literature which documents a similar effect of risk salience on risk perception in various settings (see Section 2.2). In this section we present additional, indirect evidence, based on ex-post performance of SBA loans. Our conjecture is that risk salience increases the perception of risk, therefore reducing the overall quantity of SBA loans. If so, we expect the surviving SBA loans to be less risky. In other words, if SBA office o perceives industry i as more risky, only relatively-safe loans would receive the SBA's backing.

To test our prediction, we flag loans which were eventually charged-off. For each office×industry pair, we calculate the number of SBA-guaranteed loans which were approved at time t and subsequently defaulted, scaled by the number of loans which were approved at time t and were subsequently paid in full or charged off. The resulting measure is bound between zero and one, and reflects the ex-post default rate among all "closed" loans (that is, loans which were either paid in full or defaulted).[16] We also compute a dollar-weighted default rate, which weighs loans by their dollar value within office×industry pair. For example, if a $\$1,000,000$ loan was paid in full but a $\$2,000,000$ loan was charged off, then the simple default rate is 50% but the dollar-weighted default rate is 66.6%. In a third version we convert the continuous measure to an indicator which equals one if at least one of the loans defaulted.

To study whether risk salience at the time of origination affects subsequent default rates, we adopt the baseline specification from Equation 4 except that the dependent variable is the ex-post default rate (as defined above). We use a similar set of fixed effects and controls, and estimate an OLS model as well as the IV one. For brevity, we

[16] If the loan status is still pending, such as loans whose maturity date extends beyond 2019, we treat it as zero. The results do not change if we exclude those from the analysis.

report only the latter in Table 5. In the first three columns, the dependent variable is an indicator that any loan subsequently defaulted. In the next six columns, we look on the intensive margin by restricting the sample to office×industry observations where there was at least one default. In columns (4)-(6), we look at default rates based on counts and in columns (7)-(9), default rates are based on dollar volume. Across both extensive and intensive margins, we find strong evidence that risk salience significantly reduces subsequent default rates. These results provide compelling evidence that risk salience of SBA employees leads to safer loans being made.[17] We interpret that as indirect evidence for changes in risk perception: salient defaults raise the perception of risk, reducing the overall number of loans while increasing the fraction of "safe" loans.

5.2 "Why:" Mechanical versus rational

Is it rational to rely on the salience of risk? On one hand, SBA employees could attempt to rationally extract information from salient defaults. For example, distant default rates could be driven by unobserved productivity shocks which will eventually affect the local industries, and therefore reliance on this distant credit risk could inform the SBA's local efforts to stimulate growth. On the other hand, SBA employees could be just mechanically influenced by signals they receive from past workplaces. For example, Bailey et al. 2018 note that agents are mechanically infected by the beliefs of their friends, and this response is independent of whether their friends' house price experiences contain useful information.

To asses the rational learning story, we conduct two tests. First, we split the sample into groups based on how predictive the risk salience is of future growth rates in the region. For each office×industry, we estimate the correlation between their risk salience and the subsequent growth rate of employment in the next year. We then group the office×industry pairs into five clusters based on the absolute value of the obtained correlation. The greater the correlation, the more informative is the risk salience regarding

[17] In untabulated results, we keep the loan-level data and estimate default probability with bank fixed effects, as in Granja et al. 2018. The significant results ensure that our results are not driven by unobservable bank characteristics.

future economic growth in the area. We estimate the effect of risk salience on lending decisions for each group separately, using the baseline specification (Equation 4) with year×office fixed effects. The results are in Panel A of Table 6. We find no evidence that office×industry pairs with more predictive risk saliences respond more strongly to their experiences: the difference of the coefficients for the most-informative and the least-informative subsamples is insignificant ($F-$statistic: 0.21, $p-$value: 0.65). In a separate test we estimate a pooled regression, and add the interaction of $RiskSal$ with the group's informativeness. We use either the continuous variable (absolute value of the correlations from the first step), a dummy which equals one for the most informative pairs, or the pair's ranking (from 1 to 5). If anything, we find weak evidence that lending responds *less* strongly to informative risk saliences.

Second, many plausible rational explanations of the behavior we document involve offices learning about some fundamental national shock from observing default rates across multiple geographies. If this were an important channel, we would expect a stronger response by offices whose employees represent greater geographic dispersion, since their average experience would be more informative about the national shock. We split the sample into groups based on the number of unique regions that affect the office's risk salience, and estimate the baseline specification (Equation 4 with year×office fixed effects) for each group separately. The results in panel B show that the sensitivity to risk salience varies with the number of counties employees came from, but in the opposite direction: the greater the dispersion, the lower the sensitivity. We obtain similar conclusions in the pooled sample, where we interact $RiskSal$ with the employees' dispersion, and find that the effect among high-dispersion offices is 20% lower than other offices.

These pieces of evidence point away from a rational learning explanation for our findings. This is perhaps unsurprising. Indeed, if default rates in a different part of the country were sufficiently informative to affect a rational agent's decision, then, in a world of rational learning, everybody should update their expectation equally on the basis of these defaults, which are available for free and in high frequency (the SBA updates its files at least every quarter)). We thus conclude that the evidence is most consistent with

mechanical belief updating. We should note, though, that there remain a number of possible explanations. For example, our findings could be due to the spread of irrational sentiments (Akerlof and Shiller 2010), or due to overconfident individuals overreacting to noisy signals (Barberis and Thaler 2005).

5.3 "How:" risk salience and the SBA's workflow

5.3.1 Screening on loans and lenders

In the previous section we discussed whether the reliance on risk salience could be explained by rational learning motives. Regardless of our conclusions above, a separate question involves the channel through which the local office could reduce loan quantity. Put differently, what part of the SBA's work leads to a reduction in SBA-backed loans for the "risky" industry?

One possibility is that risk salience at the district office leads to more intense screening, whereby applications for SBA-backed loans are turned down in greater numbers. To quantify the relative importance of this channel, we exploit the institutional details of the SBA 7(a) loan program. Between 2003 and 2007, the SBA completed the centralization of most 7(a) loan processing activities. The Standard 7(a) Loan Guaranty Processing Center, located in Citrus Heights, CA and Hazard, KY, processes 7(a) loan guarantee applications. The Commercial Loan Service Center, located in Fresno, CA and Little Rock, AR, is responsible for loan servicing actions and SBA Express loan purchases. The National Guaranty Purchase Center, located in Herndon, VA, processes the bulk of 7(a) guarantee purchase requests. Thus, from 2007 at the latest, district offices are rarely involved in credit determination. If risk salience affects SBA lending through screening, a natural prediction is that the effect weakens after 2007, when the centralization was completed. We test this prediction in Panel A of Table 7. We exclude the years 2003-2007 during which the centralization process took place, and split the remaining year into two subsamples: before (1998-2002), and after (2008-2019). We then estimate the same baseline specifications, using the IV, on each subsample. The results show a significant drop in the magnitude of the effect after 2008, up to 50%. Put differently, when district

offices have the option to screen SBA loans, the importance of their risk salience almost doubles.

While direct loan screening by district offices is largely legacy, their opinions might still have an indirect impact on loan approval. For example, it is possible that the loan processing centers seek their advice on particular loans. If screening is still a relevant mechanism, we expect to see a shift toward screening-free loans: risk salience raises the probability of rejection, and thus lenders and borrowers select routes that are free of SBA screening. To test this possibility, we exploit variation in the degree of screening across sub-categories of 7(a). For standard 7(a) loans, the SBA makes the final determination as to the creditworthiness of the applicant. Delegated loans, though, are subject to only a quick review by the SBA. Two types exist: preferred lenders (PLP), who must be pre-approved to participate in the program, and express loans, which are capped at $\$350,000$ and can obtain maximum of 50% SBA guarantee.[18]

In the pooled sample, express and PLP loans capture 80% of the outstanding loans and 70% of the dollar value (since express loans are by construction smaller; see Internet Appendix). We define a new dependent variable, which is the share of delegated loans as a fraction of all loans (number of loans and dollar volume). We estimate the same baseline specification and report the results in Panel B of Table 7. There is no detectable change in the share of delegated loans out of total loans, but there is a substantial increase in their share of the dollar amount. Put differently, the effect of risk salience is uneven: it affects non-delegated loans more than it affects delegated ones. The SBA-backed loan portfolio is overall shrinking, and moreover tilts toward delegated loans which require less scrutiny by the SBA.

Loan screening aside, district offices play a much more significant role in recruiting, training, and monitoring participating lenders. Generally, a potential lender would submit a request to their district office, and the staffers determine whether the lender meets the requirements to be a 7(a) participant (13 CFR §120.410). The district office can

[18]The program, initially called FA$TRAK, was established in 1995 as a pilot and made permanent in 2004. A similar program, Export Express, provides SBA-backed financing for loans and lines of credit related to export up to $\$500,000$.

affect the decision to grant and renew a PLP status, and its feedback is required when assessing the lender's performance. For example, the office can provide a recommendation and explain whether the lender can satisfactorily process and liquidate SBA loans, and discuss any unfavorable data pertaining to loan performance and defaults. The district office plays a similar role with respect to approving SBA Express authority. The district office provides training for approved lenders regarding the SBA's policies and procedures. The SBA uses an automated system to assess PLP lender performance quarterly, and lenders with an outstanding SBA balance of $10 million or more may also be subject to more in-depth reviews.

In light of that, it is possible that heightened risk salience increases the scrutiny of lenders by the local office, and in particular the scrutiny of loans extended to the "risky" industry. We do not have information on inspections and reviews made by the SBA. Therefore, we cannot directly test this channel. Instead, we focus on the distribution of loans among lenders as indirect test of that channel. If risk salience affects SBA loans through lenders, we should see changes in the industrial organization of the SBA loan market. Specifically, we expect to see a decline in the fraction of new lenders, who struggle to get training or approval. Moreover, we expect to find a decline in the overall number of lenders: there are fewer new entrants, and in addition some of the existing lenders are not re-approved.

For each office×industry observation, we calculate the number of unique lenders and the share of new lenders (out of unique lenders). We further calculate the concentration of loans among lenders, analogous to HHI: the sum of squares of the fraction of loans by each lender. Higher values indicate higher concentration, as fewer lenders capture greater share of the market for SBA loans. We calculate the HHI-like measure separately, based on number of loans and their dollar value. The results are in Panel C of Table 7. There is a decline in the number of lenders and particularly in the fraction of new lenders entering the market. Moreover, the market for SBA-backed loans becomes significantly more concentrated among a small number of lenders, both in terms of loans and dollar volume. These results are consistent with a lender-screening channel, which specifically predicts

a concentration of loans among a small number of lenders with pre-existing experience with SBA loans.

5.3.2 Demand stimulation

Finally, district offices seek to stimulate demand by local businesses for SBA loans through outreach and educational initiatives. When the risk salience of a particular industry increases, it is possible that the office would reallocate efforts toward other industries, leading in equilibrium to fewer loans for that industry.

We do not observe outreach efforts and therefore cannot test this channel explicitly. Instead, we focus on the distribution of loans among borrowers. If changes in SBA lending are driven by targeted outreach, we should see a decline in the number of new borrowers who are sensitive to the SBA's awareness campaigns. In contrast, borrowers from the "risky" industry who received SBA-backed loans in the past should not be particularly sensitive to any reduction in outreach efforts. We conduct a similar analysis as before. For each office×industry observation, we calculate the number of unique borrowers and the share of new borrowers, as well as the concentration of loans among borrowers. The results are in the right-hand side of Panel C, showing a marked decline in the number of borrowers and fraction of new borrowers, alongside a significant increase in the concentration of loans among borrowers. Combined, these results are consistent with a demand stimulation channels, which predicts a concentration of loans in the hands of fewer borrowers with pre-existing experience with SBA loans.

6 Conclusion

This paper documents that salient default risk influences the allocation of lending under the agency's flagship 7(a) lending program. When defaults become more salient, SBA lending is lower. The evidence is consistent with employees mechanically updating their perception of default risk, based on the defaults they personally experience through their current office location or links to other SBA offices they have worked at. As such, our

analysis also sheds light on the importance of the organizational structure of the SBA in determining lending outcomes. As employees transfer from one office to another, they take their experiences with them, establishing an under-explored economic link between regions.

While we do not attempt to quantify the welfare implications of our findings, the robustness of our estimates lends credence to the idea that administrative agencies are not faceless bureaucracies that implement a set of regulations but their functioning is influenced by the experiences of their employees. For the SBA in particular, its operations have recently been in the limelight due its administration of the Payroll Protection Program (PPP) during the COVID-19 pandemic. Though our sample period ends before the PPP, our analysis may shed light on some of the mechanisms behind the uneven rollout of the PPP (Granja et al. 2020; Hubbard and Strain 2020; Humphries et al. 2020; Bartik et al. 2020; Lutz et al. 2020; Barrios et al. 2020; Cororaton and Rosen 2020). Demand stimulation is an important function of the SBA and we show it is a channel through which risk salience affects lending. In the absence of any screening, as in the case of PPP, it is plausible that the risk salience of SBA employees may have played a role in outreach to potential borrowers.

Going forward, our analysis suggests that a more careful accounting of the experiences of public sector employees could contribute to our understanding the administrative state's performance. Since the United States has a fairly high degree of transparency about public employees' career paths, future research can build on our analysis to understand how government employee experiences affect the provision of public goods and enforcement of regulations.

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Figure 1: **Geographic distribution of the Small Business Administration**

Geographic distribution of the SBA's regions and local offices. **Source**: SBA Financial Report, FY 2020.

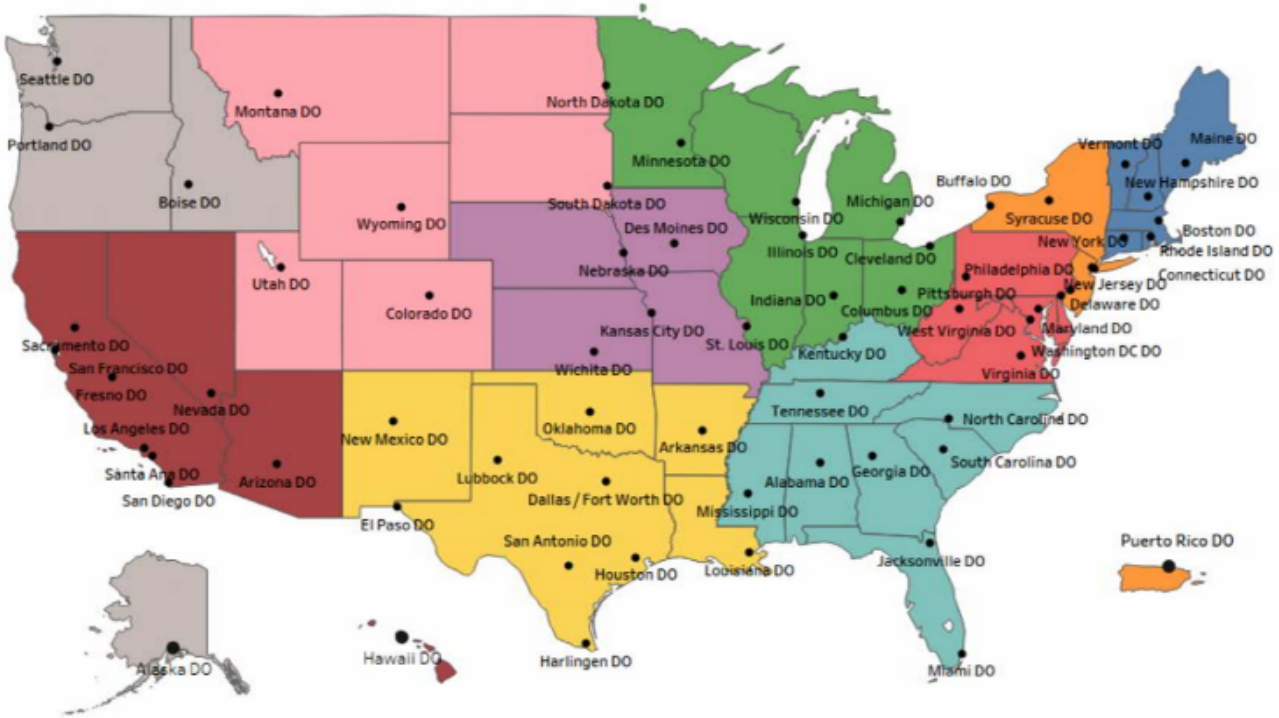
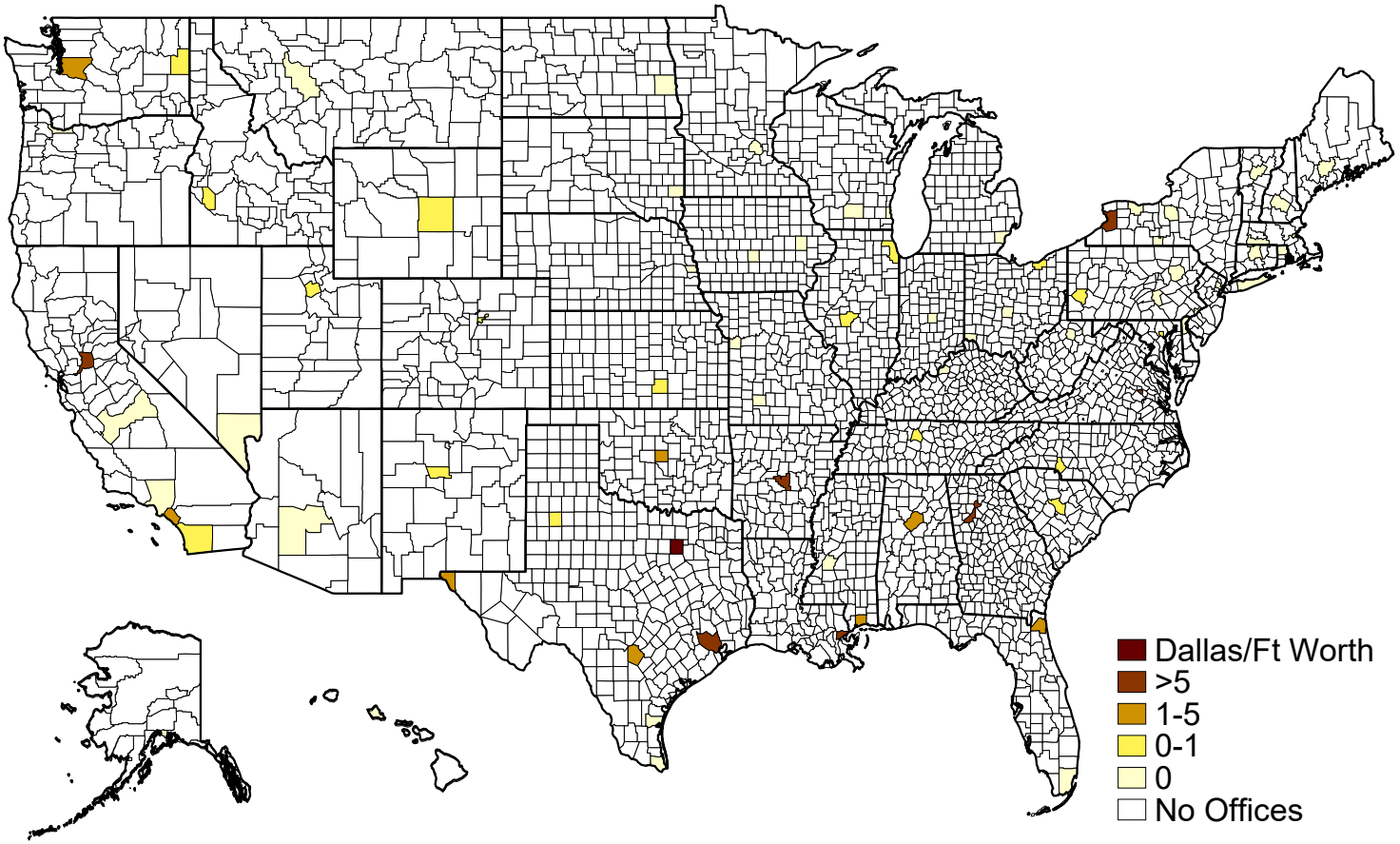


Figure 2: **Job transfers to and from the Dallas office**

Panel A. Distribution of employees who transferred out of the Dallas-Fort Worth office (brown shade) to a different SBA office. The darker shades indicate destination offices who "imported" more employees from Dallas-Fort Worth.



Panel B. Origins of employees who transferred into the Dallas-Fort Worth office (brown shade) from a different SBA office. The darker shades indicate offices who "exported" more employees to Dallas-Fort Worth.

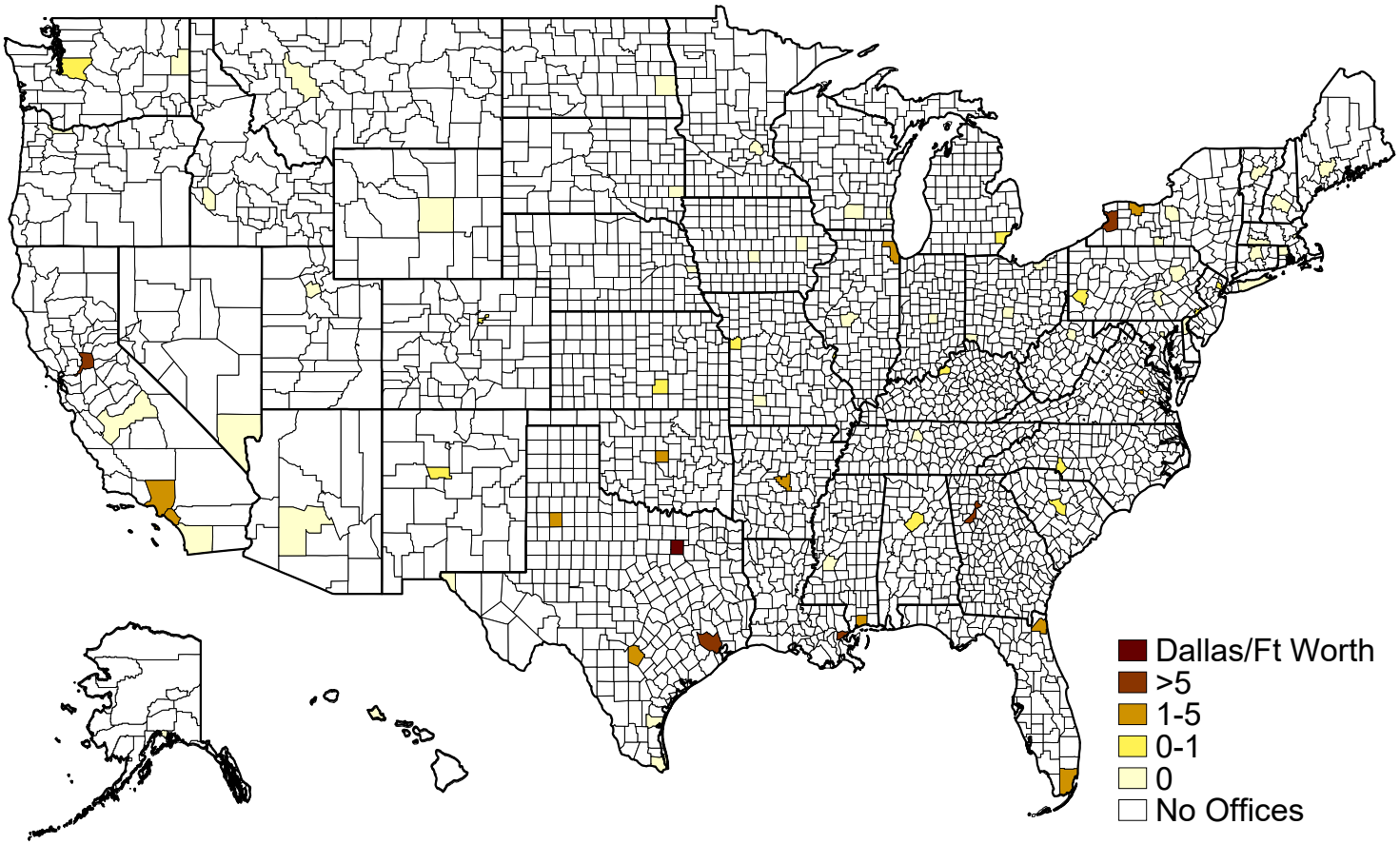
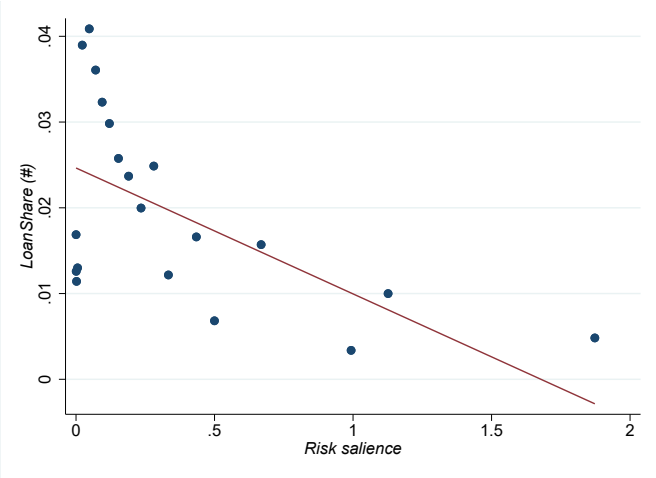


Figure 3: **Salient risk and SBA lending: Preliminary evidence**

Non-parametric relations between risk salience and the allocation of SBA lending. *Risk salience* reflects how salient are the defaults of industry i, in the eyes of SBA office o (see Section 3.2 and Equation 3). *Loan Share (#)* is the number of loans guaranteed by SBA office o to industry i, as a share of the number of loans guaranteed by SBA office o. *Loan Share ($)* is the dollar volume of loans guaranteed by SBA office o to industry i, as a share of the dollar volume of loans guaranteed by SBA office o.

Panel A. Loans



Panel B. Dollars

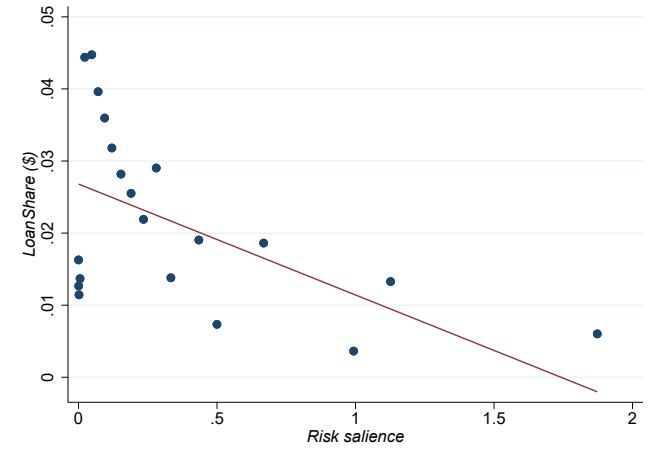


Table 1: **Summary statistics**

Panel A. Industry-SBA relations. The sample consists of office×industry pairs, based on 80 local offices of the SBA during 1998-2019. $I(Loan)$ is indicator for any loan during that year, $Loan^{\#}$ ($Loan^{\$}$) is the number (dollar volume) of loans conditional on $I(Loan) > 0$, and $LoanShare^{\#}$ ($LoanShare^{\$}$) is the share of loans (dollar volume) out of the office's total. $I(Default)$ is indicator for any default, $Default^{\#}$ ($Default^{\$}$) is the number (dollar volume) of defaulting loans conditional on $I(Default) > 0$. $I(Emp)$ is indicator for available data on employment (from the QCEW database), Emp is the number of employees, and $EmpShare$ is the share of employment out of total employment in the office's jurisdiction. $RiskSal$ (from Equation 3) the weighted average of office×industry defaults across selected regions, and $RiskSal^{far}$ is similar except that it uses only the subset of regions which are located at least $1,000$ miles away.

	Mean	Median	SD	Min	Max	Obs
Loans:						
$I(Loan)$	85.02	100.00	35.69	0.00	100.00	98,246
$Loan^{\#}$	9.54	4.00	16.77	1.00	107.00	83,531
$Loan^{\$}$	1,849,422	506,250	3,717,641	200	23,618,024	83,531
$LoanShare^{\#}$	1.94	0.95	2.50	0.03	12.73	83,531
$LoanShare^{\$}$	1.90	0.75	2.88	0.00	15.63	83,531
Defaults:						
$I(Default)$	43.53	0.00	49.58	0.00	100.00	98,246
$Default^{\#}$	3.80	2.00	5.89	1.00	39.00	42,764
$Default^{\$}$	369,502	118,887	664,640	0.00	4,178,113	42,764
Controls:						
$I(Emp)$	90.51	100.00	29.31	0.00	100.00	98,246
Emp	15,192.25	5,431.00	28,644.70	3.00	187,430.00	88,922
$EmpShare$	1.80	0.83	2.91	0.00	17.81	88,922
Risk:						
$RiskSal$	0.20	0.00	0.39	0.00	2.00	98,246
$RiskSal^{far}$	1.82	0.28	3.72	0.00	22.51	53,454

Panel B. SBA workforce. The table describes the workforce of the Small Business Administration, 1998-2019. In Panel B.1, *Tenure* is the number of years the employee has worked at the SBA and *Salary* is adjusted base pay (in 2017 USD). *Relocated* (*OutState*) is an indicator for an employee who worked in a different office (state) in the previous year, and $Relocated^{past}$ ($OutState^{past}$) is an indicator for an employee who worked in a different office (state) in any of the previous years, all left blank for the first year of service. *Locations* is the number of past and present locations (states), conditional on $Relocated^{past} > 0$ ($OutState^{past} > 0$). In Panel B.2, *Employees* is the number of employees, and the remaining variables are similar to Panel B.1 (averaged within office and then across offices).

	Mean	Median	SD	Min	Max	Obs
B.1. Employees:						
Salary	82513.03	77360.68	34437.94	0.00	208636.77	96,474
Tenure	13.43	11.00	11.14	1.00	62.00	96,533
Relocated	1.82	0.00	13.39	0.00	100.00	84,991
OutState	1.57	0.00	12.43	0.00	100.00	84,991
$Relocated^{past}$	11.91	0.00	32.39	0.00	100.00	84,991
$OutState^{past}$	10.20	0.00	30.27	0.00	100.00	84,991
Locations	2.17	2.00	0.44	2.00	5.00	10,491
States	2.16	2.00	0.41	2.00	5.00	8,970
B.2. Offices:						
Salary	84991.78	84333.11	12563.41	46982.59	131958.48	1,774
Tenure	17.04	17.43	5.77	1.00	48.00	1,774
Relocated	2.55	0.00	8.14	0.00	100.00	1,772
OutState	1.86	0.00	5.77	0.00	100.00	1,772
$Relocated^{past}$	15.12	10.59	16.72	0.00	100.00	1,772
$OutState^{past}$	11.77	8.33	13.66	0.00	100.00	1,772
Locations	2.18	2.00	0.32	2.00	5.00	1,430
States	2.16	2.00	0.30	2.00	5.00	1,324

Table 2: **Job transitions across SBA local offices**

For each of the SBA's local offices, we calculate the average annual turnover rate: number of employees transferring in and out of the office during the year, scaled by the number of employees in the office at the beginning of the year. Panel A lists the 10 offices with the highest turnover rate, and Panel B lists the ones with the lowest rate.

Office Name	**Turnover (%)**	**Employees**
Panel A. Top-10:		
Richmond District Office	14.97	145.57
Nevada District Office	9.32	17.39
North Florida District Office	8.98	88.61
Lubbock District Office	7.65	12.83
Houston District Office	7.25	44.09
Los Angeles District Office	7.14	54.48
San Diego District Office	6.91	21.35
South Florida District Office	6.68	49.05
North Carolina District Office	6.41	38.91
Arizona District Office	6.23	25.65
Panel B. Bottom-10:		
Colorado District Office	2.28	142.26
Washington District Office	2.16	785.87
Michigan District Office	2.13	35
Alabama District Office	2.12	69.78
Nebraska District Office	2.04	14.17
Dallas / Ft Worth District Office	2.03	774.87
North Dakota District Office	1.98	12.96
Des Moines District Office	1.57	13.83
Syracuse District Office	1.51	15.09
Vermont District Office	.72	11.22

Table 3: **Risk salience and SBA loans: main result**

Panel A. OLS.
Results from estimating Equation 4. $LoanShare^{\#}$ ($LoanShare^{\$}$) is the number (dollar volume) of SBA loans by office o to industry i, as a share of the number (dollar volume) of SBA loans by office o. *RiskSal* reflects how salient are the defaults of industry i in the eyes of office o (Equation 3). Controls include employment by industry i within office o's jurisdiction and the number of defaults on SBA loans in office o's jurisdiction. Industries are defined based on 3-digit NAICS codes.

Outcome:	$LoanShare^{\#}$				$LoanShare^{\$}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RiskSal	-0.096***	-0.106***	-0.095***	-0.084***	-0.078***	-0.086***	-0.078***	-0.073***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Ofc FE	-	Y	-	-	-	Y	-	-
Year×Ofc×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y
Obs.	91,199	91,198	82,993	82,954	91,199	91,198	82,993	82,954
R^2	.782	.786	.868	.892	.627	.631	.764	.792

Panel B. 2-SLS.
Results from the second stage of the 2-SLS framework (Equation 6). $LoanShare^{\#}$ ($LoanShare^{\$}$) is the number (dollar volume) of SBA loans by office o to industry i, as a share of the number (dollar volume) of SBA loans by office o. $\widehat{RiskSal}$ reflects how salient are the defaults of industry i in the eyes of office o (Equation 3), instrumented with distant default rates ($RiskSal^{far}$). Controls include employment by industry i within office o's jurisdiction and the number of defaults on SBA loans in office o's jurisdiction. Industries are defined based on 3-digit NAICS codes.

Outcome:	$LoanShare^{\#}$				$LoanShare^{\$}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskSal}$	-0.088***	-0.094***	-0.086***	-0.072***	-0.070***	-0.075***	-0.067***	-0.059***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Ofc FE	-	Y	-	-	-	Y	-	-
Year×Ofc×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y
Obs.	49,845	49,845	46,037	45,978	49,845	49,845	46,037	45,978

Panel C.

Results from estimating Equation 4 in the office×industry×county sample. $I(Loan) = 1$ if industry i in county c received SBA loan from office o. $LoanShare^{\#}$ ($LoanShare^{\$}$) is the number (dollar volume) of SBA loans by office o to industry i in county c, as a share of the number (dollar volume) of SBA loans by office o to county c. $RiskSal$ reflects how salient are the defaults of industry i in the eyes of office o (Equation 3). Controls include the number of employees by industry i in county c and the number of defaults by that industry. Industries are defined based on 3-digit NAICS codes.

Outcome:	$I(Loan)$		$LoanShare^{\#}$		$LoanShare^{\$}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$RiskSal$	-0.024***	-0.056***	-0.032***	-0.118***	-0.022***	-0.092***
	(0.001)	(0.002)	(0.001)	(0.008)	(0.001)	(0.009)
Controls	Y	-	Y	-	Y	-
Year×Ofc×County×NAICS2 FE	Y	-	Y	-	Y	-
Year×NAICS3 FE	Y	-	Y	-	Y	-
Year×Ofc×County×NAICS3 FE	-	Y	-	Y	-	Y
Obs.	1,271,888	71,212	1,271,888	71,212	1,271,888	71,212
R^2	.569	.693	.488	.555	.465	.538

Table 4: **Risk salience based on lifetime experience**

Dependent variables, controls, and fixed effects are similar to Panel B inTable 3. $\widehat{RiskLifetime}$ reflects how salient are the defaults of industry i in the eyes of office o, based on the lifetime experiences of the office's employees, and instrumented with past default rates (see Section 4.3).The results below are from the second stage (Equation 10). Industries are defined based on 3-digit NAICS codes.

Outcome:	$LoanShare^{\#}$				$LoanShare^{\$}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskLifetime}$	-0.093***	-0.109***	-0.082***	-0.042***	-0.089***	-0.104***	-0.086***	-0.056***
	(0.016)	(0.021)	(0.010)	(0.012)	(0.016)	(0.019)	(0.013)	(0.016)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Ofc FE	-	Y	-	-	-	Y	-	-
Year×Ofc×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y
Obs.	82244	82242	73599	73479	82244	82242	73599	73479

Table 5: **Risk salience and future defaults**

Results from the second stage of the 2-SLS framework (Equation 6). $I(Defaults) = 1$ if any loan from office o to industry i defaulted, conditional on having any loan. $DefShare^{\#}$ is the fraction of loans defaulted out of total loans, conditional on $I(Defaults) = 1$. $DefShare^{\$}$ is the fraction of dollars in default out of total dollar lending, also conditional on $I(Defaults) = 1$. $\widehat{RiskSal}$ reflects how salient are the defaults of industry i in the eyes of office o (Equation 3), instrumented with distant default rates ($RiskSal^{far}$). Industries are defined based on 3-digit NAICS codes.

Outcome:	$I(Defaults)$			$DefShare^{\#}$			$DefShare^{\$}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{RiskSal}$	-0.016***	-0.012**	-0.012**	-0.010	-0.052**	-0.052**	-0.046*	-0.082**	-0.082**
	(0.005)	(0.005)	(0.005)	(0.018)	(0.020)	(0.020)	(0.022)	(0.031)	(0.031)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year×Ofc FE	Y	-	-	Y	-	-	Y	-	-
Year×Ofc×NAICS2 FE	-	Y	Y	-	Y	Y	-	Y	Y
Year×NAICS3 FE	-	-	Y	-	Y	Y	-	-	Y
Obs.	41865	38189	38189	14293	9836	9836	14293	9836	9836

Table 6: **Informativeness of risk salience**

Panel A. We estimate the same specification as Table 3, Panel B, column 2, separately for five groups of office×industry pairs. The groups reflect how informative is the risk salience for future employment growth rates (absolute value of the correlation between *RiskSal* and employment growth, estimated separately for each office×industry pair). The difference between the coefficients in columns 1 (least informative) and 5 (most informative)) is statistically insignificant ($F-$statistic: 0.21, $p-$value: 0.65). In columns 6-8, we estimate the same specification for the full sample and add the interaction of *RiskSal* with *Dispersion*, which is based on the estimated informativeness: a continuous variable (column 6), the group's rank from 1 (least informative) to 5 (most informative; column 7), and an indicator for the most informative group (column 8).

Outcome:	$LoanShare^{\#}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskSal}$	-0.062***	-0.083***	-0.093***	-0.083***	-0.058***	-0.080***	-0.091***	-0.083***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)	(0.003)	(0.005)	(0.003)
$Dispersion \cdot \widehat{RiskSal}$						0.002	0.005**	0.029***
						(0.003)	(0.002)	(0.008)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year×Ofc FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	9,153	10,059	9,808	9,957	9,020	48,015	48,015	48,015

Panel B. We estimate the same specification as Table 3, Panel B, column 2, separately for five groups of offices. The groups reflect how many unique past locations are incorporated into the office's risk salience. The difference between the coefficients in columns 1 (few locations) and 5 (many locations) is statistically significant at the 1% level ($F-$statistic: 231, $p-$value: 0.00). In columns 6-8, we estimate the same specification for the full sample and add the interaction of *RiskSal* with *Dispersion*, which is based on the number of unique past locations: a continuous variable (column 6), the group's rank from 1 (few locations) to 5 (many locations; column 7), and an indicator for the group with the highest number of past locations (column 8).

Outcome:	$LoanShare^{\#}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskSal}$	-0.131***	-0.111***	-0.095***	-0.083***	-0.075***	-0.098***	-0.117***	-0.096***
	(0.018)	(0.008)	(0.010)	(0.005)	(0.004)	(0.004)	(0.009)	(0.004)
$Dispersion \cdot \widehat{RiskSal}$						0.006**	0.007***	0.014**
						(0.003)	(0.002)	(0.006)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year×Ofc FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	2,355	13,088	5,250	14,778	14,466	52,963	52,963	52,963

Table 7: **Risk salience and SBA lending: Mechanisms**

Panel A. Screening borrowers. The table replicates the first four columns from Panel B in Table 3, except that we estimate the regressions separately before (1998-2003) and after (2008-2019) the 2003-2007 reform, during which the SBA centralized the 7(a) loan process.

Outcome:	$LoanShare^{\#}$							
	Period: $1998-2003$				**Period:** $2008-2019$			
$\widehat{RiskSal}$	-0.174***	-0.178***	-0.170***	-0.142***	-0.069***	-0.075***	-0.072***	-0.069***
	(0.018)	(0.018)	(0.020)	(0.018)	(0.003)	(0.003)	(0.003)	(0.003)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Ofc FE	-	Y	-	-	-	Y	-	-
Year×Ofc×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y
Obs.	6,178	6,178	5,289	5,233	30,636	30,636	28,490	28,462

Panel B. Delegated loans. The table is similar to Panel B in Table 3, except that we use different dependent variables and limit the sample to office×industry observations with non-zero loans. $DelegateShare^{\#}$ ($DelegateShare^{\$}$) is the number (dollar volume) of delegated SBA loans by office o to industry i, as a share of the number (dollar volume) of SBA loans by office o to industry i. Delegated loans are either express loans or those approved by a preferred lender (PLP).

Outcome:	$DelegateShare^{\#}$				$DelegateShare^{\$}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskSal}$	-0.002	0.006	0.007	0.002	0.019***	0.027***	0.032***	0.025***
	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)	(0.006)	(0.008)	(0.009)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Ofc FE	-	Y	-	-	-	Y	-	-
Year×Ofc×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y
Obs.	43,023	43,022	38,831	38,741	43,023	43,022	38,831	38,741

Panel C. Lenders and borrowers. The table is similar to Table 3, Panel B, column 4, except that we use a different set of dependent variables and limit the sample to office×industry observations with non-zero loans. *Lenders* is the number of unique institutions providing SBA-backed loans. $Lend^{new}$ is the share of new lenders out of total lenders. $Lend^{HHI,\#}$ ($Lend^{HHI,\$}$) is the sum of squares of the fraction of loans (dollars) offered by each lender, analogous to HHI. Equivalently, *Borrowers* is the number of unique borrowers; $Borr^{new}$ is the share of new borrowers out of total borrowers; and $Borr^{HHI,\#}$ ($Borr^{HHI,\$}$) is the sum of squares of the fraction of loans (dollars) received by each borrower.

Outcome:	$Lenders$	$Lend^{new}$	$Lend^{HHI,\#}$	$Lend^{HHI,\$}$	$Borrowers$	$Borr^{new}$	$Borr^{HHI,\#}$	$Borr^{HHI,\$}$
$\widehat{RiskSal}$	-0.083***	-0.030***	0.187***	0.166***	-0.047***	-0.022**	0.200***	0.177***
	(0.003)	(0.008)	(0.006)	(0.006)	(0.003)	(0.010)	(0.006)	(0.006)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ofc×Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year×Ofc×NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	38,741	38,741	38,741	38,741	38,741	38,741	38,741	38,741