Regulatory Risk Perception and Small Business Lending

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Abstract

We uncover a significant friction in small business lending: perception of risk by Small Business Administration employees. Using novel data on SBA employees transferring across offices, we find that more current defaults on SBA loans in their previous location reduce SBA loans and job creation in their current location. The effect is independent of local economic conditions and the informational content of the non-local defaults, suggesting that SBA employees update their risk assessment irrationally. Our results are the first to document that regulators' misperception of economic conditions affects the ability of small businesses to obtain access to finance.

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1 Introduction

In many developed and emerging markets, government programs aim to provide credit support for small businesses. In the United States, this task is handled primarily by the Small Business Administration (SBA). Through its flagship program, known as 7(a), the SBA guarantees loans made by private lenders to small businesses which are unable to obtain credit elsewhere. By providing access to finance, the SBA crucially affects the ability of small businesses to survive and grow (Brown and Earle (2017)). In this paper we rely on novel data to uncover a misperception of default risk by SBA employees, who irrationally update their expectation for future defaults on SBA loans. The misperception affects the allocation of SBA resources with important consequences for credit supply, employment, and firm entry.

To monitor the default risk, the SBA regularly collects plethora of hard information from lenders and from other agencies, creating a set of lender-specific risk scores. The structured, data-driven approach to risk management should crowd out any misperception of risk developed by individual employees. However, such misperception could arise if SBA employees are exposed to salient defaults. For example, after a hurricane, managers express more concerns about hurricane risk even though the actual risk did not change (Dessaint and Matray (2017)). We hypothesize that a similar effect could take place at the SBA. When defaults by small businesses are more salient, SBA employees perceive the default risk to be higher, even though the actual risk did not change. Worrying about budget constraints and the reputation costs from engaging with risky businesses, they approve fewer guarantees. Conversely, if defaults are less salient, perception of risk is lower which leads to more guarantees.

To test the idea, we source a unique dataset which tracks the job histories of each individual SBA employee.[1] The following example illustrates our strategy. Imagine an SBA employee stationed in Houston. From her perspective, defaults on SBA loans in Houston are salient and she relies on them to update her perception of risk. Now suppose she moves from Houston to Boston. While she no longer works in Houston,

[1]The data set is available on our website.

defaults in Houston are still somewhat salient in her mind. She may pay more attention to data coming from Houston or perhaps retains social connections there. Therefore, *current* defaults in both Boston and Houston are salient, the former more than the latter.[2] We merge the employment data with a loan-level dataset on 7(a) guarantees, which records the SBA office responsible for the loan and whether the loan has defaulted. We calculate risk salience for each employee, based on current defaults in 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 Houston retailers become salient only after an ex-Houston employee transfers into Boston.[3]

In a series of regressions, we document a significant impact of risk salience on the allocation of SBA loans. Industries with more salient risk are less likely to obtain any SBA loan. Conditional on non-zero loans, the number of loans and their dollar value declines. Equivalently, industries with less salient risk receive more SBA loans. The effect is conditional on the number of workers and establishments in the local industry as well as year×office, office×industry, and year×industry fixed effects. Those help rule out factors which typically affect the allocation of SBA loans: demand for SBA loans, local economic conditions, long-run relations between the local industry and the local SBA office, and national industry trends, respectively.

Since risk salience affects the availability of credit for small businesses, it could consequently affect job growth and the ability of new small firms to enter the market. To test those predictions, we exploit the fact that lenders report the number of jobs created and retained as a result of each loan, and we obtain additional data on firm entry from the County Business Patterns. Using a similar set of regressions, we find that higher risk

[2]Formally, risk salience is the weighted average of current defaults across past and present workplaces. The results are robust to several weighting schemes.

[3]It is possible that employees develop a general risk perception, rather than industry-specific one. We construct an alternative to capture this idea and obtain similar results.

salience reduces the number of new small firms (10 employees or less)[4] and the number of jobs created. These results point to a knock-on effect of SBA risk perception on the ability of small businesses to survive and grow. It is particularly important, given that the SBA's strategic goal is to support job growth.

Next, we seek to separate risk salience from confounding factors. In the example above, imagine a negative productivity shock which triggers defaults only by Boston retailers, and is not subsumed by any of the fixed effects and controls. That shock increases their risk salience in the eyes of the Boston office, but also changes their actual risk and demand for loans. Thus, the effect we document could be tainted by the latent shock.[5] We address this possibility with an instrument that uses only defaults in distant workplaces, at least $1,000$ miles away from the current workplace (similar to Bailey et al. (2018)). In our example, we instrument for the risk salience of Boston-retail using only defaults in Houston-retail. The F-statistic in the first stage is high, since the endogenous variable (Houston and Boston defaults) directly builds on the instrument (Houston defaults). We find a highly significant effect in the second stage, conditional on the same tight set of fixed effects and controls. Now, the effect is identified off variation in risk salience based on relocations of SBA employees, while being plausibly (conditionally) orthogonal to local industry trends. We find that if a Houston employee moves to Boston, and Houston retailers default, then Boston retailers lose access to SBA loans. The effect is independent of Boston's local conditions, retailers' national and local conditions, and the average SBA lending for Boston retailers. However, absent any relocation, credit supply in Boston is not significantly affected by Houston events.

The results from both methods (OLS and IV) are all significant and qualitatively similar. We reach similar conclusions in a reduced form strategy, where we regress the outcome directly on the instrument and the same set of controls and fixed effects. We find a similar effect in another large SBA guarantee program, known as 504, which supports long-term investment in major assets.[6] To alleviate any remaining concerns, we exploit within-

[4] Reassuringly, there is no impact on entry of large firms (500 employees or more).

[5] The direction of the bias is not clear, ex-ante. For example, if the negative productivity shock increases the demand for SBA loans, our results suffer from downward bias.

[6] To that end, we construct a parallel measure of risk salience which is based on defaults on 504 loans,

borrower variation in risk salience across offices (similar to Khwaja and Mian (2008)). Suppose retailers in Hillsborough County, New Hampshire, can match to two nearby SBA offices: Boston and Vermont. We use tight fixed effects (year×county×industry) to absorb the current risk and demand of Hillsborough retailers, and compare the simultaneous decisions of Boston and Vermont with respect to this local industry, based on how each office subjectively perceives the industry's risk. Again, we find a significant effect with similar economic magnitude.[7]

Our interpretation of the results relies on risk perception. We cannot test this mechanism directly because risk perception is unobservable. Instead, we report several indirect tests. For instance, the risk salience effect is stronger in smaller local offices, where diffusion of personal perceptions is more likely to occur. We also show that higher risk salience reduces future default rates. This is consistent with our interpretation: more salient risk increases the perception of risk, which leads the SBA to prefer safer (and fewer) borrowers. It is inconsistent, though, with a concern that risk salience is correlated with an unobserved negative productivity shock.

In subsequent tests, we investigate whether SBA employees use rational learning to recalibrate their risk perception. In one test, we find that risk salience is less consequential when the local SBA office relies on performance-based cash bonuses. It suggests that risk salience does not contain a valuable signal, and therefore employees use it less when their compensation is tied to performance. In another test, we find that the effect does not increase with the informativeness of risk salience. For example, when the local SBA workforce is geographically diverse, their collective perceptions likely mirrors some fundamental national shock, and could thus be considered more informative. However, the effect of risk salience does not increase with geographic diversity. Those tests point away from a rational learning explanation and are more consistent with the idea that SBA employees mechanically update their risk perceptions based on signals from past workplaces (Akerlof and Shiller (2010)).

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and use similar OLS and IV specifications.

[7] Here, the effect is identified off borrowers who can contact multiple SBA offices at the same time (nearly a third of U.S. counties).

A natural question is what drives relocations across SBA offices. We use cross-sectional regressions and a detailed case study to establish two main facts. First, "movers" tend to be better-paid employees who receive a promotion upon moving to the new office. Second, conditional on moving, economic similarities between two offices[8] do not predict the decision to relocate from one office to the other. Combined, those facts support our conclusions: they suggest that relocations are largely driven by the emergence of internal job opportunities, and mitigate concerns that "movers" are immaterial to the decision-making process, or that they are serial low performers who routinely reject loan applications. Another key assumption in our analysis is that individual employees exert some influence over office-level outcomes. To substantiate this, we interview a senior SBA director and also examine a large sample of SBA job listings from USAJobs.gov, the government's job portal. For example, a typical rank-and-file employee is expected to build "effective relationships with a portfolio of small business CEOs," market "all SBA lending programs," and conduct "outreach, training, education, development, lender recruitment, consultation and working with assigned lenders."

Finally, we highlight three mechanisms through which risk salience affects SBA lending. First, we show that risk salience reduces the number of new lenders and increases market concentration among the remaining lenders. This suggests that risk salience motivates SBA employees to raise the barriers for participation in the SBA loan market, for example by tightly monitoring local lenders. We document a similar decline in new borrowers and rise in concentration of loans among the remaining ones. It indicates that risk salience discourages SBA outreach to "risky" industries, which especially hurts business owners who are not yet familiar with the agency's financing opportunities. Lastly, we exploit a major reform of the SBA's screening process, after which local SBA offices largely ceased to review guarantee applications (that task is now conducted at two central locations). The effect of risk salience on SBA guarantees was significant before and after the reform,[9] but it was nearly twice as high in the earlier period (before) relative to

[8] For example, the similarity between the loan portfolios of the two offices.

[9] Note that the first two mechanisms continue to be relevant post-reform, even though local SBA offices no longer participate in the screening of individual loans.

the latter period (after). It implies that risk salience could motivate SBA employees to exercise greater caution while reviewing guarantee requests.

In sum, misperception of risk reallocates SBA resources across local industries. Building on the estimated coefficients, we quantify the costs of misperceived risk as follows. Suppose a wave of defaults by Houston retailers increases the risk salience of Boston retailers by one standard deviation. Holding all else equal, Boston retailers would lose access to 1.2-2.2 SBA loans worth \$274,800-\$412,600 (9-15% of the sample average). The credit crunch will eliminate 12-18 jobs (9-14% of the sample average) and there would be 1-6 fewer new small retailers in Boston (18-67% of the sample average). On the other hand, since the Boston office now prefers safer retailers, it would avoid 0.2-0.4 future defaults by Boston retailers and thus save taxpayers \$21,100-\$32,200 (13-20% of the sample average). While we do not attempt to quantify the net welfare effect, those numbers highlight the potential costs triggered by risk salience.

Our findings contribute to several strands in the literature. First, we advance the emerging literature on the performance of regulatory agencies, which is currently focused on incentives and other organizational features.[10] In contrast, we study the decision-making process of frontline employees, showing that their risk perceptions propagate across employment-based networks and cause substantial reallocation of SBA resources with significant real effects. We also find that performance-based compensation and the centralization of loan screening activities can mitigate this reallocation. Moving forward, it is worth noting that data on federal employees are fairly transparent. Thus, future research can study how biases in their decision-making process affect other economic areas subject to intense government intervention.

We also contribute to the literature on small business financing. 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

[10]Incentives include salaries (Dal Bó et al. (2013)), bonuses (Ashraf et al. (2014)), outside careers (Bond and Glode (2014); Lucca et al. (2014)), promotions (Kalmenovitz (2021)), and intrinsic motivation (Bénabou and Tirole (2006)). Organizational features are fee schedules (Kisin and Manela (2018)), field offices (Gopalan et al. (2021b)), supervision (Hirtle et al. (2020); Eisenbach et al. (2016)), and jurisdictional overlap (Kalmenovitz et al. (2021)). Perhaps the closest paper to ours is Malmendier et al. (2021), who show that lifetime experiences shape inflation expectations of central bankers.

Paycheck Protection Program during the COVID-19 epidemic triggered a renewed interest in those questions.[11] However, the role of individual SBA employees is often overlooked. Against this backdrop, our paper is the first to analyze this critical component of the value chain and to show that risk perceptions of individuals at the SBA have real economic implications. The agency's data-driven approach to risk management should crowd out any misperception of risk developed by individual employees. Nevertheless, we find that employee-level misperceptions affect the allocation of SBA guarantees and consequently the ability of small businesses to survive and grow. Finally, we add to the literature on how experiences affect lending decisions.[12] We expand the analysis to the realm of the federal government and specifically the SBA, a crucial actor in the market for small business loans.

2 Background and hypotheses

2.1 Institutional setting

This section describes the aspects of the SBA operations which are essential to the paper. We rely on publicly-available SBA reports and a background interview with a senior SBA director, who provided vital information on the agency's inner workings.

7(a) loan program - the paper is centered upon 7(a) loans, the flagship loan guarantee program of the Small Business Administration. 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.[13]

[11] See Granja et al. (2020); Hubbard and Strain (2020); Humphries et al. (2020); Bartik et al. (2020); Lutz et al. (2020); Barrios et al. (2020); and Cororaton and Rosen (2020).

[12] Examples are macroeconomic and bank-specific shocks (Bouwman and Malmendier (2015)), exposure to bankruptcy (Koudijs and Voth (2016) and Gopalan et al. (2021a)), lender optimism (Carvalho et al. (2020)), and payment defaults (Murfin (2012)). A related literature examines how information transmits along social networks of mutual fund managers (Cohen et al. (2008)), equity analysts (Cohen et al. (2010)), and individual homeowners (Bailey et al. (2018); Bailey et al. (2019)).

[13] While 7(a) loans are at the center of this paper, we conduct a similar analysis on a different program

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.[14] 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.

Charge-offs - a 7(a) loan is charged-off after all efforts to 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 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 announced plans to improve its risk management systems, increase the transparency of its portfolio performance, and implement "best practices" for lender oversight (Small Business Administration (2011)).

SBA organization - the SBA 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.[15] 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, Indi-

known as 504 (see Section 4.2).

[14]See Code of Federal Regulations (13 CFR §120.150), Small Business Administration (2020), and Congressional Research Service (2021c).

[15]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.

anapolis, Cincinnati, Cleveland, Columbus, and Detroit. The local offices are responsible for the delivery of the SBA's many programs and services throughout the country. They provide counseling and training services to educate the public about financing opportunities, and promote SBA products to lending partners, the small business community, and local trade associations. Local offices also play a key role in screening and training lenders who participate in the 7(a) loan program.[16] We add further details below (Section 5.2).

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 effort into managing the default risk and tracking its progress. Our focus is on risk *salience*. We hypothesize that the default risk could become more salient, or conspicuous, and that could affect the SBA's activities. We elaborate on our empirical proxy for risk salience below (Section 3.2). Here, we discuss why and 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 update the probability of an event, even though the actual probabilities did not change.[17] 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

[16]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).

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

in actual volatility (actual risk) (Kaplanski and Levy (2010)).

Motivated by this literature, we hypothesize that risk salience increases the perception of risk by SBA employees, which in turn affects the origination of SBA guarantees.[18] Note that the null hypothesis is that risk salience should not affect SBA lending. First, the SBA discourages reliance on "soft information" and instead promotes a structured, data-driven approach to assess the default risk of its loan portfolio. We discuss the agency's protocols at length in the Internet Appendix (Appendix A.1). Therefore, risk salience should not affect the agency's risk assessment and should not interfere with how the agency allocates its resources. Moreover, individual SBA employees are never personally liable for SBA loans, and the bulk of their compensation is tied to their rank and tenure, not performance (Kalmenovitz (2021)). Therefore, even if risk salience increases risk perception, that should not affect the allocation of SBA resources.

For those reasons, the null hypothesis is that risk salience does not affect how the SBA chooses to allocate its resources. We seek to reject the null and show that risk salience affects SBA loans. However, the direction of the effect is not clear. On one hand, the SBA chooses its loan portfolio under budget constraints.[19] Those constraints could encourage the SBA to pull away from industries which are perceived as riskier, and instead back industries which are perceived as safer. This logic applies if employee incentives are aligned with their employer (the SBA). But even if the incentives are misaligned, individual employees might still want to avoid industries which they perceive as more likely to fail. They might believe that ex-post defaults would hurt their internal value (cash bonus or promotion) or their external career opportunities. Either way, when choosing between two enterprises, the SBA would support the one with the lowest perceived risk, all else equal.

On the other hand, perceived risk could incentivize SBA loans. Since the SBA's strategic goal is to enhance job creation, it might in fact prioritize investment in riskier ventures, to stimulate employment growth in the long run. From another perspective,

[18] Note that the guarantee *rate* is largely pre-determined (Bachas et al. (2021)), and thus should not depend on loan-specific factors or the salience of default risk.

[19] For example, the agency grappled with repeated budget cuts between 2004-2007.

Gopalan et al. (2021a) document that firms take more risks when one of their directors experiences a bankruptcy at another firm. The reason is that directors lower their estimate of distress costs, after experiencing a bankruptcy firsthand. In our context, employees may be willing to engage with industries which they perceive as more risky, if they conclude that ultimately those defaults are inconsequential.

To study the competing predictions, we proceed in the following way. First, we propose a methodology to estimate risk salience based on a novel employee-level dataset (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). Specifically, we re-visit our hypotheses and investigate in greater detail the link between risk salience and risk perception, which SBA activities likely respond to risk perceptions, does the response reflect rational learning by SBA employees, and what is the role of budget constraints and personal career consequences.

3 Empirical framework

3.1 Data sources

Our pivotal dataset 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, a total of $19,733$ unique employees and $105,238$ employee-year observations. The dataset includes each employee's occupation and date of accession, and annual information on location (state, county, city), salary, pay plan and pay grade, tenure, and bonus. To the best of our knowledge, the dataset is free of selection bias and includes the universe of SBA employees from that period.[20]

We match the employee-level data set to public loan-level data on the 7(a) program. The latter dataset includes information about the borrower and lender (name, address, and industry), loan characteristics (loan amount, guarantee rate, interest rate),

[20] Since our empirical strategy exploits employee transitions across offices, we removed $1,908$ observations with undisclosed place of employment, undisclosed names, and duplicate names.

and ex-post loan performance and charge-offs. Crucially for our analysis, we observe the SBA office responsible for the loan and the date of guarantee approval.[21] We augment the analysis with industry-level information from the Quarterly Census of Employment and Wages (QCEW). Published by the Bureau of Labor Statistics, this dataset includes county×industry information on employment and wages, based on all establishments in the region.

3.2 Measuring risk salience

We measure the salience of default risk in a two-step strategy. 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 it 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.[22] Industries are defined based on 3-digit NAICS codes. Past locations may be less salient, and we capture that with the weight $\omega_{l,t}$. 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 t. The

[21] In a subsequent test we use a dataset on the SBA's 504 loan program, which has a similar structure (see Section 4.2).

[22] 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.

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 definition has several desirable properties.[23] The weight decreases with the number of years which have passed since working in that location. 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. There are several sources of variation in Equation (1): default rates ($Default_{l,i,t}$) vary across and within-industry, while their relative importance ($\omega_{l,t}$) varies 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.

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.

We consider several permutations of the baseline measure of risk salience. For example, we aggregate variables to the office level (instead of office×industry). This version accounts for the possibility that employees develop a general perception about the riskiness of SBA loans, not an industry-specific perception of risk. We discuss this version and others in Appendix A.4.

[23] See an illustrative example in Appendix A.2.

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 the null hypothesis, whereby perceived default risk is not a dominant consideration for the SBA as a whole and even less so for individual SBA employees. If risk perception matters, it could either increase or decrease SBA loans. To evaluate the competing predictions, we aggregate the loan-level data into office×industry pairs, that is, we combine all the guarantees approved by SBA office o to industry i at time t. We then estimate the following regression:

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

where $y_{o,i,t+l}$ captures the allocation of SBA resources across local industries. We use two primary outcomes. *Loans* is the number of loans guaranteed by SBA office o to industry i, out of total loans guaranteed by SBA office o (we multiply by 100 for easier interpretation). For example, $Loans = 1.5$ means that the industry captures 1.5% of the office's loan portfolio. Equivalently, *Dollars* is the dollar value of loans guaranteed by SBA office o to industry i, scaled by total dollar value of loans guaranteed by SBA office o and multiplied by 100. 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.[24] We exclude office×industry pairs which have no lending relations throughout the entire period, for example if industry i has no facilities around SBA office o. The baseline specification is in contemporary values ($l = 0$), and we double-cluster standard errors at the office and year level to account for serial correlation.

$RiskSal_{o,i,t}$ reflects the salience of defaults by industry i at time t, in the eyes of office o. Our goal is to estimate β, and see whether risk salience affects the allocation of SBA guarantees and if so in what direction. However, $RiskSal_{o,i,t}$ is not randomly assigned and could be correlated with local demand for SBA lending. For example, imagine a negative

[24] The QCEW's employment measure is based on the number of employees in the pay period including March 12, roughly the midpoint of the government's fiscal year.

productivity shock affecting the retail industry in Boston. That shock triggers defaults by Boston retailers (higher $RiskSal_{o,i,t}$). It could increase the demand for SBA loans if local businesses seek government support, leading to more SBA guarantees for Boston retailers. In this scenario, the potential negative effect of $RiskSal_{o,i,t}$ on $y_{o,i,t+l}$ is attenuated by the increased demand (downward bias). Alternatively, the negative productivity shock could reduce the demand for SBA support simply because many small businesses cease to exist. In this scenario, the negative effect between $RiskSal_{o,i,t}$ on $y_{o,i,t+l}$ is inflated by the contemporaneous productivity shock (upward bias).

To handle these challenges, our first strategy is based on 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 further control for the number of workers and establishments in the borrowing industry, as a proxy for its demand for SBA loans. To illustrate the strategy, suppose an ex-Houston SBA employee now works in the Boston office. We seek to explain SBA guarantees from the Boston office to Boston retail stores, controlling for the national conditions of the retail industry (year×industry FE), the size of the local Boston retail industry, and its average lending relationship with the Boston office (office×industry FE), as a function of default rates by retail stores in Boston and Houston where one 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 Houston. We construct the instrument using a cutoff of $1,000$ miles, which is the median distance between a pair of SBA local offices (a 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 (Table A.1). The reason is that the instrumented variable directly builds on the instrument. For example, suppose the Boston office has two employees, one of them previously worked in Houston and the other stayed in Boston his entire career. In that case, $RiskSal_{o,i,t}$ would account for defaults in both Houston and Boston, while $RiskSal^{far}_{o,i,t}$ would account only for defaults in Houston. In the second-stage, our estimates of β^{IV} are identified only by variation in $RiskSal_{o,i,t}$ that is driven by Houston defaults, independent of the variation in Boston defaults.[25]

We also considered a third empirical strategy, which exploits within-borrower variation in risk salience (similar to Khwaja and Mian (2008)). For brevity, we defer the discussion of this strategy to the Internet Appendix (Appendix A.4.2).

3.4 Summary statistics

The sample consists of 81 local offices between 1998 and 2019.[26] Combined with 3-digit NAICS industries, they yield nearly $190,000$ hypothetical office×industry pairs. We exclude observations that answer to any of the following criteria: office×industry with no lending relations throughout the entire period, industry×year with no loans, or office×year with no loans. The final sample includes $6,965$ unique office×industry pairs

[25]A threat to the identification arises if a shock affects *new* SBA guarantees to Boston-area retailers, and also moves equilibrium default rates on *past* SBA-guaranteed loans by retailers in Houston, from which the Boston office "imported" employees. That shock is unique to Boston and Houston; does not affect all industries in Boston (year×office FE), similar industries in Boston (year×office×NAICS2 FE), or retailers in other regions (year×industry FE); and appears only after an ex-Houston employee moved to Boston.

[26]The underlying employee-level dataset starts in 1996, but we start the analysis from 1998 in order to be able to track job transitions.

and 99,273 office×industry×year observations. Table 1 reports descriptive statistics. The unconditional probability of receiving any SBA-guaranteed loan is 95%. Conditional on any loan, the average industry secured 12.5 loans worth \$2.9 million in total (constant 2020 USD), and captured 1.7% of the office's portfolio. Our main independent variable, $RiskSal$, ranges from 0 to 2 and its median value is zero.[27] It peaked during the global financial crisis, as expected, when many small businesses defaulted on their loans (Figure 2).[28]

The Internet Appendix includes additional statistics for the office×industry sample and for the cross-section of industries, offices, and employees (Appendix A.3). We also discuss the roles of individual employees, using separate data on SBA job openings.

3.5 Employee transitions

Our empirical strategy relies on employee transfers across SBA offices. A natural question, though, is what motivates employees to relocate in general and to move from office A to office B in particular. We start by studying the decision to relocate. Two specific concerns are related to our empirical strategy. First, perhaps relocations are restricted to lower-ranked employees, whose risk perceptions matter less for the SBA's decision-making process. Second, perhaps relocations are restricted to low-performance employees, who signed off on bad loans in their previous workplace and are also more likely to reject guarantee applications in their current workplace.[29] To assess these possibilities, we estimate the following employee-level regression:

$$Out_{o,i,t+l} = \alpha + \beta \cdot \overrightarrow{X}_{o,i,t} + \lambda_i + \lambda_{o,t} + \epsilon_{o,i,t} \tag{7}$$

[27]Defaults are scaled by number of loans, and since the defaulting loans are from an earlier vintage the rate could be greater than one. Our results are robust to specification that includes only values lower than 1, and to a version of $RiskSal$ that focuses on the extensive margin of defaults (an indicator for any default in the employee's workplaces).

[28]In untabulated results we exclude the years 2008-2012, where $RiskSal$ was abnormally high, and obtain similar results.

[29]The first concern suggests that the estimated effect of risk salience is attenuated, and the latter suggests that it is inflated. Note that we address these concerns partially by using salary weights in one of our robustness tests (Appendix A.4). Presumably, employees with higher salaries have better performance and more seniority.

The dependent variable takes the value 1 if employee i transfers to another SBA location in year $t+1$, and 0 otherwise. We investigate the role of several employee-level factors: indicators for whether the employee received a promotion in year $t+1$, their salary was above the median SBA employee in year t, their tenure at the SBA was greater than the median SBA employee in year t, and if they had been transferred in the past. We also add the salary growth the employee experienced in year t and several combinations of fixed effects based on year, office, and employee. With employee fixed effects, our estimation is based only off those employees who transfer at least once. With office×year fixed effects, we remove the impact of local economic conditions and focus on employee-specific factors within the office. The results are in Table 2, Panel A, showing that transferring employees tend to be better-paid and to be promoted upon moving to the new office. This mitigates the concerns that "movers" are immaterial to the decision-making process, or that they are low performers who will routinely reject loan applications. Lastly, when we include employee fixed effects, the coefficient on *PastTransfer* is negative and significant. It indicates that once an employee transfers, they are much less likely to transfer again in the future. In other words, we find no evidence that a certain subset of employees transfer frequently while most never transfer.

Finally, we examine the choice of destination. The main question is whether economic similarity between regions drives relocations. For instance, if firms in Houston are similar to those in Boston (but not to those in New York), will the employee move from Houston to Boston (but not to New York)?[30] To assess this possibility, we compute the pairwise cosine similarity between the loan portfolios of each two offices (as in Hoberg and Phillips (2016) and Cohen et al. (2020)). The cosine score is calculated annually for each pair of offices, ranges from 0 to 1, and increases when the two offices guarantee loans to the same industries at the same time. We also compute the cosine similarity between the two office's default rates, which increases when the same industries in the two SBA regions default on their loans at the same time. Combined, the default-based and loan-based

[30]If so, it suggests that Houston defaults contain useful information about loans in Boston, consistent with rational learning story. We address this in greater detail in Section 5.1.2.

cosine scores capture the economic similarity between each pair of offices.[31] We then estimate the following regression in the panel of office×office pairs:

$$Out_{o_1,o_2,t+1} = \alpha + \beta_1 \cdot Sim^{loan}_{o_1,o_2,t} + \beta_2 \cdot Sim^{def}_{o_1,o_2,t} + \overrightarrow{X}_{o_1,o_2,t} + \lambda_{o_1 \times o_2} + \epsilon_{o,i,t} \qquad (8)$$

The dependent variable is an indicator, which equals one if any employee moved from the focal (o_1) to the peer (o_2) at time $t+1$. Sim^{loan}_t and Sim^{def}_t are the cosine scores between the two offices, representing similar lending and default patterns, respectively. We control for three organizational similarities between the offices: the ratios between the average salary, average tenure, and number of employees in both offices. We add pair fixed effects[32] and consider several combinations of year, focal, and peer fixed effects. The results are in Table 2, Panel B. Overall, neither Sim^{loan}_t nor Sim^{def}_t emerge as clear predictors of future transitions. The only exception is Sim^{def}, which is statistically significant in one of the specifications. Year×focal fixed effects eliminate the significance, meaning that Sim^{def} cannot significantly explain relocation decisions out of a given focal office. Thus, we find little evidence that economic similarity is driving employee transitions between SBA offices.

In sum, relocations at the SBA are more prevalent among well-paid employees, who are typically promoted to a more senior position in the new office. We find no evidence that employees are relocated between offices that share a fundamental similarity. Combined, the evidence suggests that relocations are largely driven by the availability of internal job opportunities within the SBA. While we do not claim that this is a comprehensive explanation of transition patterns at the SBA, we believe that these findings help mitigate potential concerns about our empirical strategy.[33]

[31]For brevity, we formally define the cosine measures in the Internet Appendix (Appendix A.3).

[32]This effectively excludes pairs where the focal never exports employees to the peer, resulting in a panel of 928 unique pairs.

[33]The Internet Appendix (Appendix A.3) contains additional analyses, such as a case study on turnovers at the Dallas-Fort Worth District Office.

4 Main results

4.1 Allocation of loans

To obtain a visual impression, Figure 3 plots the non-parametric relation between risk salience and loan allocation, that is, the industry's share within the office's portfolio. There is a significant negative relation, consistent with the idea that salient defaults raise the perception of risk among SBA employees, who consequently reallocate resources from industries perceived as risky toward 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. 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 and managerial style, and explicitly compares the allocation of SBA guarantees within the same office across industries. In the third column we apply year×office×NAICS2 fixed effects (recall that $RiskSal$ is measured at the year×office×NAICS3 level). Here, we compare the allocation across 3-digit industries within the office's 2-digit portfolio, ruling out regional industry trends at the 2-digit level.[34] In the fourth column we add year×NAICS3 fixed effects, to remove national industry trends (3-digit level). Here we further narrow down the identifying variation and exploit local deviation off the industry's national average. All specifications include proxies for demand by the local industry (number of employees and establishments). Panel B reports the results from the IV strategy (Equation (6)), using the same set of FE, while focusing on the variation in risk salience driven only by external default rates.

Across all specifications and strategies, risk salience has a statistically significant impact on the allocation of SBA loans. The economic magnitude is stable and large. For example, in column 4 we estimate the tightest OLS specification with loan shares as the outcome variable. The coefficient is -0.34, the standard deviation of $RiskSal$

[34] For example, the 2-digit code 72 is for Accommodation and Food Services, while the 3-digit code 722 is for Food Services and Drinking Places.

is 0.435, and the average outcome is 1.464 (meaning that the average industry share is 1.464%). This implies that a one-standard-deviation increase in risk salience reduces loan share by 14.8 basis points which is 10.1% of the average ($\frac{-0.340 \cdot 0.435}{1.464} = \frac{0.1479}{1.464} = 10.1\%$). The IV coefficients are slightly larger than the OLS coefficients,[35] but the differences are not statistically significant and both strategies point to a substantial impact on SBA lending. We obtain similar results when the dependent variable is based on the dollar value 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, but the difference is statistically insignificant.

The Internet Appendix includes a large number of tests, to verify the prevalence and robustness of our main results. In Appendix A.4, we consider multiple versions of *RiskSal* (e.g., focusing on risk perception of senior employees); use different clustering methods and winsorizing windows; test the persistence of the effect across years, regions, and industries; and present a third identification strategy which exploits within-borrower variation. Across all tests, the results remain highly significant and consistent with our baseline estimates. In Appendix A.6, we study the impact on loan quantity and dollar volume (rather than portfolio shares). Finally, in Appendix A.5, we aggregate all variables to the office level (instead of office×industry). This version helps quantify aggregate effects, and it also accounts for the possibility that employees develop a general risk perception rather than industry-specific one.

4.2 External validity: 504 loans

Our analysis is centered around 7(a) loans, and in this section we discuss the role of risk salience in the 504 loan program. While in 7(a) loans the money can be used for various business purposes, in 504 loans the focus is on long-term investment in major assets, such as real estate and heavy equipment.[36] Despite this difference, the 504 loan program is a natural place to test the external validity of our hypothesis. If the effect we document

[35] As explained in Section 3.3, the omitted variable could cause either upward or downward bias.

[36] The finance mechanism is also different. In a 504 loan, the business owner borrows up to 40% from a Certified Development Company (CDC), and the loan is backed by a debenture, which is sold to private investors and is 100% guaranteed by the SBA (Congressional Research Service (2021b)).

in 7(a) loans is indeed driven by risk perception, a similar effect should be found in 504 loans: defaults on 504 loans should increase the perception of 504 default risk, leading to a crunch in new 504 loans.

To test this idea, we follow the step-by-step methodology outlined in Section 3. We first download loan-level data on all 504 loans from the SBA's website, and aggregate the information to the office×industry level. We then calculate office×industry measure of risk salience, based on 504 defaults, and an equivalent office×industry instrument based only on distant 504 defaults. Finally, we estimate the impact of risk salience on lending using OLS (Equation (4)) and 2-SLS (Equation (5)-Equation (6)) models, with the same set of fixed effects and controls used previously. The results from the second stage of the 2-SLS estimation are in Table 4.[37] Across all specifications, we find that salient 504 default risk has a significant and large impact on the allocation of 504 guarantees. The results are identified off the variation in distant 504 defaults, and conditional on tight fixed effects. The point estimates are significantly larger than the ones obtained for 7(a) loans, but the economic magnitudes are quite similar. For example, a one-standard-deviation increase in 504 risk salience reduces the number of 504 loans by 13.6%-17.8% relative to the average, while a one-standard-deviation increase in 7(a) risk salience reduces 7(a) loans by 10.3%-12.0% relative to the average. Overall, our findings corroborate our main hypothesis, showing that risk salience affects the allocation of SBA resources. The impact of risk salience is not confined to a particular segment of the SBA's financial endeavors, but is rather prevalent across different programs.

4.3 Effects on employment and firm entry

The strategic goal of the SBA is to support job growth, and loan guarantees are intended to serve that purpose. Since risk perception affects the allocation of credit, a natural follow-up question is whether it also affects employment. On one hand, when risk becomes more salient and SBA loans decrease, it should slow down job creation. This is consistent with previous studies which document the positive impact of SBA loans on the formation

[37]The first stage, as well as the reduced-form and the OLS regressions (which yield similar results), are all available on request.

of new business and on employment (Brown and Earle (2017)). On the other hand, the salient risk could incentivize the SBA to support "safer" industries without compromising on their employment goals.

To examine the question, we exploit the fact that the lender reports the number of jobs created and retained as a result of each loan.[38] We aggregate the data to the office×industry level, to match our level of analysis.[39] We then adopt our baseline OLS and IV specifications except with the number of jobs supported as the dependent variable. Here, our identifying assumption in the IV regressions is that non-local defaults ($RiskSal^{far}$) affect local employment only through their impact on risk salience, and not through any other channel. The results are summarized in Table 5, Panel A, showing a significant negative impact of risk salience on job creation. A one-standard-deviation increase in risk salience eliminates 11.8-18.4 jobs in the local industry, which are 9.0%-13.6% relative to the average number of jobs supported by the SBA. This suggests that risk salience affects credit allocation and additionally has a knock-on effect on the number of jobs supported by the SBA guarantee program.

Along the same lines, we predict that risk salience affects the creation of new small firms. Using data from the County Business Patterns (CBP), we compute the net change in new small establishments, defined as the difference in the number of establishments with 1-4 employees between time t and time $t-1$.[40] The results are in Table 5, Panel B. The coefficient is negative and significant, even with the inclusion of our tightest set of fixed effects. Here, a one-standard-deviation increase in risk salience prevents the creation of 1.2-6.1 new businesses in the local industry, which are 18%-74% relative to the average number of new businesses. These results suggest that the reallocation of credit, driven by risk salience, further affects the formation of new small businesses. We find a similar effect, albeit smaller, on establishments with 5-9 employees, and no effect on large establishments (≥ 500 employees).

[38] Since the numbers are self-reported by the lender in good faith, but not audited by the SBA, the measurement error likely attenuates the true effect.

[39] The average number of jobs created is 102 (see Table 1).

[40] The average number of new small firms is 5 (see Table 1). The outcome is measured with error, since some small business do not seek SBA-guaranteed loans, and on the other hand eligibility for SBA loans changes over time and across industries (Title 13 of the Code of Federal Regulations, Subpart A).

4.4 Risk perception

Our interpretation for the baseline results relies on risk perception, and assumes that salient defaults increase the perception of default risk. We cannot directly link risk salience to risk perception, since the latter is unobservable. In this section, we discuss two indirect tests to support our interpretation. The first is based on ex-post loan performance, and the second on office size.[41]

Our headline result is that an increase in risk salience reduces the number of loans. If the effect is indeed driven by risk perceptions, we expect the "surviving" SBA loans to be less risky because relatively-safe loans would receive the SBA's backing. On the other hand, if our results are driven by a latent negative demand shock, then the "surviving" loans should in fact be riskier. To test the predictions, we estimate the baseline IV specification (Equation (5)-Equation (6)) with ex-post defaults as a dependent variable. One outcome is an indicator, which equals one if any office$\times$industry loan was approved at time t and subsequently defaulted. Two other outcomes measure the default rate: number of loans (dollar value) which were approved at time t and subsequently defaulted, scaled by the number of loans (dollar value) which were approved at time t and were subsequently paid in full or charged off ("closed" loans).[42] The results are summarized in Table 6. Across all specifications, we find strong evidence that risk salience significantly reduces subsequent default rates. A one-standard-deviation increase in risk salience reduces the probability of future defaults by 12.2%-12.4% relative to the unconditional probability. When taking into account the default rate (columns 4-9), the economic magnitudes are smaller: a one-standard-deviation increase in risk salience reduces future default rates by 5.3%-8.6% relative to the unconditional probability.[43]

The second test exploits variation in office size. We hypothesize that risk perceptions

[41]Note that the analysis in this section is independent of whether employees update their risk perception rationally or irrationally. We will return to that question below in Section 5.1.2.

[42]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. The unconditional default probability is 37%. The average industry defaulted on 1.4 loans worth $\$177,870$ (constant 2020 USD), and the average default rates are 10-16% (Table 1).

[43]In untabulated results, we keep the loan-level data and estimate default probability with $RiskSal$ as the main independent variables. We add bank fixed effects, as in Granja et al. (2018). The significant results we obtain ensure that our results are not driven by unobservable bank characteristics.

plays a bigger role in small offices: colleagues are better acquainted and have ample opportunities to exchange ideas, which facilitates the diffusion of personal perceptions. To examine this possibility, we define the indicator $Small$ which equals one for offices below the median size and zero otherwise. We add to the baseline IV specification the interaction of $RiskSal$ with $Small$, and the interaction of $RiskSal^{far}$ with $Small$ as an additional instrument. The results are summarized in the first three columns of Table 7. Across all specifications, we find that the effect is 58-76% stronger among small offices relative to large offices. In the tightest specification, the baseline coefficient is -0.356 and the interaction coefficient is -0.272, so the effect in small offices is 76% stronger ($\frac{0.272}{0.356}$). Note that this test is less powerful than the previous one, because we can only exploit variation across offices, while our baseline specification is *within* office (year×office FE) across industries.

Overall, the results provide additional evidence that risk salience affects loan allocation via changes in risk perception. Greater salience leads to ex-post safer loans, and the effect is particularly strong in small offices. The Internet Appendix (Appendix A.7) includes additional results and further discussion of the economic implications.

5 Mechanisms

In the previous section, we documented the impact of risk salience on the allocation of SBA loans. In this section we explore in greater detail potential mechanisms. We first ask why risk salience affects risk perception. Specifically, we investigate the role of budget concerns and career consequences, and the tension between rational and irrational belief formation. Finally, we discuss how risk salience affects various aspects of the SBA's workflow, eventually leading to significant changes in the allocation of loans.

5.1 "Why:" risk perception and changes in behavior

5.1.1 Budget and career concerns

In Section 2.2, we highlighted two possible links between risk perception and SBA lending: expectation of budget cuts and career and reputation considerations. In this section we explore these possibilities in greater detail.

If risk salience affects SBA guarantees due to budget considerations, we expect to find a stronger effect during budget cuts. We test that conjecture using data on the SBA's annual appropriation for each of the fiscal years 2000-2020 (from Congressional Research Service (2021a)). The focus is on the SBA's business loan administration account, which provides funding for administrative expenses to carry out the SBA's business loan programs, including 7(a) loans.[44] Exploiting the time-series variation in the SBA's budget, we add to our baseline specification the interaction of $RiskSal$ with $Budget$, the year-on-year budget change, and use the interaction of $RiskSal^{far}$ with $Budget$ as an additional instrument. The results are in the middle three columns of Table 7. Across all specifications, the effect is substantially stronger when the SBA's budget is slashed. For instance, 10% decrease in the agency's budget strengthens the impact of risk salience by as much as 29% ($\frac{1.242 \cdot -0.1}{-0.428}$). In other words, the perception of risk is significantly more important when the SBA's budget is lower.

Additionally, we investigate the possibility that SBA employees are personally motivated to monitor defaults. Here, data limitations pose a significant challenge: we observe each employee's compensation and promotions inside the SBA, but we do not observe their individual decisions with regards to loans and guarantees, nor do we know their outside option (for example, expected salary upon leaving the SBA for the private sector; see Kalmenovitz et al. (2022)). With those caveats in mind, we estimate the following regression in the cross-section of SBA offices:

$$y_{o,t+l} = \alpha + \beta \cdot Default_{o,t} + \overrightarrow{X}_{o,t} + \epsilon_{o,t} \tag{9}$$

[44] On average, the budget is $\$141,000,000$ and increases by 0.9% annually. A period of budget cuts between 2004-2007 was followed by significant surges during 2008-2010.

The main independent variable, $Default$, is the number of SBA loans supervised by office o defaulting at time t. The outcomes reflect internal rewards for SBA employees: average salary, salary growth, and promotion rate (defined as the number of promotions scaled by number of employees), all measured at time $t+1$ (one lag). We control for office size (number of employees) and include office and year fixed effects. If defaults affect the internal rewards for SBA employees, we expect to find that $\beta < 0$. The results are summarized in Table A.2. We find a negative association between defaults and subsequent pay growth and internal promotions, the latter one statistically significant at conventional levels (5%). We interpret that as suggestive evidence that SBA employees have an incentive to monitor defaults: in offices with low default rates, employees are more likely to be promoted and their salaries grow faster.

5.1.2 Rational learning versus mechanical updating

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, if distant default rates reflect unobserved productivity shocks which will eventually affect the local industries, then reliance on distant defaults could inform the SBA's local activities. 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 how one person's expectations regarding house prices are affected by her friends' experiences, independent of whether the friends' experiences contain useful information.[45]

To assess the rational learning story, we conduct three tests. The first utilizes the SBA's bonus program, a pay-for-performance scheme which rewards employees who perform above and beyond normal job requirements (5 U.S.C 45). It is a rarity in the federal government, where salary is largely determined by a fixed system of ranks and tenure (Kalmenovitz (2021)). In our context, when the local office relies on bonuses to stimulate performance, employees will likely exert more effort. If risk salience provides valuable in-

[45] In a rational learning story, if employees move from Houston to Boston and then rely on Houston defaults to determine SBA loans in Boston, it is because Houston and Boston share a fundamental economic similarity. However, in Section 3.5 we concluded that economic links between SBA regions cannot explain employee transitions.

formation, bonuses should lead employees to rely even more on those signals. Conversely, if risk salience is merely a convenient heuristic, employees will rely less on risk salience and instead look for relevant sources of information. We test this idea by adding to our baseline IV specification the interaction of $RiskSal$ with $Bonus$, the fraction of employees receiving bonus in the previous year.[46] We use the interaction of $RiskSal^{far}$ with $Bonus$ as an additional instrument. The results, in the last three columns of Table 7, show that risk salience is far less important in bonus-intensive offices: a one-standard-deviation increase in bonuses cuts the effect by 17-19%. For instance, in the tightest specification, the baseline coefficient is -0.467, the interaction coefficient is 0.227, and the standard deviation of $Bonus$ is 0.364. so the effect in bonus-intensive offices is 17.7% weaker ($\frac{0.364 \cdot 0.227}{-0.467}$). It suggests the risk salience does not contain a valuable signal, and therefore employees use it less frequently when their compensation is tied to performance.[47]

A second test is based on the informativeness of risk salience. In a rational learning story, where employees extract information from distant defaults, we expect the effect to increase with the informativeness of those defaults. One proxy for informativeness is geographic dispersion: for each office×year, we calculate the number of distinct counties from which the employees arrived. When employees hail from many different counties, their risk perception is more likely to mirror some fundamental national shock, and should thus be considered more informative. An alternative proxy for informativeness is based on statistical correlations: for each office×industry, we estimate the correlation between risk salience and the next year's employment growth, and use the absolute value as proxy for informativeness. If risk salience has strong predictability over local employment growth, it should be considered more informative.[48] We add to our baseline IV specification the interaction of $RiskSal$ with either measure of informativeness, and use the interaction of $RiskSal^{far}$ with the informativeness measure as an additional instrument. The results

[46] The previous year provides ex-ante expectation for this year's bonus intensity. The government-wide bonus program was suspended between 2010-2016, so we exclude those years from the current test. Nearly a third (35%) of SBA employees earned a bonus, which was on average $1,222 or 1.5% of the employee's base compensation.

[47] More precisely: employees *believe* that risk salience contains no valuable signal.

[48] The first proxy is calculated at the office×year level, and does not vary across industries. The second proxy is estimated at the office×industry level, and does not vary over time.

are in Table 8. Across all specifications, the effect is largely indifferent to the degree of informativeness. The coefficients on the interaction variables are statistically and economically insignificant, showing little support for rational learning mechanism.

The third test is based on randomized risk salience. Suppose employee i moved from Houston to Boston. In the baseline measure, we use default rates from Houston to calculate employee i's risk perception. Now, we randomly select for employee i default rates from across the country. If Houston defaults merely represent a national shock, replacing them with random defaults from a different location should produce a similar effect. Conversely, if employee i relies on Houston-specific events, the randomization should eliminate the effect. To carry out this test, we create a pseudo $RiskSal$ by randomizing $Default_{l,i,t}$ in the employee×industry measure (Equation (1)), and then re-calculating the final office×industry measure (Equation (3)). We then re-estimate the baseline IV specification, using the pseudo $RiskSal$, year×office FE, and office×industry FE. We repeat this process 200 times and plot the resulting coefficients in Figure 4. Clearly, randomizing risk salience yields insignificant results clustered around zero. It suggests that employees learn from events that are idiosyncratic to their previous locations, rather than representative of broader economic trends.[49]

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)).

[49] In untabulated results, we interact $RiskSal$ with a proxy for workload: number of industries receiving loans from office o, divided by the number of employees in the office. The effect of risk salience is stronger among offices with heavier workload, consistent with mechanical belief updating, whereby overwhelmed offices rely on heuristics to manage their growing portfolio.

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

5.2.1 Screening on loans

What part of the SBA's work responds to the changes in risk salience? One possibility is that risk salience affects screening, whereby applications for SBA guarantees are turned down in greater numbers.[50] 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.[51] Most importantly, from 2007 at the latest, local offices are rarely involved in credit determination which affects the approval of the guarantee application. 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 9. 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 baseline IV specification on each subsample. The results show a significant drop in the magnitude of the effect after 2008, up to 45%. In our tightest specification, the $RiskSal$ coefficient before the reform is -0.48 but -0.33 after the reform, which means a decline of 31%. Put differently, when local offices have the option to screen SBA loans, the importance of their risk salience almost doubles.

5.2.2 The lending channel

Local offices play a significant role in recruiting, training, and monitoring participating lenders (Small Business Administration (2020)). Generally, a potential lender must submit a request to the local SBA office, which determines whether the lender meets the requirements (13 CFR §120.410). The local office can affect the decision to grant and renew a preferred lender (PLP) status, and its feedback is required when assessing the

[50]We do not observe loan applications and therefore cannot analyze rejection/acceptance rates.

[51]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.

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 local 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, with active input from the local offices.

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, although the direction is not clear. On one hand, risk salience could reduce the entrance of new lenders, who struggle to get training or approval. Consequently, risk salience could reduce the overall number of lenders: there are fewer new entrants, and in addition some of the existing lenders are not re-approved. On the other hand, new lenders could be more eager to enter the SBA loan market, believing that the SBA employees are doing a better job of screening or discouraging risky borrowers from requesting SBA-backed loans. In that case, the predictions are reversed.

For each office$\times$industry$\times$year 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. For simplicity, the scaled variables (share of new lenders and the two HHI measures) are multiplied by 100. The results are in Panel B of Table 9. 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 value. For example, a one-standard-deviation increase in risk salience drives out 1.5 lenders and increases concentration (HHI) by 12.6-13.1 points. Those magnitudes reflects 9.7% and 9.5-11.9% of their respective averages. These results highlight the role of the lending channel, whereby risk salience among SBA employees leads to the concentration of loans among a small number of lenders, especially those with pre-existing relation with the SBA.

5.2.3 Demand stimulation

Finally, local 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×year observation, we calculate the number of unique borrowers and the share of new borrowers, as well as the concentration of loans among borrowers. As before, the scaled variables (share of new borrowers and the two HHI measures) are multiplied by 100. The results are in the right-hand side of Panel B, 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. For example, a one-standard-deviation increase in risk salience drives out 4.3 borrowers and increases concentration (HHI) among the remaining borrowers by 14.3-15.9 points. Those magnitudes reflect 13% and 12.1-17.7% of their respective averages.

Combined, these results are consistent with a demand stimulation channel, which predicts a concentration of loans in the hands of fewer borrowers with pre-existing experience with SBA loans. They are also consistent with our finding that higher risk salience reduces the number of new small firms (see Table 5, Panel B).

6 Conclusion

This paper uncovers a significant friction in the allocation of small business loans: perception of defaults risk among rank-and-file Small Business Administration employees. We find that when defaults become more salient in the eyes of local SBA employees, the number and value of SBA loans declines. Further tests indicate that SBA employees mechanically update their perception of default risk, based on the defaults they observe around their current workplace or learn about through social links to their previous workplaces. Broadly speaking, our analysis highlights how the organizational structure of the SBA determines lending outcomes. As employees relocate from one SBA office to another, they take their social networks with them, establishing an under-explored economic link between regions.

The robustness of our estimates highlights how administrative agencies are not faceless bureaucracies which implement a set of regulations. Instead, their functioning is influenced by the perceptions of individual employees, which in turn is shaped by each employee's social network and job history. For the SBA in particular, its operations have recently been in the limelight, due to its administration of the Paycheck 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 is one of the channels 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 of 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 the experiences of government employee affect the provision of public goods and the enforcement of regulations.

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Figure 1: **Small Business Administration: Geographic jurisdictions**

Geographic jurisdictions of the SBA's ten regions. New England (Region 1) includes Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont. Atlantic (Region 2) includes New Jersey and New York. Mid-Atlantic (Region 3) includes Delaware, Maryland, Pennsylvania, Virginia, West Virginia, and District of Columbia. Southeast (Region 4) includes Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee. Great Lakes (Region 5) includes Illinois, Indiana, Michigan, Minnesota, Ohio, and Wisconsin. South Central (Region 6) includes Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. Great Plains (Region 7) includes Iowa, Kansas, Missouri, and Nebraska. Rocky Mountains (Region 8) includes Colorado, Montana, North Dakota, South Dakota, Utah, and Wyoming. Pacific (Region 9) includes Arizona, California, Hawaii, and Nevada. Pacific Northwest (Region 10) includes Alaska, Idaho, Oregon, and Washington.

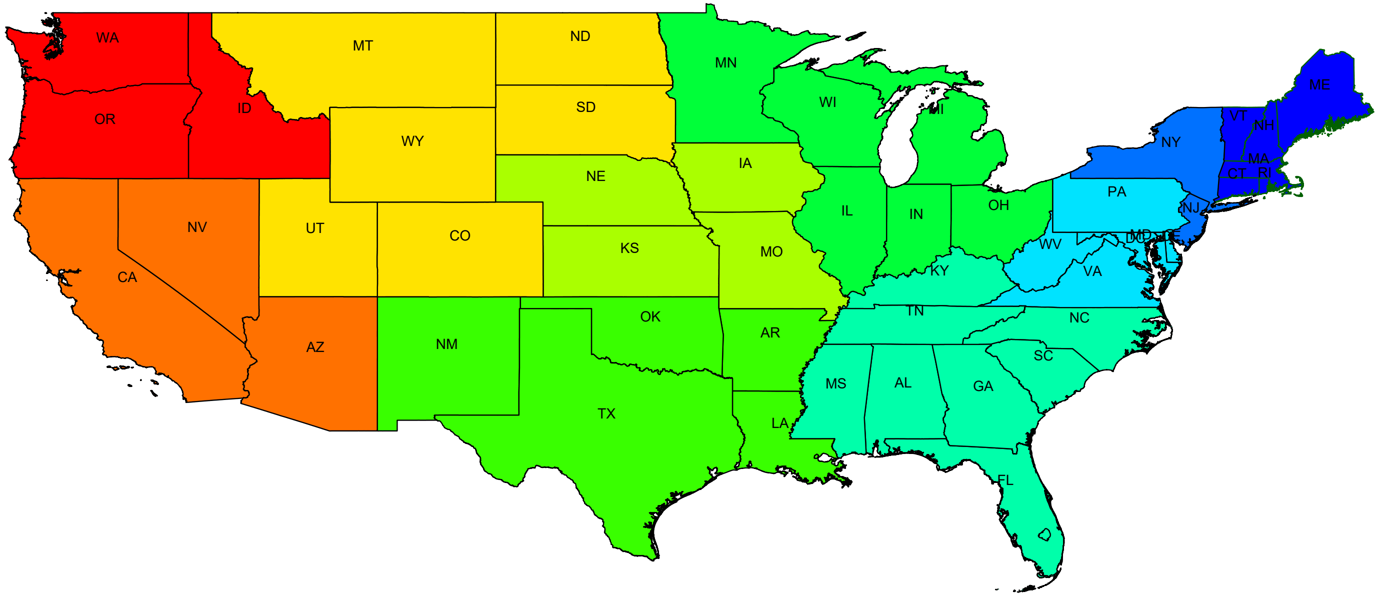
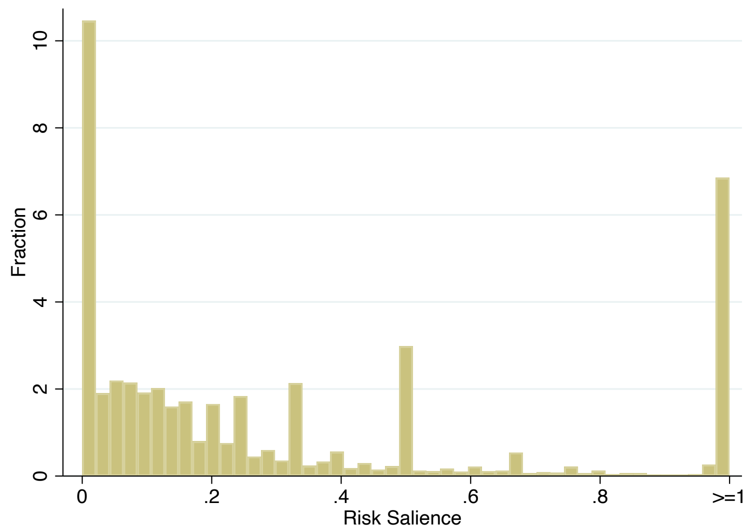


Figure 2: **Distribution of risk salience**

Panel A plots the distribution of our primary measure, $RiskSal$, in the sample of office×industry observations (excluding instances where $RiskSal = 0$). Panel B shows the time series of mean and median $RiskSal$. See Section 3.4.

Panel A: Histogram



Panel B: Time Series

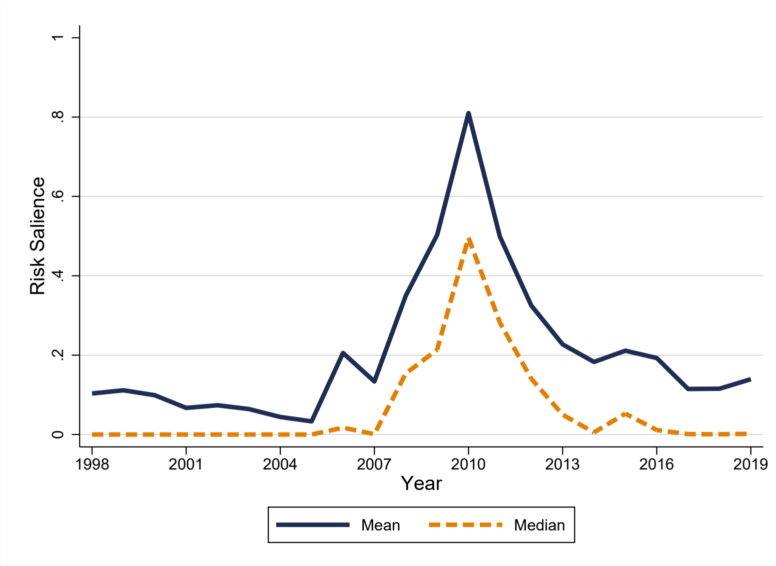


Figure 3: **Salient risk and SBA guarantees: Preliminary evidence**

Non-parametric relations between risk salience and the allocation of SBA 7(a) guarantees. $RiskSal$ reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). *Loan Share (#)* is the number of loans guaranteed by SBA office o to industry i, out of total loans guaranteed by SBA office o. *Loan Share ($)* is the dollar value of loans guaranteed by SBA office o to industry i, out of the total dollar value of loans guaranteed by SBA office o. Industries are based on 3-digit NAICS codes. See Section 4.1.

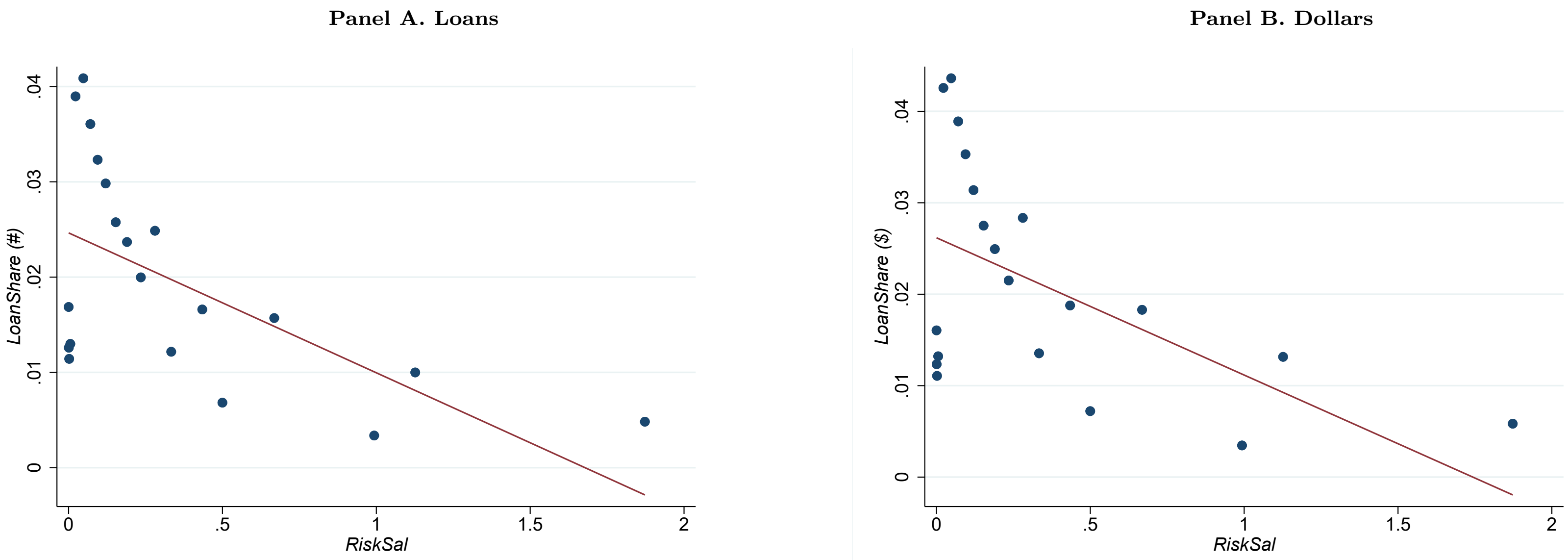


Figure 4: **Randomizing risk salience**

We create a pseudo *RiskSal* measure, by randomizing default rates across locations and recalculating employee×industry and office×industry risk salience. We then estimate the baseline IV specification with year×office and office×industry FE, using the pseudo *RiskSal*. We repeat this process 200 times and plot the resulting coefficients below, against our baseline result (using the true *RiskSal*) in the red dashed line. See Section 5.1.2.

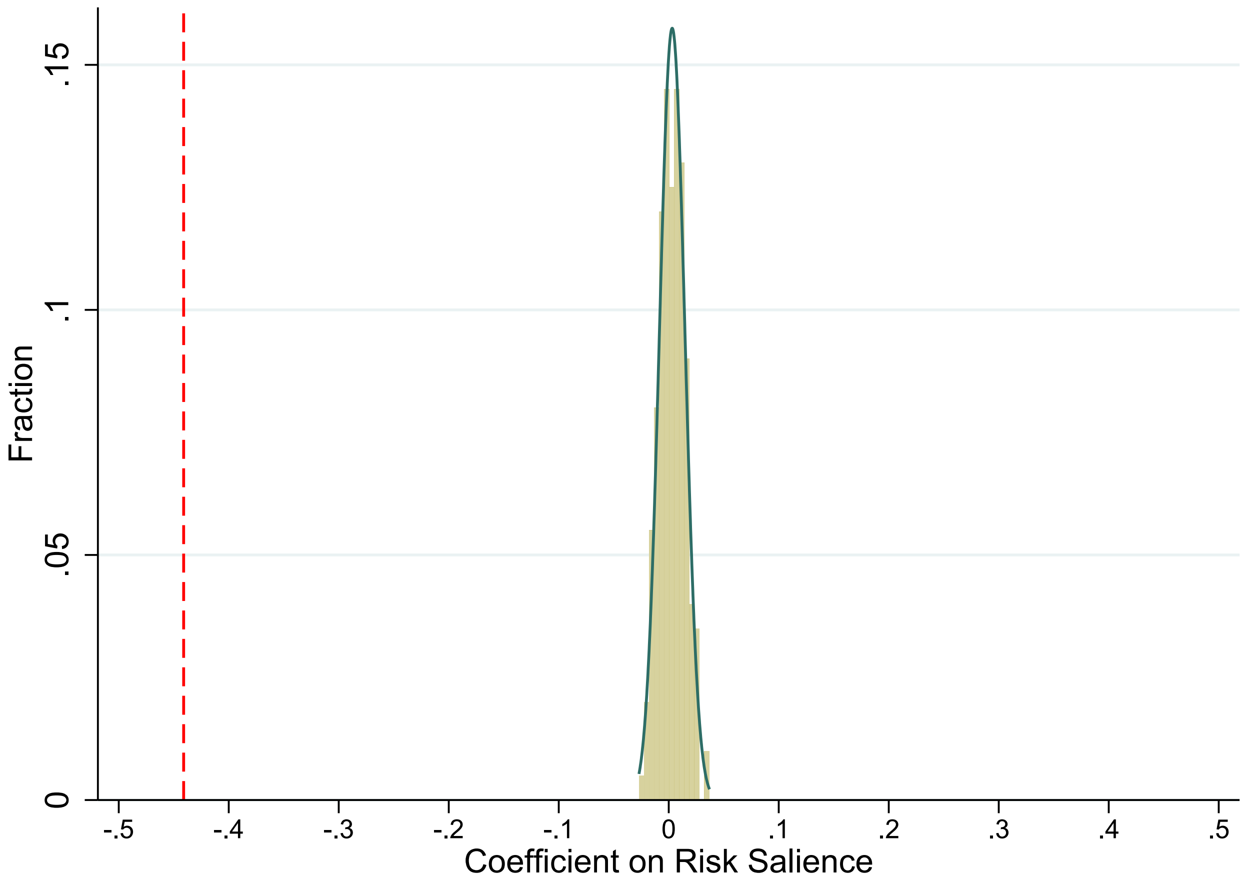


Table 1: **Summary statistics**

The sample consists of office×industry pairs, based on local SBA offices and 3-digit NAICS industries. $RiskSal$ is our main measure of risk salience and $RiskSal^{far}$ is the instrument we use in the IV specification. $I(Loan)$ is indicator for any 7(a) loan guaranteed by office o to industry i during that year. Conditional on $I(Loan) = 1$, we compute the number of loans ($Loans^{raw}$) and their share out of the office's portfolio ($Loans$). Similarly, we compute the dollar value of loans in thousand USD ($Dollars^{raw}$) and their share out of the office's portfolio ($Dollars$). $Employment$ is number of jobs supported. New^{1-4} is number of new small establishments (<5 employees). $I(Default)$ is indicator for any default on SBA loan. We compute the number of loans defaulting ($Defaults^{\#}$) and their share out of the office's loan portfolio ($DefRate^{\#}$). Similarly, we compute the dollar value of defaulting loans ($Defaults^{\$}$) and their share out of the office's dollar value of loans ($DefRate^{\$}$). $EmpShare$ and $EstabShare$ are the number of employees (establishments) in industry i out of total employment (establishments) in office o's jurisdiction. All variables are winsorized at the 99^{th} percentile. Dollar variables ($Dollars$ and $Defaults^{\$}$) are in constant 2020 thousand USD. Scaled variables ($Loans$, $Dollars$, $DefRate^{\#}$, $DefRate^{\$}$, $EmpShare$ and $EstabShare$) are multiplied by 100. For example, the average loan share ($Loans$) is 1.73%.

	Mean	Median	SD	Min	Max	Obs
$RiskSal$	0.20	0.00	0.39	0.00	2.00	99,273
$RiskSal^{far}$	1.81	0.28	3.71	0.00	22.50	54,088
$I(Loan)$	94.95	100.00	21.89	0.00	100.00	99,273
$Loans^{raw}$	12.54	4.00	23.01	1.00	146.00	94,262
$Dollars^{raw}$	2,907.17	839.97	5,849.96	0.30	51,310.40	94,262
$Loans$	1.73	0.80	2.37	0.02	12.21	94,262
$Dollars$	1.70	0.67	2.56	0.00	13.69	94,262
$Employment$	102.48	23.00	223.76	0.00	1,453.00	99,273
New^{1-4}	5.07	0.00	61.94	-7,242.00	298.00	99,273
$I(Default)$	37.33	0.00	48.37	0.00	100.00	99,273
$Defaults^{\#}$	1.43	0.00	3.72	0.00	26.00	99,273
$Defaults^{\$}$	177.87	0.00	514.63	0.00	4,236.92	99,273
$DefRate^{\#}$	16.24	0.00	25.18	0.00	100.00	80,217
$DefRate^{\$}$	10.40	0.00	19.97	0.00	93.99	80,217
$EstabShare$	1.74	0.66	2.84	0.00	15.73	93,063
$EmpShare$	1.74	0.87	2.61	0.00	15.43	93,062

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

Panel A. The choice to move out. Results from estimating Equation (7), in a panel of SBA employees. $Out = 1$ if employee i transfers to another SBA office in year t, $Promotion = 1$ if the employee received a promotion in year t (in the new office), $HighSalary = 1$ if their salary was above the median SBA employee in year $t-1$ (before the relocation), $LongTenure = 1$ if their tenure at the SBA was greater than the median SBA employee in year $t-1$, $PastTransfer = 1$ if they had been transferred in the past, and $\Delta Salary$ is salary growth the employee experienced in year $t-1$. See Section 3.5.

Outcome:		Out_t		
$Promotion_t$	0.044***	0.041***	0.040***	0.039***
	(0.005)	(0.005)	(0.005)	(0.005)
$HighSalary_{t-1}$	0.015***	0.013***	0.020***	0.018***
	(0.002)	(0.002)	(0.004)	(0.003)
$LongTenure_{t-1}$	-0.014***	-0.014***	0.004	0.003
	(0.002)	(0.002)	(0.003)	(0.002)
$\Delta Salary_{t-1}$	0.008	0.006	-0.002	0.001
	(0.020)	(0.020)	(0.013)	(0.015)
$PastTransfer_{t-1}$	0.030***	0.030***	-0.267***	-0.262***
	(0.004)	(0.004)	(0.019)	(0.019)
Obs.	61,714	61,671	59,932	59,885
R^2	0.029	0.083	0.286	0.324
Year FE	Y	-	Y	-
Office FE	Y	-	Y	-
Year×Office FE	-	Y	-	Y
Employee FE	-	-	Y	Y

Panel B. The choice of destination. Results from estimating Equation (8), in a panel of office×office pairs. $Out = 1$ if at least one employee moved from the focal office to the peer office, and $In = 1$ if at least one employee moved from the peer office to the focal office. Sim^{loan} and Sim^{def} are the cosine similarities between the focal and the peer, representing how similar are the loan portfolios and the default rates between the two offices (Appendix A.3). *Employees*, *Tenure*, and *Salary* are the ratios between the number of employees, average tenure, and average salary in both offices, respectively. See Section 3.5.

Outcome:		Out_t		
Sim^{loan}_{t-1}	0.002	-0.005	-0.009	-0.005
	(0.003)	(0.004)	(0.005)	(0.007)
Sim^{def}_{t-1}	0.003	0.009**	0.006	0.002
	(0.002)	(0.004)	(0.005)	(0.007)
In_{t-1}	0.037**	0.037**	0.029*	0.022
	(0.016)	(0.016)	(0.016)	(0.017)
$Salary_{t-1}$	0.006	0.006	0.022**	-0.047
	(0.007)	(0.007)	(0.010)	(0.047)
$Tenure_{t-1}$	0.003	0.002	0.013*	-0.028
	(0.005)	(0.005)	(0.007)	(0.022)
$Employees_{t-1}$	0.019***	0.017***	-0.010	-0.017
	(0.006)	(0.006)	(0.011)	(0.012)
Obs.	15,109	15,109	15,021	14,964
R^2	.106	.111	.19	.292
Focal×Peer FE	Y	Y	Y	Y
Year FE	-	Y	-	-
Year×Focal FE	-	-	Y	Y
Year×Peer FE	-	-	-	Y

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

Panel A. OLS.
Results from estimating Equation (4). The variables are calculated at the year×office×industry level based on 3-digit NAICS codes. *Loans* (*Dollars*) is the number (dollar value) of SBA loan guarantees by office o to industry i, as a share of the number (dollar value) of SBA loan guarantees by office o. *RiskSal* reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument is based on default rates of industry i which occurred at least $1,000$ miles away from office o. Controls include employment and establishments by industry i within office o's jurisdiction (*EmpShare* and *EstabShare*). We report the effect of a one-standard-deviation increase in *RiskSal* on the outcome (standard deviation × coefficient), and that effect as percentage of the average outcome variable. See Section 4.1.

Outcome:	*Loans*				*Dollars*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskSal}$	-0.374***	-0.417***	-0.364***	-0.340***	-0.346***	-0.386***	-0.340***	-0.332***
	(0.010)	(0.011)	(0.012)	(0.010)	(0.016)	(0.017)	(0.018)	(0.018)
Obs.	50,598	50,598	46,837	46,778	50,598	50,598	46,837	46,778
R^2	.886	.887	.926	.95	.774	.776	.852	.884
Effect	-0.160	-0.178	-0.158	-0.148	-0.148	-0.165	-0.148	-0.144
Effect (%)	-10.2	-11.4	-10.8	-10.1	-9.5	-10.6	-10.0	-9.7
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Office FE	-	Y	-	-	-	Y	-	-
Year×Office×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y

Panel B. 2-SLS.

Results from the second stage of the 2-SLS framework (Equation (6)). The variables are calculated at the year×office×industry level based on 3-digit NAICS codes. *Loans* (*Dollars*) is the number (dollar value) of SBA loan guarantees by office o to industry i, as a share of the number (dollar value) of SBA loan guarantees by office o. *RiskSal* reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument is based on default rates of industry i which occurred at least $1,000$ miles away from office o. Controls include employment and establishments by industry i within office o's jurisdiction (*EmpShare* and *EstabShare*). We report the Kleibergen-Paap $F-$ statistic for weak identification, the effect of a one-standard-deviation increase in *RiskSal* on the outcome (standard deviation × coefficient), and that effect as percentage of the average outcome variable. See Section 4.1.

Outcome:	*Loans*				*Dollars*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskSal}$	-0.396***	-0.441***	-0.383***	-0.346***	-0.366***	-0.405***	-0.354***	-0.330***
	(0.033)	(0.030)	(0.023)	(0.018)	(0.036)	(0.034)	(0.033)	(0.027)
Obs.	50,598	50,598	46,837	46,778	50,598	50,598	46,837	46,778
$F-$statistic	622	697	712	684	622	697	712	684
Effect	-0.169	-0.188	-0.167	-0.151	-0.156	-0.173	-0.154	-0.144
Effect (%)	-10.8	-12.0	-11.4	-10.3	-10.1	-11.2	-10.4	-9.7
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Office FE	-	Y	-	-	-	Y	-	-
Year×Office×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y

Table 4: **External validity: Impact of risk salience on 504 loans**

This table uses data on 504 loans, as opposed to 7(a) loans used elsewhere in the paper. We construct a parallel set of variables, reflecting the information on 504 loans: $Loans_{504}$ and $Dollars_{504}$ (number and dollar values of loans), $RiskSal_{504}$ (the main independent variable), and $RiskSal^{far}_{504}$ (the instrument). We then estimate a 2-SLS specification, which is identical to the one reported in Panel B of Table 3, except that it relies on the 504-based variables. We report the Kleibergen-Paap $F-$ statistic for weak identification, the effect of a one-standard-deviation increase in $RiskSal$ on the outcome (standard deviation $\times$ coefficient), and that effect as percentage of the average outcome variable. See Section 4.2.

Outcome:	$Loans_{504}$				$Dollars_{504}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskSal}$	-2.241***	-2.449***	-1.881***	-1.737***	-2.426***	-2.668***	-2.106***	-1.982***
	(0.211)	(0.242)	(0.194)	(0.173)	(0.250)	(0.279)	(0.263)	(0.246)
Obs.	21,730	21,727	16,630	16,436	21,730	21,727	16,630	16,436
$F-$statistic	1,069	1,015	938	1,134	1,069	1,015	938	1,134
Effect	-0.5	-0.6	-0.5	-0.4	-0.6	-0.6	-0.5	-0.5
Effect (%)	-16.2	-17.8	-14.9	-13.6	-17.9	-19.7	-16.3	-15.3
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office$\times$NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year$\times$Office FE	-	Y	-	-	-	Y	-	-
Year$\times$Office$\times$NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year$\times$NAICS3 FE	-	-	-	Y	-	-	-	Y

Table 5: **Real effects of risk salience**

Panel A. *Employment* is total jobs created and retained thanks to the SBA's 7(a) loans. *RiskSal* reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument is based on default rates of industry i which occurred at least $1,000$ miles away from office o. Controls include employment and establishments by industry i within office o's jurisdiction (*EmpShare* and *EstabShare*). All variables are calculated at the year×office×industry level based on 3-digit NAICS codes. We report the effect of a one-standard-deviation increase in *RiskSal* on the outcome (standard deviation × coefficient), and that effect as percentage of the average outcome variable. For the IV specifications, we also report the Kleibergen-Paap $F-$statistic for weak identification. See Section 4.3.

Outcome:	*Employment*							
Model:	OLS				IV			
RiskSal	-38.1***	-33.6***	-28.1***	-26.4***				
	(1.7)	(1.7)	(1.8)	(1.7)				
$\widehat{RiskSal}$					-43.0***	-37.8***	-30.0***	-27.1***
					(5.4)	(4.9)	(4.3)	(2.9)
Obs.	50,598	50,598	46,837	46,778	50,598	50,598	46,837	46,778
R^2	.794	.805	.883	.913				
$F-$statistic					622	697	712	684
Effect	-16.3	-14.4	-12.2	-11.5	-18.4	-16.2	-13.1	-11.8
Effect (%)	-12.0	-10.6	-9.4	-8.8	-13.6	-11.9	-10.0	-9.0
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Office FE	-	Y	-	-	-	Y	-	-
Year×Office×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y

Panel B. New^{1-4} is the number of new establishments, for industry i in office o, with 1-4 employees. New establishments are the change in establishments from $t-1$ to t. $RiskSal$ reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument is based on default rates of industry i which occurred at least $1,000$ miles away from office o. Controls include total employment and establishments by industry i within office o's jurisdiction. All variables are calculated at the year×office×industry level based on 3-digit NAICS codes. We report the effect of a one-standard-deviation increase in $RiskSal$ on the outcome (standard deviation × coefficient), and that effect as percentage of the average outcome variable. For the IV specifications, we also report the Kleibergen-Paap F−statistic for weak identification. See Section 4.3.

Outcome:	New^{1-4}							
Model:	OLS				IV			
$RiskSal$	-11.8***	-10.2***	-9.5***	-3.0***				
	(0.8)	(0.8)	(0.9)	(0.8)				
$\widehat{RiskSal}$					-14.2***	-12.0***	-11.1***	-2.7**
					(4.2)	(3.4)	(3.4)	(1.1)
Obs.	50,598	50,598	46,837	46,778	50,598	50,598	46,837	46,778
R^2	.32	.339	.571	.73				
F−statistic					622	697	712	684
Effect	-5.0	-4.4	-4.1	-1.3	-6.1	-5.1	-4.8	-1.2
Effect (%)	-56.4	-48.9	-63.8	-20.1	-67.7	-57.3	-74.2	-18.4
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Office FE	-	Y	-	-	-	Y	-	-
Year×Office×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y

Table 6: **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 in subsequent years, conditional on having any loan. $DefRate^{\#}$ is the fraction of loans defaulted out of total loans, and $DefRate^{\$}$ is the fraction of dollars in default out of total dollar lending. $RiskSal$ reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument is based on default rates of industry i which occurred at least $1,000$ miles away from office o. Controls include employment and establishments by industry i within office o's jurisdiction ($EmpShare$ and $EstabShare$). All variables are calculated at the year×office×industry level based on 3-digit NAICS codes. We report the Kleibergen-Paap $F-$ statistic for weak identification, the effect of a one-standard-deviation increase in $RiskSal$ on the outcome (standard deviation × coefficient), and that effect as percentage of the average outcome variable. See Section 4.4.

Outcome:	$I(Defaults)$			$DefRate^{\#}$			$DefRate^{\$}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{RiskSal}$	-11.718***	-11.175***	-11.340***	-3.224***	-2.901***	-2.314***	-2.392***	-2.177***	-1.669***
	(1.587)	(1.213)	(1.067)	(0.840)	(0.768)	(0.798)	(0.664)	(0.627)	(0.566)
Obs.	50,598	46,837	46,778	40,948	36,593	36,463	40,948	36,593	36,463
$F-$statistic	697	712	684	587	613	582	587	613	582
Effect	-5.0	-4.9	-4.9	-1.3	-1.2	-1.0	-1.0	-0.9	-0.7
Effect (%)	-12.4	-12.0	-12.2	-7.4	-6.7	-5.3	-8.6	-7.8	-6.0
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year×Office FE	Y	-	-	Y	-	-	Y	-	-
Year×Office×NAICS2 FE	-	Y	Y	-	Y	Y	-	Y	Y
Year×NAICS3 FE	-	-	Y	-	Y	Y	-	-	Y

Table 7: **Heterogeneous impact of risk salience**

Results from the second stage of the 2-SLS framework (Equation (6)). *Loans* is the number of SBA loan guarantees by office o to industry i, as a share of the number of SBA loan guarantees by office o. *RiskSal* reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument ($RiskSal^{far}$) is based on default rates of industry i which occurred at least $1,000$ miles away from office o, and we use the interaction of $RiskSal^{far}$ with *Small*, *Budget*, and *Bonus*, respectively, as the additional instrument. $Small = 1$ if the number of employees in the office is below the median in a given year, *Budget* is the year-on-year change in the SBA's budget, and *Bonus* is the fraction of employees in the office who received cash bonus in the previous year. Controls include employment and establishments by industry i within office o's jurisdiction (*EmpShare* and *EstabShare*). *Budget* is subsumed under year fixed effects, while *Bonus* and *Small* are subsumed under year×office fixed effects, but are otherwise included as control variables. All other variables are calculated at the year×office×industry level based on 3-digit NAICS codes. See Section 4.4, Section 5.1.1, and Section 5.1.2.

Outcome:	*Loans*								
$\widehat{RiskSal}$	-0.373***	-0.410***	-0.356***	-0.428***	-0.463***	-0.403***	-0.488***	-0.547***	-0.467***
	(0.030)	(0.028)	(0.021)	(0.028)	(0.027)	(0.021)	(0.041)	(0.043)	(0.032)
$Small \cdot \widehat{RiskSal}$	-0.222***	-0.240***	-0.272**						
	(0.070)	(0.081)	(0.100)						
$Budget \cdot \widehat{RiskSal}$				1.242***	1.077***	0.738**			
				(0.247)	(0.305)	(0.258)			
$Bonus \cdot \widehat{RiskSal}$							0.229***	0.292***	0.227***
							(0.076)	(0.082)	(0.068)
Obs.	48,440	48,440	45,051	47,041	47,041	43,878	31,569	31,569	29,008
$F-$statistic	69	116	128	404	295	299	270	301	355
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	Y	-	-	Y	-	-
Year×Office FE	-	Y	-	-	Y	-	-	Y	-
Year×Office×NAICS2 FE	-	-	Y	-	-	Y	-	-	Y

Table 8: **Informativeness of risk salience**

Results from the second stage of the 2-SLS framework (Equation (6)). *Loans* is the number of SBA loan guarantees by office o to industry i, as a share of the number of SBA loan guarantees by office o. *RiskSal* reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument ($RiskSal^{far}$) is based on default rates of industry i which occurred at least $1,000$ miles away from office o, and we use the interaction of $RiskSal^{far}$ with *Geog* and *Predic*, respectively, as the additional instrument. *Geog* is the number of unique counties in which the office's employees previously worked. *Predic* is the absolute value of the correlation between *RiskSal* and employment growth, estimated separately for each office×industry pair. Controls include employment and establishments by industry i within office o's jurisdiction (*EmpShare* and *EstabShare*). *Predic* is subsumed under office×industry fixed effects, while *Geog* is subsumed under year×office fixed effects, but is otherwise included as a control variable. All other variables are calculated at the year×office×industry level based on 3-digit NAICS codes. See Section 5.1.2.

Outcome:	*Loans*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{RiskSal}$	-0.467***	-0.540***	-0.469***	-0.428***	-0.470***	-0.526***	-0.424***	-0.388***
	(0.052)	(0.047)	(0.043)	(0.021)	(0.043)	(0.042)	(0.031)	(0.016)
$Geog \cdot \widehat{RiskSal}$	0.002	0.005*	0.005	0.004**				
	(0.002)	(0.003)	(0.003)	(0.002)				
$Predict \cdot \widehat{RiskSal}$					0.674	0.705	-0.191	-0.093
					(0.440)	(0.441)	(0.416)	(0.224)
Obs.	42,204	42,204	38,237	38,166	42,204	42,204	38,237	38,166
$F-$statistic	269	308	293	42,433	257	230	229	42,445
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Office FE	-	Y	-	-	-	Y	-	-
Year×Office×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y

Table 9: **Risk salience and SBA guarantees: Mechanisms**

Panel A. Screening borrowers. Results from the second stage of the 2-SLS framework (Equation (6)). *Loans* is the number of SBA loan guarantees by office o to industry i, as a share of the number of SBA loan guarantees by office o. $RiskSal$ reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument is based on default rates of industry i which occurred at least $1,000$ miles away from office o. Controls include employment and establishments by industry i within office o's jurisdiction ($EmpShare$ and $EstabShare$). All variables are calculated at the year×office×industry level based on 3-digit NAICS codes. We estimate the regressions separately before (1998-2003) and after (2008-2019) the reform which centralized the 7(a) loan process, and report the percentage difference between the coefficients and its statistical significance. See Section 5.2.1.

Outcome:	*Loans*							
Period:	(98-03)	(08-19)	(98-03)	(08-19)	(98-03)	(08-19)	(98-03)	(08-19)
$\widehat{RiskSal}$	-0.61***	-0.34***	-0.63***	-0.38***	-0.52***	-0.34***	-0.48***	-0.33***
	(0.06)	(0.01)	(0.07)	(0.01)	(0.07)	(0.01)	(0.06)	(0.01)
Obs.	8,144	31,073	8,144	31,073	7,071	28,952	7,007	28,926
Δ (in %)		0.45		0.41		0.34		0.31
$p-$val		0.00		0.00		0.00		0.00
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Office FE	-	Y	-	-	-	Y	-	-
Year×Office×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y

Panel B. Lenders and borrowers. Results from the second stage of the 2-SLS framework (Equation (6)). All variables are calculated at the year×office×NAICS3 level, and the sample includes observations with non-zero loans. $Lenders$ is the number of unique institutions providing SBA-backed loans and $Lend^{new}$ is the number of new 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 number of new borrowers; and $Borr^{HHI,\#}$ ($Borr^{HHI,\$}$) is the sum of squares of the fraction of loans (dollars) received by each borrower. $RiskSal$ reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). The instrument is based on default rates of industry i which occurred at least $1,000$ miles away from office o. Controls include employment and establishments by industry i within office o's jurisdiction ($EmpShare$ and $EstabShare$). We report the Kleibergen-Paap $F-$ statistic for weak identification, the effect of a one-standard-deviation increase in $RiskSal$ on the outcome (standard deviation × coefficient), and that effect as percentage of the average outcome variable. See Section 5.2.2 and Section 5.2.3.

Outcome:	$Lenders$	$Lend^{new}$	$Lend^{HHI,\#}$	$Lend^{HHI,\$}$	$Borrowers$	$Borr^{new}$	$Borr^{HHI,\#}$	$Borr^{HHI,\$}$
$\widehat{RiskSal}$	-1.515***	-0.583***	13.103***	12.616***	-4.330***	-4.125***	15.887***	14.338***
	(0.152)	(0.056)	(1.107)	(0.908)	(0.683)	(0.660)	(1.213)	(1.018)
Obs.	48,906	48,906	48,906	48,906	48,906	48,906	48,906	48,906
$F-$statistic	719	719	719	719	719	719	719	719
Effect	-0.611	-0.235	5.287	5.091	-1.747	-1.664	6.410	5.785
Effect (%)	-9.7	-11.7	11.9	9.5	-12.6	-13.0	17.7	12.1
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year×Office FE	Y	Y	Y	Y	Y	Y	Y	Y

Internet Appendix

A.1 Risk management at the SBA

In Section 2.2 we explained that the SBA emphasizes a rigorous, structured, data-driven approach to assess the default risk of its loan portfolio. In light of that, it is surprising that distant defaults in past workplaces have any impact on the agency's loan program. In this section we add more information on the SBA's risk management activities. We rely on the interview we conducted with a senior SBA director, as well as numerous publicly available sources.[1]

The agency views default risk as a significant challenge. For example, in its most recent financial report for FY 2022, the agency recognized that its risk management and oversight practices "need improvement to ensure the integrity of loan programs." Specific weaknesses include insufficient oversight of high-risk lenders and a "blind spot" related to third party contractors, especially loan agents and lender service providers. To improve its performance, the SBA has a dedicated division with the overarching task of managing the agency's credit risk: the Office of Credit Risk Management (OCRM). The OCRM is based at the agency's headquarters in Washington, D.C., and oversees the SBA's various lending programs across the United States. Although operating for many years, in 2018 Congress passed the Small Business 7(a) Lending Oversight Reform Act, to officially codify the existence of the OCRM and define its duties.

Led by the OCRM, the agency implements risk-based protocols (RBP) to track and quantify the default risk. The tools and protocols are described in the agency's Standard Operating Procedures (SOP), mainly SOP 50 10 6 and SOP 50 53 (2).[2] For example, the SBA conducts quarterly meetings to facilitate communication and information sharing among its various divisions. The centerpiece of the agency's risk management efforts are two risk-management tools, known as PARRiS (for 7(a) loans) and SMART (for 504

[1] Those include policy papers of the Congressional Research Service (Congressional Research Service (2021a), Congressional Research Service (2021b), and Congressional Research Service (2021c)), external audits by the Office of Inspector General, and the SBA's annual reports and operating protocols.

[2] See also SOP 50 10, 51 00, 50 55, 52 00, and 50 57.

loans).[3] Essentially, those tools assign a risk-based score to each lender. The scores identify the overall level of risk a lender poses to the SBA, highlight specific risk areas, and flag lenders who may be subject to more in-depth reviews. At a higher level, the aggregated scores provide a solid assessment of the default risk the SBA faces.

To compute the scores, the SBA continuously collects granular loan-level data. The primary data storage facility is the Loan and Lender Monitoring System (L/LMS). Lenders upload information to the system via SBA Form 1502 and SBA Form 172, and supplementary forms such as Annual Reports, Quarterly Reports, and Quarterly Capital Certification. The SBA also collects data from reliable external sources such as the FDIC, the SEC, and the IRS; audited financial statements; regulatory actions taken by other agencies such as Orders, Consent Agreements, and federal or state on-site examinations; and court filings. The data are converted into a series of risk factors. The factors are benchmarked against risk tolerance thresholds established by the SBA, producing the final PARRiS and SMART Scores. A related tool is the SBA's Lender Portal. The portal allows an individual lender to view its own PARRiS and SMART scores, as well as its quarterly Lender Risk Ratings (LRR), which is based upon the SBA loan portfolio credit quality and other risk and program integrity related factors.

The level of monitoring depends primarily on SMART and PARRiS scores, as well as the lender's loan volume. Naturally, larger dollar-volume lenders are subject to greater monitoring, as they expose SBA to greater potential risk. For example, lenders with more than 10 million USD SBA loans will be subject to in-depth reviews and on-site examinations, while those below that threshold will be monitored primarily off-site using existing database.

[3] PARRiS stands for Portfolio performance, Asset management, Regulatory compliance, Risk management, and Special items. SMART stands for Solvency and financial condition, Management and board governance, Asset quality and servicing, Regulatory compliance, Technical issues and missions.

A.2 Calculating risk perception

This section illustrates how weights are assigned across past locations ($\omega_{l,t}$ from Equation (1) and Equation (2)):

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

Consider a simple case where the employee works in office 1, and has never worked in any other office. In that case, as long as the employee stays at office 1:

$$\omega_{1,t} = \frac{\frac{1}{1+\tau_{1,t}}}{\frac{1}{1+\tau_{1,t}}} = 100\%.$$

Now suppose that the employee moved to office 2. Recall that for the current location (office 2), $\tau_{2,t} = 0$ for all t. Therefore, from now on, the weight of office 1 equals:

$$\omega_{1,t} = \frac{\frac{1}{1+\tau_{1,t}}}{\frac{1}{1+\tau_{1,t}} + \frac{1}{1+\tau_{2,t}}} = \frac{\frac{1}{1+\tau_{1,t}}}{\frac{1}{1+\tau_{1,t}} + 1} = \frac{1}{2+\tau_{1,t}}.$$

Consequently, the weight of office 2 equals:

$$\omega_{2,t} = 1 - \omega_{1,t} = 1 - \frac{1}{2+\tau_{1,t}} = \frac{1+\tau_{1,t}}{2+\tau_{1,t}}.$$

In the first year after the relocation, $\omega_{1,t} = 33\%$ and , $\omega_{2,t} = 67\%$. In the second year, $\omega_{1,t} = 25\%$ and , $\omega_{2,t} = 75\%$. The weight on the current location increases while the weight on the past location decreases.

The table below provides an illustration with three offices. Suppose the employee was stationed in Chicago until 2011, in New York during 2012-2013, and in Boston from 2014 onwards. In 2012, upon moving to New York, the weight on Chicago is 33% ($= \frac{1}{2+1}$) and the weight on New York is 67%. In 2013, the weight on New York increases to 75% while the weight on Chicago drops to 25% as it becomes a more distant memory. Starting from 2014, Boston replaces New York as the dominant location and its importance gradually increases over time as New York and Chicago slowly fade.

Year	Location	Weights (#1)			Weights (#2)		
		Chicago	New York	Boston	Chicago	New York	Boston
2004	Chicago	100%	0%	0%	100%	0%	0%
2005	Chicago	100%	0%	0%	100%	0%	0%
2006	Chicago	100%	0%	0%	100%	0%	0%
2007	Chicago	100%	0%	0%	100%	0%	0%
2008	Chicago	100%	0%	0%	100%	0%	0%
2009	Chicago	100%	0%	0%	100%	0%	0%
2010	Chicago	100%	0%	0%	100%	0%	0%
2011	Chicago	100%	0%	0%	100%	0%	0%
2012	New York	50%	100%	0%	33%	67%	0%
2013	New York	33%	100%	0%	25%	75%	0%
2014	Boston	25%	50%	100%	14%	29%	57%
2015	Boston	20%	33%	100%	13%	22%	65%
2016	Boston	17%	25%	100%	12%	18%	71%
2017	Boston	14%	20%	100%	11%	15%	74%
2018	Boston	13%	17%	100%	10%	13%	77%
2019	Boston	11%	14%	100%	9%	11%	80%

A.3 Additional descriptive statistics

General statistics - In Table A.3, Panel A, we describe the employee×year sample. The average employee has 14 years of experience and earns $82,516 (excluding bonus). Similar to other federal agencies (Kalmenovitz (2021)), employees are grouped into nine hierarchy ranks (Figure A.1): junior employees are in GS-8 through GS-12 (71% of the sample), supervisors and mid-level managers are in GS-13 through GS-15 (28%), and top managers are on the ES and EX pay schedules (1%). In Table A.3, Panel B, we describe the office×year sample. The average office has 54 employees, with only six offices having more than 100 employees.

Relocation statistics - In Table A.3 and Figure A.2 we provide more information on relocations. At the employee level, 1.9% have relocated in the previous year and 9.2% have relocated in any of the previous years (“mover”). At the office level, 36.8% have at least one employee who has relocated in the previous year, and 74.1% have at least one "mover" (employee who has relocated in any of the previous years). Conditional on having at least one "mover", there are on average 6.8 movers representing 15.7% of the office's workforce. Relocations peaked around 2007, likely as part of the SBA reorganization which we discuss in Section 5.2.1.

SBA job titles - In Table A.4 we describe the five most common SBA positions. To that end, we submitted a FOIA request and obtained the list of all $1,789$ job openings at local SBA offices between 2017 and 2020.[4] Those listings were originally advertised on USAJobs.gov, the federal government's job portal. Each listings includes basic details such as location, rank, and salary, and a description of the duties associated with the position. For example, duties of a typical Business Opportunities Specialist include "building effective relationships with a portfolio of small business CEOs," "gaining awareness of the needs, goals and challenges faced by firms," and assisting firms "with increasing revenue and business development." A Lender Relations Specialist is required to "market all SBA lending programs and services," "conduct outreach, training, education, development, lender recruitment, consultation and working with assigned lenders in the district," "conduct face-to-face visits with individual lending institution," and "provide assistance through consultative and customer interactions with lenders."

Defaults and turnover - In the main text we conclude that employees are more likely to receive a promotion upon relocating to a new office, suggesting that they tend to be better performers. Another way to show this is by studying the relation between defaults and turnover at the office level. We estimate the following regression in the cross-section of SBA offices:

$$y_{o,t+l} = \alpha + \beta \cdot Default_{o,t} + \overrightarrow{X}_{o,t} + \epsilon_{o,t} \tag{A.1}$$

The dependent variable is either inbound (employees moving into office o), outbound (employees leaving office o), or turnover (inbound plus outbound), all measured at time $t+1$ and scaled by beginning-of-period number of employees. The main independent variable is the number of SBA loans supervised by office o which defaulted in year t. We control for office size and include office and year fixed effects, focusing on variation within-

[4] The government does not retain records from earlier years.

office over time. The results are summarized in the first three columns of Table A.2. We find a significant negative association between defaults and employee turnover, driven especially by lower inbound and to a lesser extent by lower outbound employees. Put differently, when the focal office appears to perform better (fewer defaults), employees are more likely to move out. At the same time, the successful focal office is able to attract more new employees. Combined with the employee-level analysis in the main text, the results are indicative of a "virtuous cycle:" in offices with few defaults, the better-paid employees get promoted and move to other well-performing offices.

Dallas-Fort Worth Office - Figure A.3 visually depicts inbound and outbound trends for the Dallas-Fort Worth District Office, the largest office after Washington DC. The map in Panel A depicts outbound transfers, that is, peer offices to which employees transferred *from* Dallas, while Panel B depicts inbound transfers. 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. Looking at the top ten locations of outbound and inbound employees, we confirm the dispersed nature of employee movement as 40% of the locations are over $1,000$ miles away from Dallas. Related to that, in Table A.5 we list the top and bottom ten offices by average turnover rates. We first compute the annual turnover rate for each office, defined as the sum of employees joining or leaving the office, scaled by the number of employees at the beginning of the year. We then compute the average turnover across all years within the office. The average-of-average turnover is 4.7% or 2.5 employees per year. The Richmond District Office has the highest average turnover (15%), while Vermont has the lowest one ($< 1\%$). These facts suggest that turnover rates do not follow a specific geographic pattern, and offices with high and low turnover are spread all over the country.

Cosine similarity - In the main text we discuss an office$\times$office similarity score, representing how similar is the loan portfolio between each two offices. We provide below a formal definition and an illustrative example. For each office i at time t, we create a word collection of the industries which received at least one SBA-guaranteed loan. We then compute the cosine similarity between each two collections at time t, that is, between each pair of offices in a given year. Denote with D_i^t and D_j^t the collections for office i and j, respectively, at time t. Let T be the union of the collections and t_n be the n^{th} element of T. The frequency vector of $D_i^{t,f}$ is then:

$$D_i^{t,f} = [nD_i^t(t_1), nD_i^t(t_2), ..., nD_i^t(t_N)]$$

where $nD_i^t(t_n)$ is the number of loans for industry t_n in D_i^t. Finally, the cosine similarity between D_i^t and D_j^t is defined as:

$$Cosine_{i,j}^t = \frac{D_i^{t,f} \cdot D_j^{t,f}}{\|D_i^{t,f}\| \times \|D_j^{t,f}\|} \tag{A.2}$$

To illustrate the working of our measure, suppose office 1 mainly provides agricultural loans while office 2 is engaged with electronic equipment retailers. Further suppose that D_1^t = [corn, milk, transportation] and D_2^t = [computers, cellular, transportation]. That is, both offices extend at least one loan to a local transportation company. In this hypothetical example, T = [corn, milk, transportation, computers, cellular]. It follows that $D_1^{t,f} = [1, 1, 1, 0, 0]$ and $D_2^{t,f} = [0, 0, 1, 1, 1]$. Therefore:

$$Cosine_{1,2}^t = \frac{1 \times 0 + 1 \times 0 + 1 \times 1 + 0 \times 1 + 0 \times 1}{\sqrt{3 \times 1^2} \times \sqrt{3 \times 1^2}} = 0.333$$

If in a given year office 2 also extended a loan to a corn producer, then D_2^t = [computers, cellular, transportation, corn]. In this case D_1^t, $D_1^{t,f}$ and T remain unchanged, but now $D_2^{t,f} = [1, 0, 1, 1, 1]$. Therefore:

$$Cosine_{1,2}^t = \frac{1 \times 1 + 1 \times 0 + 1 \times 1 + 0 \times 1 + 0 \times 1}{\sqrt{3 \times 1^2} \times \sqrt{4 \times 1^2}} = 0.577$$

The similarity score has increased significantly, reflecting the fact that office 2 extended a loan to the corn producer and thus became more similar to office 1.

A.4 Main results: robustness and persistence

A.4.1 General

Our main result, reported in Table 3, is that risk salience reduces SBA loans. In this section we discuss several tests which verify the robustness of that result and its persistence across sub-samples.

In Table A.6, we estimate a reduced-form regression of Equation (4): replacing $RiskSal$ with $RiskSal^{far}$ (the instrument) and otherwise keeping the same structure. This specification captures the average effect of risk salience, based only on distant defaults, on local SBA guarantees. The magnitude of β in the reduced-form specification is similar to the magnitude of β^{IV}, scaled by the average share of relocating employees.

In Figure A.4, we examine how the importance of past workplaces fades away gradually. We run our baseline IV specification with year×office fixed effects successively by changing the number of years we look back to identify past locations. For instance, looking back 8 years means we only include locations that the employee worked at in the previous eight years. We vary this number from 1 to 21, which is the maximum number of years in our data (and equals our baseline measure). We continue to weight locations by the inverse of time elapsed, as in the baseline measure. Looking only one year back, the coefficient on $RiskSal$ is -0.367. Looking back two years, the coefficient becomes -0.393 which is 7% increase in absolute value. After the inclusion of seven years, the coefficient reaches the level of our final coefficient: -0.441. Thus, we conclude that the effect is driven by more recent workplaces and much less so by workplaces from the distant past. It could be explained by the idea that, with the passage of time, their work and social networks in the prior location becomes weaker.

Finally, in Figure A.5, we re-estimate the baseline IV specification with year×office fixed effects for different 2-digit NAICS industries, and plot the coefficients from the second stage. The negative impact of risk salience on loans is significant and negative for all industries. The largest effect (in absolute value) is among Healthcare and Other Services (codes 62 and 81), while the smallest is among Information, Finance, and Transportation (codes 51, 52, and 48-49).

Additional tests are available on request. We construct a version of *RiskSal* based only on employees who hold core positions, such as "loan specialist," and a set of nine different versions of *RiskSal* to account for differences in seniority (e.g., pay grades and salaries). We consider different clustering methods to account for serial correlations by office×industry, year, office, industry, and several double-clustering options. To ensure that our conclusions are not driven by outliers, we winsorize variables at the 99%, 97.5%, 95%, and 90% levels; estimate regressions iteratively, each time excluding one year or one state; exclude the years 2008-2012, where *RiskSal* was abnormally high (Figure 2); and exclude observations where $RiskSal > 1$. We consider versions of *RiskSal* based on the dollar value of defaults; dollar value of guarantees; and an indicator for any default. In a separate test we construct a version of *RiskSal* that includes only defaulting loans that originated *after* the employee has left the office. The results show a substantial effect, which emphasizes the uniqueness of our setting: the employee's decision-making process is affected by events which are unrelated to his personal experiences in the past (as opposed to Malmendier and Nagel (2011) and Murfin (2012)).

A.4.2 Main result: alternative identification

In the main text, we discuss two strategies to identify the impact of risk salience on loans: saturated fixed effects specification, and instrumental variable approach. In this section we introduce a third strategy which exploits within-borrower variation in risk salience, similar to Khwaja and Mian (2008). Suppose retailers in Hillsborough County, New Hampshire, can match to two nearby SBA offices: Boston and Vermont. Using tight fixed effects (year×NAICS3×county), we absorb the current risk and demand of Hillsborough retailers, and compare the simultaneous decisions of Boston and Vermont with respect to this local industry, based on how each office subjectively perceives the industry's risk. Formally, we aggregate the loan-level data into office×NAICS3×county triplets, that is, we group together all loans approved by SBA office o to industry i in county c. As before, we exclude triplets which have no lending relations throughout the entire period. We then estimate a similar regression to Equation (4):

$$y_{o,i,c,t+l} = \alpha + \beta \cdot RiskSal_{o,i,t} + \overrightarrow{X} + \epsilon. \tag{A.3}$$

The dependent variables are measured at the year×office×NAICS3×county level: the number (dollar value) of loans guaranteed by SBA office o to industry i in county c at time t, as a share of the number (dollar value) of loans guaranteed by SBA office o to county c at time t. Our main independent variable, $RiskSal$, is the same one defined in Equation (3). It is measured at the year×office×NAICS3 level, and does not vary across counties. We control non-paramterically for the borrower's conditions with year×NAICS3×county fixed effects. 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.

Note that this strategy builds on local industries which have the capacity to choose between SBA offices. This sub-sample includes $128,628$ year×office×NAICS3×county observations. In nearly half of those cases the borrowing involves multiple states, that is, the local industry borrows from SBA offices across state lines. Nearly a third of the U.S. counties (1,053) have borrowed from multiple offices in the same year, and all the SBA offices have been part of a "multi-office borrowing" arrangement.

The results are summarized in Table A.7. The dependent variables are the probability of receiving a loan, as well as number of loans and their dollar value. We report two specifications. The first includes year×county×NAICS2 fixed effects, essentially repeating the tight specifications from Panels A and B and ruling out local industry trends (2-digit). We find a substantial negative impact of salient defaults on SBA lending, similar to the one reported earlier. 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 offices. 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. The coefficient is -0.044, the standard deviation of risk salience is 0.377, and the loan probability is 31.9% (within this subsample). Therefore, a one-standard-deviation increase in risk salience reduces loan probability by 1.7 percentage points, which is 5.2% of the unconditional probability ($\frac{-0.044 \cdot 0.377}{0.319}$). Similar calculations show reductions of 9.3% and 12.3% in the number of loans and the dollar volume, relative to their respective average, in response to one-standard-deviation increase in risk salience.[5]

A.5 Office-level analysis

Our primary analysis uses industry-specific risk salience. A potential limitation is that employees might develop a general risk perception, rather than industry-specific one. Moreover, our regressions compares outcomes within office, and are largely silent on how risk salience affects aggregate outcomes. To overcome those limitations, we conduct an analysis where employee risk salience is based on defaults in all industries. We begin by altering our measure of risk salience. Instead of Equation (1) and Equation (3), we define:

$$RiskSal_{j,t} = \sum_{l \in L_{j,t}} \omega_{l,t} Default_{l,t}, \tag{A.4}$$

and:

$$RiskSal_{o,t} = \frac{1}{N} \sum_{j \in E_{o,t}} RiskSal_{j,t}, \tag{A.5}$$

where $Default_{l,t}$ is the number of SBA loans guaranteed by office l and charged-off at time t, $E_{o,t}$ is the set of employees who work at office o at time t, and N is the number of employees who work at office o at time t. In other words, we compute an office-level measure rather than office×industry measure. Next, similar to the baseline analysis, we

[5]For loans, the coefficient is -0.844, the standard deviation of risk salience is 0.377, and the average number of loans is 3.406. For dollars, the coefficient is -1.328, the standard deviation of risk salience is 0.377, and the average dollar value of loans is 4.057.

instrument this risk salience measure with the component of risk salience based only on distant offices. Since our focus here is on aggregate outcomes, our dependent variables are in quantities rather than shares. We control for number of employees and average tenure, and include office and year fixed effects.

The results are in Table A.8. We find a strong negative effect of risk salience on office-level lending, job creation and firm entry. For example, a one-standard-deviation increase in risk salience eliminates 250 loans worth \$36.4 million USD. Additionally, risk salience has a significant impact on the overall risk of the office's portfolio: a one-standard-deviation increase in risk salience prevents 51 future defaults worth \$4.1 million USD, saving taxpayers \$2.9 million USD. Despite the small sample size, the results are all highly significant and consistent with the analysis throughout the paper.

A.6 Quantities

Our primary outcome variables are expressed in percentages. For example, loans granted to industry i by office o as a fraction of office o's portfolio. To better understand the economic magnitudes, we re-estimate our main tables using raw quantities instead of percentages (dollar outcomes are in constant 2020 USD). For each outcome, we estimated four levels of fixed effects using both the IV and OLS methods, total of eight specifications per outcome. For brevity, we report in Table A.9 only the IV specification with year$\times$office fixed effects. We find that a one-standard-deviation increase in risk salience leads to 1.8 fewer loans worth \$360,200, eliminates 16.2 jobs, and reduces the number of new firms by 5.1.[6] In the 504 program, a one SD increase in risk salience leads to 0.4 fewer loans worth \$297,200. Looking at future defaults, a one SD increase in risk salience leads to 0.4 fewer defaults worth \$33,100, which saves taxpayers \$28,200 (since otherwise the SBA must have purchased the defaulting loans).

[6] The last two are also reported in the main text (Table 5).

A.7 Risk perception: additional evidence

Our interpretation for the baseline results relies on risk perception. According to our interpretation, distant defaults matter because employees pay attention to current events in their previous workplaces. This could happen if, for example, employees maintain social ties to their previous location.[7]

To verify this possibility, we utilize the Social Connectedness Index (SCI) from Bailey et al. (2018). For each county×county pair, the SCI measures the number of friend links between active Facebook users in both counties, scaled by the product of the number of active users in both counties. We construct equivalent measures based on SBA relocation data: an indicator if a link exists (for example, if at least one employee worked in both Boston and Chicago); raw count of links (the number of employees who worked in both Boston and Chicago); and the raw number scaled by the product of the total number of employees in the two offices (analogous to SCI). We then regress SCI on our three measures and report the results in Table A.10. In odd-numbered columns, we include all county pairs. In even-numbered columns, we focus on pairs which are more than 1,000 miles apart. We include the distance between counties as a control throughout. Across all specifications, we find a significant positive correlation between SCI connections and SBA relcoation linkages. Clearly, those results do not provide a causal effect in either direction. However, they provide suggestive evidence that SBA employees could rely on social connections to their previous workplaces to update their risk perceptions.[8]

Another possibility is that our results are driven by perceived ability. According to this theory, defaults in the previous workplace shake the employee's self-confidence and thus lead to fewer loans. We conducted two tests, available on request, which seem inconsistent with this possibility. First, we construct a version of $RiskSal$ that includes only defaulting loans that originated *after* the employee has left the office. We then estimate our standard IV specification with the new version of $RiskSal$. We find a substantial effect, statistically

[7]Other mechanisms could be at play. For instance, perhaps all SBA employees receive identical data on defaults, but each employee focuses on the information which pertains to their previous workplace.

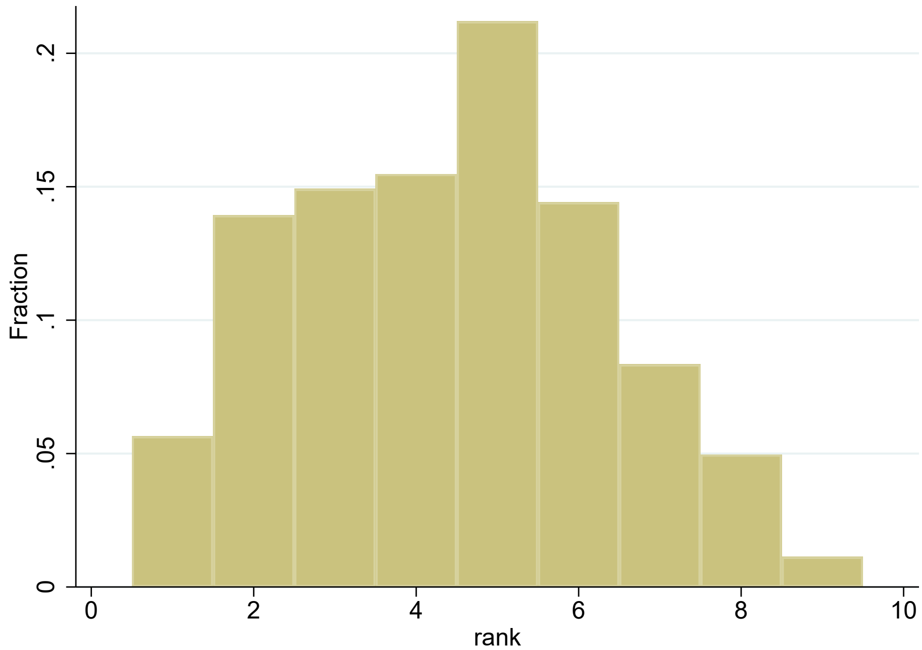
[8]Since SCI is time-invariant, the regressions here are at the county×county level. In the rest of the paper, on the other hand, we exploit a more granular variation: within office×year and across industries. This effectively absorbs those fixed county×county connections.

significant and economically large. This result is less consistent with a confidence/ability story, because the employee had nothing to do with the loans that are now defaulting. It is, however, consistent with the overarching interpretation presented in our paper: irrational updating of the employee's risk perception.

Additionally, we distinguish between systemic and idiosyncratic defaults. First, we compute the average default rate at the industry×year level (Def^{avg}), and regress the industry×office×year default rate on Def^{avg}. The predicted values from this regression represent the systemic component of the defaults, while the residuals represent the idiosyncratic defaults. This approach is similar to the one found in the executive compensation literature, such as Jenter and Kanaan (2015) and Albuquerque (2009). We then construct two measures of $RiskSal$, one using only the systemic default component ($RiskSal^{sys}$) and another using only the idiosyncratic default component ($RiskSal^{id}$), and a parallel set of instruments. We estimate our baseline IV specifications twice, once for each version of $RiskSal$. We find that the effect of systemic defaults ($RiskSal^{sys}$) is substantially stronger than the effect of idiosyncratic ones ($RiskSal^{id}$). The differences are all statistically significant at the 1% level, except for the tightest specification with dollar loans as outcome. This is less consistent with a confidence/ability story, whereby the employee should be more sensitive to idiosyncratic losses that are likely related to his/her ability. It is, on the other hand, more consistent with a risk salience mechanism.

Figure A.1: **Distribution of employees across ranks**

Distribution of SBA employees across ranks. The SBA has nine hierarchy ranks. The table below lists the specific pay grades within each rank. See Section 3.4.



List of pay grades within each rank:

Rank	Obs.	Pct	Pay grades
1	5,388	5.7%	GS-1 through GS-5
2	13,289	13.9%	GS-6 through GS-7
3	14,232	14.9%	GS-8 through GS-10
4	14,764	15.5%	GS-11
5	20,223	21.2%	GS-12
6	13,752	14.4%	GS-13
7	7,956	8.3%	GS-14
8	4,734	5.0%	GS-15
9	1,077	1.1%	ES and EX

Figure A.2: **Employee relocations: additional**

Panel A plots the average percentage of employees that relocate (worked in a different office in the previous year) at different levels of aggregation. Panel B plots the percentage of employees who have relocated at the office×year level. Panel C shows the time series of the percentage of employees who have relocated, and the percentage of employees who relocated greater than 1000 miles (*far*). See Appendix A.3.

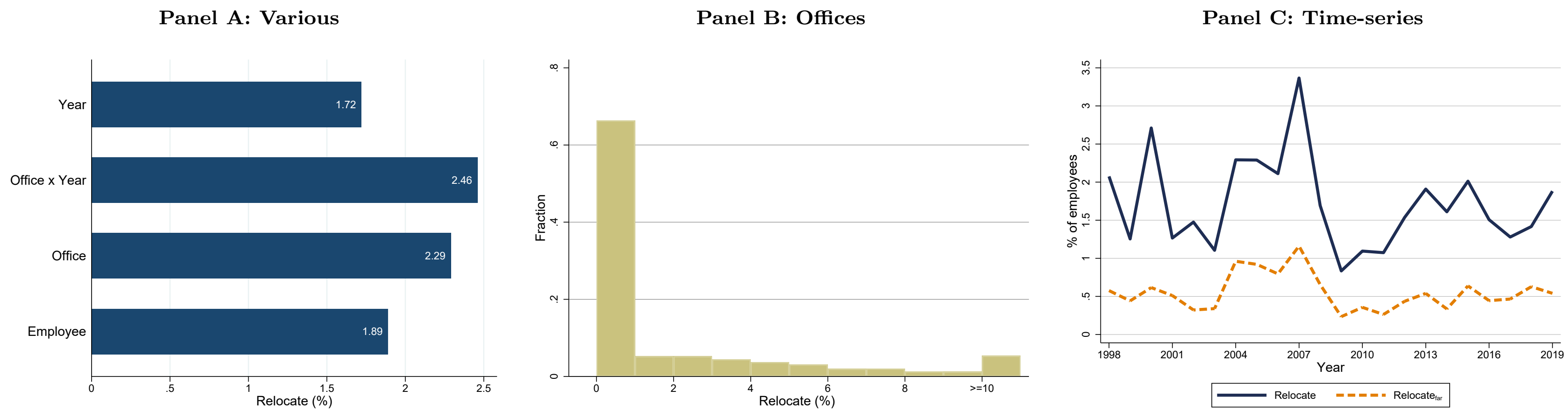
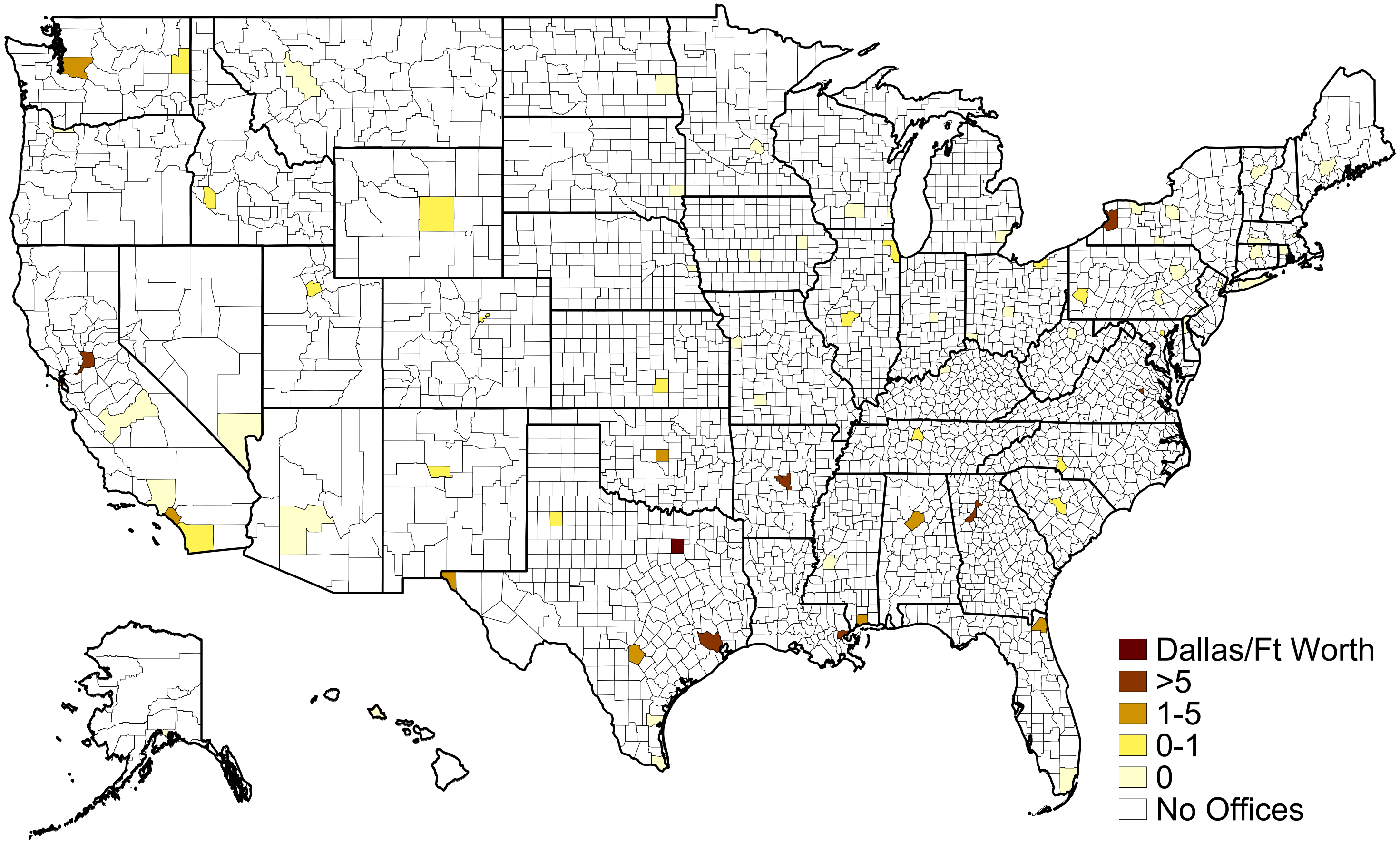


Figure A.3: **Job transfers to and from the Dallas office**

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. See Appendix A.3.



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. See Appendix A.3.

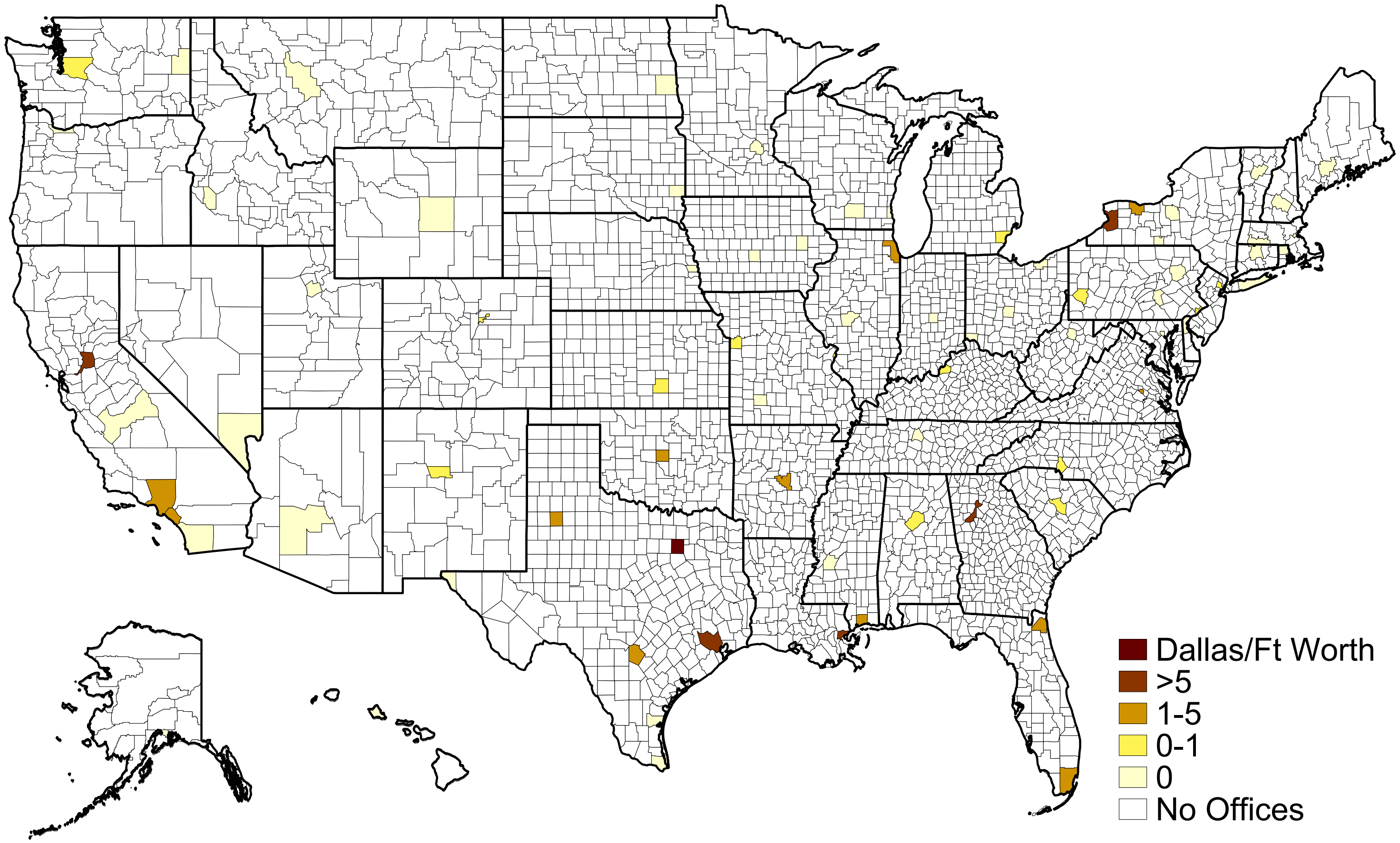


Figure A.4: **Past locations: Decay rate**

We include increasingly longer time horizon in the calculation of *RiskSal* and the corresponding instrument. The baseline specification includes 21 years. For each version, we estimate the baseline IV specification with year×office fixed effects and retain the coefficient.

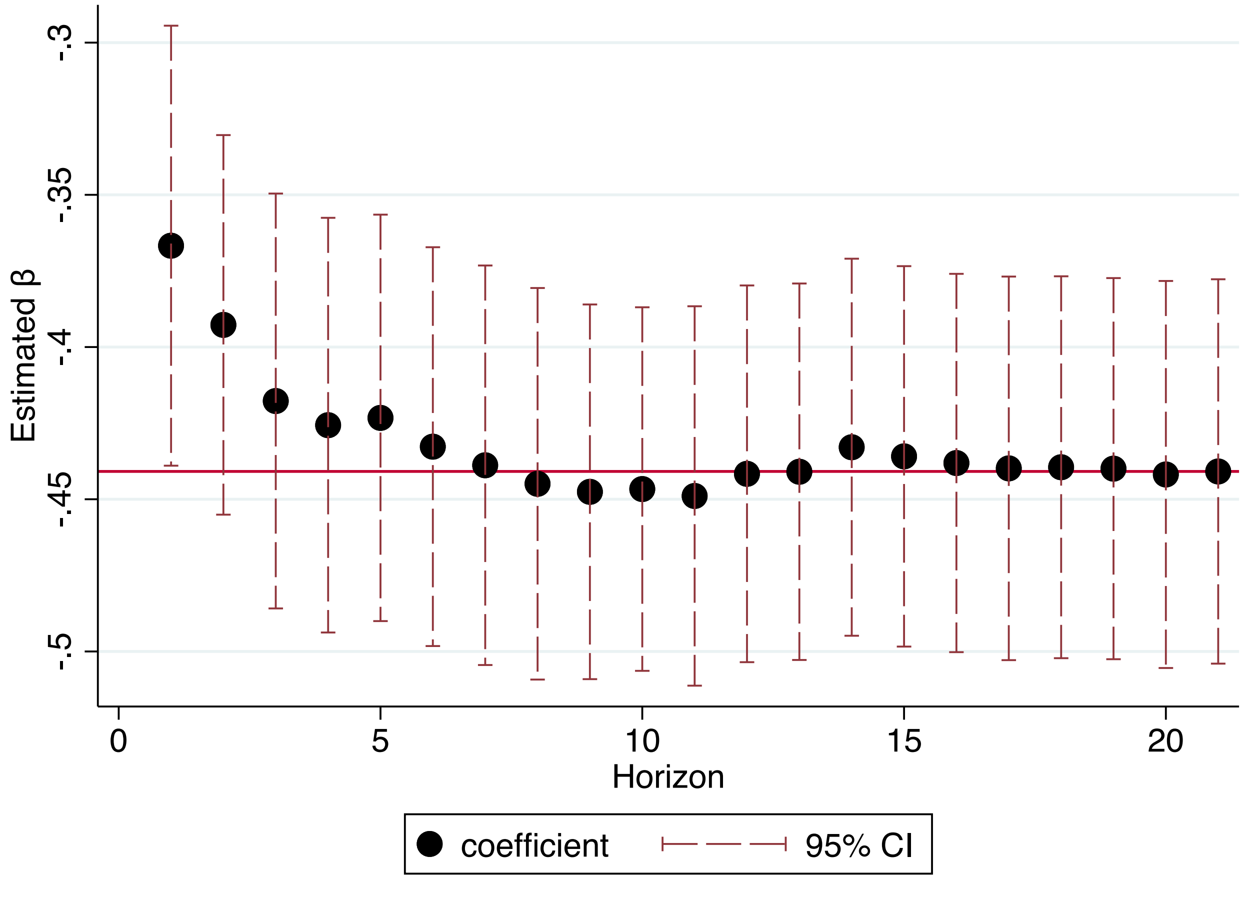


Figure A.5: **Impact of risk salience on loans, by industry**

We re-estimate the baseline IV specification with year×office fixed effects (similar to Table 3, Panel B, column 2), separately for each 2-digit NAICS industry. We then plot the coefficient from the second stage on our main independent variable, $\widehat{RiskSal}$.

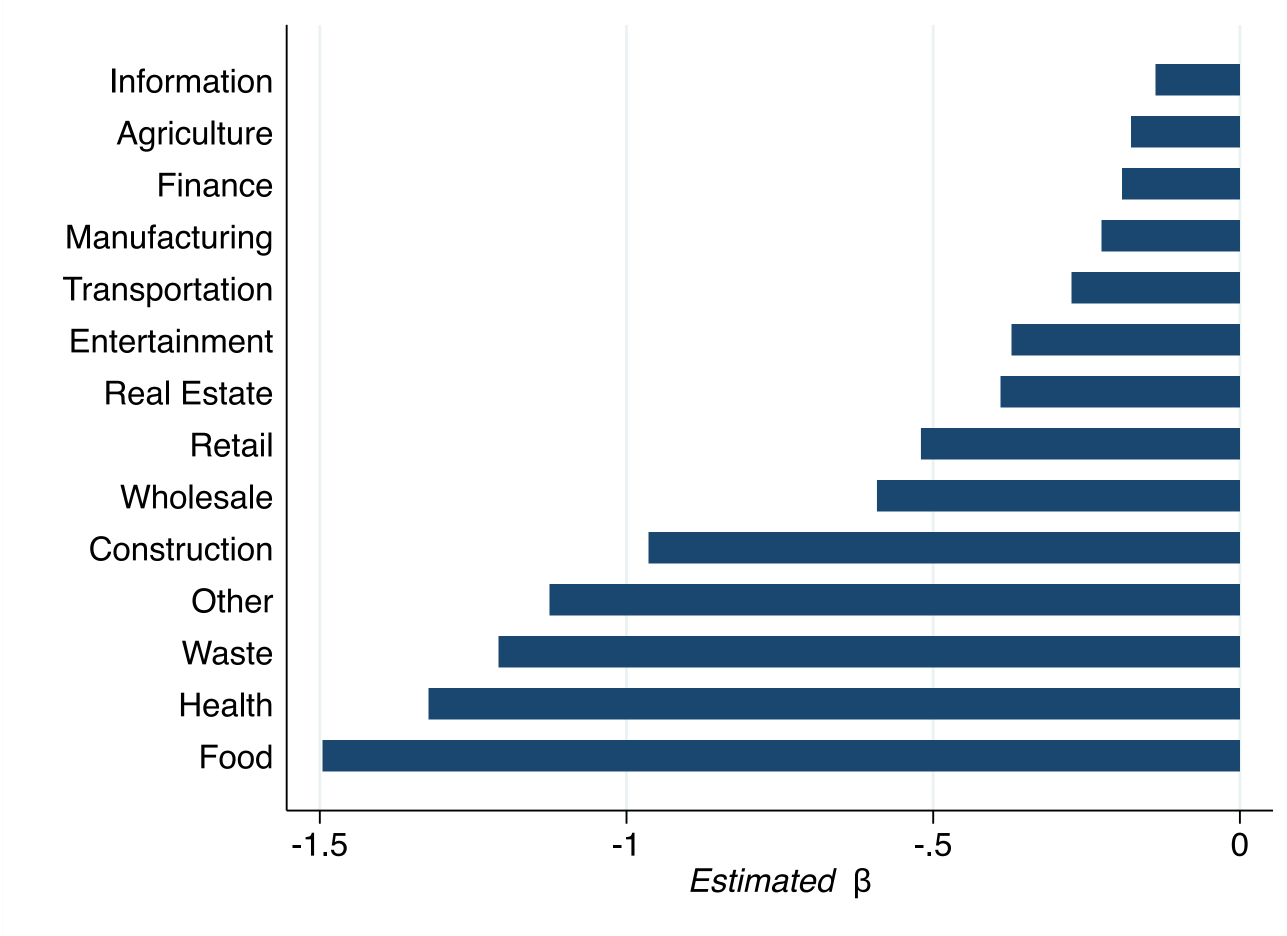


Table A.1: **IV approach: First stage**

Results from the first stage (Equation (5)). *RiskSal* reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). $RiskSal^{far}$ is based on default rates of industry i which occurred at least $1,000$ miles away from office o. Controls include employment and establishments by industry i within office o's jurisdiction (*EmpShare* and *EstabShare*). All variables are calculated at the year×office×industry level based on 3-digit NAICS codes. We report the Kleibergen-Paap $F-$statistic for weak identification. See Section 3.3.

Outcome:	*RiskSal*			
$RiskSal^{far}$	0.107***	0.113***	0.113***	0.114***
	(0.004)	(0.004)	(0.004)	(0.004)
Obs.	50,598	50,598	46,837	46,778
R^2	.85	.893	.923	.927
$F-$statistic	618	697	712	684
Controls	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y
Year FE	Y	-	-	-
Year×Office FE	-	Y	-	-
Year×Office×NAICS2 FE	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y

Table A.2: **Defaults and office dynamics**

Results from estimating Equation (A.1) in the cross-section of SBA offices. *Inbounbd* is the number of new employees, *Outbound* is the number of employees leaving the office, *Turnover* is the sum of *Inbounbd* and *Outbounbd*, *Salary* is the average salary in the office, $\Delta Salary$ is the average pay raise, and *Promotions* is number of promotions. *Inbounbd*, *Outbound*, *Turnover*, and *Promotions* are scaled by beginning-of-period number of office employees. $Default_{t-1}$ is the number of defaults on SBA loans, lagged by one year. We also control for the lagged office size (number of employees). See Section 5.1.1.

Outcome:	*Inbound*	*Outbound*	*Turnover*	*Salary*	$\Delta Salary$	*Promotions*
$Default_{t-1}$	-0.011***	-0.006	-0.017**	-0.007	-0.016	-0.045**
	(0.003)	(0.007)	(0.008)	(0.018)	(0.011)	(0.018)
Controls	Y	Y	Y	Y	Y	Y
Office FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	1635	1635	1635	1407	1325	1635
R^2	0.103	0.093	0.140	0.750	0.297	0.219

Table A.3: **Additional descriptive statistics**

Panel A. Employee statistics. Employee-level information on the Small Business Administration's workforce, 1998-2019. *Salary* is adjusted base pay (in 2017 USD), *Tenure* is the number of years the employee has worked at the SBA, $I(Bonus) = 1$ if the employee received any cash bonus, and *Bonus* is the bonus in 2017 USD (conditional on $I(Bonus) = 1$). In 2010-2016, the bonus program was suspended and thus $I(Bonus)$ and *Bonus* are blank. $Relocated = 1$ if the employee worked in another office in the previous year, and $Relocated^{past} = 1$ if the employee ever worked in another office before. Similarly, $Relocated_{Far} = 1$ if the employee worked in a far office ($> 1,000$ miles) in the previous year, and $Relocated^{past}_{Far} = 1$ if the employee ever worked in a distant office before; $Relocated_{State} = 1$ if the employee worked in a different state in the previous year, and $Relocated^{past}_{State} = 1$ if the employee ever worked in a different state before. Appendix A.3.

	Mean	Median	SD	Min	Max	Obs
$Salary$	82,516	77,361	34,435	20,545	208,637	96,471
$I(Bonus)$	0.35	0.00	0.48	0.00	1.00	78,136
$Bonus$	1,222	1,023	1,468	6	69,491	27,011
$Tenure$	14.24	12.00	10.96	1.00	62.00	96,534
$Relocated$	1.89	0.00	13.63	0.00	100.00	88,196
$Relocated^{past}$	9.22	0.00	28.93	0.00	100.00	96,535
$Relocated_{Far}$	0.62	0.00	7.87	0.00	100.00	87,069
$Relocated^{past}_{Far}$	3.30	0.00	17.86	0.00	100.00	96,535
$Relocated_{State}$	1.61	0.00	12.60	0.00	100.00	87,947
$Relocated^{past}_{State}$	7.92	0.00	27.00	0.00	100.00	96,535

Panel B. Office statistics. Office-level information on the Small Business Administration's workforce, 1998-2019. *Employees* is the number of employees. *Salary* is the average adjusted base pay (in 2017 USD), *Tenure* is the average number of years the employee has worked at the SBA, $I(Bonus)$ is the fraction of employees receiving cash bonus, and *Bonus* is the average bonus in 2017 USD (conditional on $I(Bonus) > 0$). In 2010-2016, the bonus program was suspended and thus $I(Bonus)$ and *Bonus* are blank. $I(Relocate) = 1$ if at least one employee worked in another office at any point in the past. Conditional on $I(Relocate) = 1$, we report the number (*Relocate* (#)) and fraction (*Relocate* (%)) of employees who relocated at any point in the past, and the cumulative number of relocations (*Relocations*). Similarly, $I(Relocate^{far}) = 1$ if at least one employee worked in another office located more than 1,000 miles away at any point in the past. Conditional on $I(Relocate^{far}) = 1$, we report the number ($Relocate^{far}$ (#)) and fraction ($Relocate^{far}$ (%)) of employees who relocated from distant locations at any point in the past, and the cumulative number of distant relocations ($Relocations^{far}$). See Appendix A.3.

	Mean	Median	SD	Min	Max	Obs
Employees	54	19	142	1	2,380	1,774
Salary	84,993	84,333	12,561	46,983	131,958	1,774
$I(Bonus)$	43.96	50.00	38.21	0.00	100.00	1,450
Bonus	1,063	1,058	541	87	5,263	948
Tenure	17.77	17.94	5.48	1.00	48.00	1,774
$I(Relocate)$	74.07	100.00	43.84	0.00	100.00	1,774
Relocate (%)	15.71	11.43	15.25	0.42	100.00	1,314
Relocate (#)	6.77	3.00	13.63	1.00	119.00	1,314
Relocations	8.66	4.00	17.13	1.00	129.00	1,314
$I(Relocate^{far})$	42.33	0.00	49.42	0.00	100.00	1,774
$Relocate^{far}$ (%)	7.93	6.45	6.35	0.31	44.44	751
$Relocate^{far}$ (#)	5.04	2.00	9.35	1.00	71.00	751
$Relocations^{far}$	4.24	2.00	8.18	1.00	66.00	751

Table A.4: **The role of individual SBA employees**

We obtain the list of all SBA job openings between 2017-2020 and match each position to its verbal description on USAJobs.gov, the official job portal of the Federal government. Below are representative quotes from USAJobs.gov for five common SBA positions, describing the duties and responsibilities associated with each position. See Section 3.4.

Position	**Duties**
Business opportunities specialist	Building effective relationships with a portfolio of small business CEOs; Gaining awareness of the needs, goals and challenges faced by firms and recommending options and solutions; Public speaking is required to conduct or participate in training and outreach activities; Provide training and entrepreneurial coaching to small businesses regarding federal socioeconomic government contracting programs requiring certification; Provide assistance with small businesses, procuring entities, collaborative partners, resource partners and the general public regarding SBA programs and services; Reviews firms' annual business plans and assists with increasing revenue and business development
Economic development specialist	Building and maintaining a local network of collaborative partnerships with small business stakeholders, such as [...] chambers of commerce, business associations, small business lending programs, educational institutions, and civic/community organizations; Conduct community outreach events and small business presentations; Advise and counsel small businesses and individuals that contact SBA directly for assistance; Develop relationships with SBA resource partners that build skills and capacity toward economic development
Lender relations specialist	Market all SBA lending programs and service through outreach and marketing; Conduct outreach, training, education, development, lender recruitment, consultation and working with assigned lenders in the district; Conduct face-to-face visits with individual lending institution for the purpose of delivering SBA loan programs and services in the district; Conduct or participate in training sessions designed to ensure SBA programs and services are optimized in the various financial organizations served by the district; Provide assistance through consultative and customer interactions with lenders

Position	**Duties**
Outreach & marketing specialist	Marketing SBA programs and services through outreach, training, and education to various organizations and small business; Participate in outreach, training, education, development, lender recruitment, and consultations with all lenders in the district; Support senior specialists in collaborative alliances and partnerships with resource partners, economic development organizations and small business owners; Assist in monitoring co-sponsorships
Area director	Review market research on the economic environment and perform extensive analysis of the data in market focus areas; Represent the agency at significant engagements such as media events, tradeshows, workshops, etc.; Support the successful accomplishment of events [...] and the development of partnerships with [...] community organizations; Build and maintain a viable network of collaborative partnerships with small business stakeholders; Provide assistance to small businesses through consultative and customer interactions with lenders, small businesses, procurement officials, collaborative partners and the general public

Table A.5: **Offices with high turnover rates**

For each of the SBA's local offices, we calculate the annual turnover rate: number of employees transferring in and out of the office during the year (regardless of the distance between the new and the old office), scaled by the number of employees in the office at the beginning of the year. We then take the average turnover across all years, and list the 10 offices with the highest and lowest turnover rate. We also report the number of employees (averaged across all years). See Appendix A.3.

Office Name	**Turnover (%)**	**Employees**
Top-10:		
Richmond District Office	15.0	145.57
Nevada District Office	9.3	17.39
North Florida District Office	9.0	88.61
Lubbock District Office	7.7	12.83
Houston District Office	7.3	44.09
Los Angeles District Office	7.1	54.48
San Diego District Office	6.9	21.35
South Florida District Office	6.7	49.05
North Carolina District Office	6.4	38.91
Arizona District Office	6.2	25.65
Bottom-10:		
Colorado District Office	2.3	142.26
Washington District Office	2.2	785.87
Michigan District Office	2.1	35
Alabama District Office	2.1	69.78
Nebraska District Office	2.0	14.17
Dallas / Ft Worth District Office	2.0	774.87
North Dakota District Office	2.0	12.96
Des Moines District Office	1.6	13.83
Syracuse District Office	1.5	15.09
Vermont District Office	.7	11.22

Table A.6: **IV approach: Reduced form**

A reduced-form regression of Equation (4). We replace the main independent variable ($RiskSal$) with the instrument ($RiskSal^{far}$), which is the component of risk perception driven only by distant locations. Controls include employment and establishments by industry i within office o's jurisdiction ($EmpShare$ and $EstabShare$). See Appendix A.4.

Outcome:	*Loans*				*Dollars*			
$RiskSal^{far}$	-0.042***	-0.050***	-0.043***	-0.039***	-0.039***	-0.046***	-0.040***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	50,598	50,598	46,837	46,778	50,598	50,598	46,837	46,778
R^2	.886	.887	.926	.95	.774	.775	.852	.884
Effect	-0.153	-0.180	-0.160	-0.145	-0.141	-0.166	-0.148	-0.138
Effect (%)	-9.8	-11.5	-10.9	-9.9	-9.1	-10.7	-10.0	-9.3
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	-	-	-	Y	-	-	-
Year×Office FE	-	Y	-	-	-	Y	-	-
Year×Office×NAICS2 FE	-	-	Y	Y	-	-	Y	Y
Year×NAICS3 FE	-	-	-	Y	-	-	-	Y

Table A.7: **Alternative identification: Multi-office lending**

Results from estimating Equation (A.3). The dependent variables are calculated at the year×office×NAICS3×county level. $I(Loan) = 1$ if industry i in county c received any SBA loan guarantee from office o. *Loans* (*Dollars*) is the number (dollar value) of SBA loan guarantees by office o to industry i in county c to county c. *RiskSal* reflects how salient are the defaults of industry i in the eyes of office o, as defined in Equation (3). *RiskSal* is calculated at the year×office×NAICS3 level and does not vary across counties. Controls include the number of employees by industry i in county c, out of total employees in county c. It is calculated at the year×county×NAICS3 level and does not vary across offices. We report the effect of one-standard-deviation increase in *RiskSal* (standard deviation times coefficient divided by the mean of the independent variable).

Outcome:	$I(Loan)$		$Loans$		$Dollars$	
	(1)	(2)	(3)	(4)	(5)	(6)
RiskSal	-0.253***	-0.044***	-0.990***	-0.844**	-0.901***	-1.328**
	(0.004)	(0.013)	(0.044)	(0.403)	(0.089)	(0.620)
Obs.	134,258	17,146	134,258	17,146	134,258	17,146
R^2	0.653	0.841	0.851	0.598	0.769	0.571
Effect (%)	-11.2	-5.2	-10.3	-9.3	-8.7	-12.3
Controls	Y	-	Y	-	Y	-
Office×NAICS3×County FE	Y	Y	Y	Y	Y	Y
Year×NAICS3 FE	Y	-	Y	-	Y	-
Year×County×NAICS2 FE	Y	-	Y	-	Y	-
Year×County×NAICS3 FE	-	Y	-	Y	-	Y

Table A.8: **Aggregate risk-salience**

Results from the second stage of the 2-SLS framework (Equation (6)). The variables are calculated at the year×office level (Equation (A.4) and Equation (A.5)). *Loans* (*Dollars*) is the number (value in thousand USD) of SBA guarantees by office o; *Employment* is number of jobs supported; New^{1-4} is number of new small establishments (<5 employees); $Defaults^{\#}$ ($Defaults^{\$}$) is the number (value in thousand USD) of defaulting SBA loans; and *Losses* is the SBA's loss due to those defaults (in thousand USD). *RiskSal* reflects how salient are defaults of all industries in the eyes of the employees of office o, and the instrument is based on defaults which occurred at least $1,000$ miles away from office o. Controls include number of employees and average tenure in office o. We report the Kleibergen-Paap $F-$statistic for weak identification. See Appendix A.4.

Outcome:	*Loans*	*Dollars*	*Employment*	New^{1-4}	$Defaults^{\#}$	$Defaults^{\$}$	*Losses*
$\widehat{RiskSal}$	-1,306.0***	-190,457.2***	-9,566.1***	-3,536.4***	-267.5***	-21,604.0***	-15,151.3***
	(146.5)	(39,369.4)	(1,487.0)	(491.0)	(69.4)	(6,540.3)	(5,481.7)
Obs.	837	837	837	835	837	837	837
$F-$statistic	676	676	676	672	676	676	676
Effect	-249.9	-36,441.9	-1,830.4	-662.5	-51.2	-4,133.7	-2,899.0
Effect (%)	-26.6	-17.5	-20.2	-86.2	-38.3	-30.7	-29.4
Controls	Y	Y	Y	Y	Y	Y	Y
Office FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y

Table A.9: **Quantities as outcome variables**

We estimate our baseline IV specification with year×office×NAICS2 FE and the following outcomes: $Loans^{raw}$ ($Dollars^{raw}$) is the number (value in constant 2020 thousand USD) of SBA guarantees; $Loans^{raw}_{504}$ ($Dollars^{raw}_{504}$) are similar outcomes but for the 504 program; *Employment* is number of jobs supported; New^{1-4} is number of new small establishments (<5 employees); $Defaults^{\#}$ ($Defaults^{\$}$) is the number (value in constant 2020 thousand USD) of defaulting SBA loans; *Losses* is the SBA's loss due to those defaults (in constant 2020 thousand USD).

Outcome:	$Loans^{raw}$	$Dollars^{raw}$	$Employment$	New^{1-4}	$Defaults^{\#}$	$Defaults^{\$}$	$Losses$	$Loans^{raw}_{504}$	$Dollars^{raw}_{504}$
$\widehat{RiskSal}$	-4.2***	-842.5***	-37.8***	-12.0***	-0.9***	-77.4***	-66.0***	-1.8***	-1,257.7***
	(0.6)	(151.5)	(4.9)	(3.4)	(0.3)	(19.3)	(18.3)	(0.2)	(109.9)
Obs.	50,598	50,598	50,598	50,598	50,598	50,598	50,598	21,755	21,755
$F-$statistic	697	697	697	697	697	697	697	1,016	1,016
Effect	-1.8	-360.2	-16.2	-5.1	-0.4	-33.1	-28.2	-0.4	-297.2
Effect (%)	-12.5	-11.2	-11.9	-57.3	-19.9	-17.4	-17.7	-16.3	-18.0
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Office×NAICS3 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year×Office×NAICS2 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table A.10: **SBA relocations and social connections**

The variables are calculated at the county×county level. *SCI* is the Social Connectedness Index from Bailey et al. (2018), representing the Facebook connections between each two counties. The independent variables are based on SBA relocation data, aggregated over the sample period: an indicator if a link exists (for example, if at least one employee worked in both Boston and Chicago); raw count of links (the number of employees who worked in both Boston and Chicago); and the raw number scaled by the product of the total number of employees in the two offices (analogous to SCI). Odd-numbered columns include all county pairs, while even-numbered columns include only pairs which are more than 1,000 miles apart. Controls are the distance between the two counties. See Appendix A.7.

Outcome:	*SCI*					
	(1)	(2)	(3)	(4)	(5)	(6)
$Links > 0$	0.037***	0.012***				
	(0.004)	(0.002)				
$No.of Links$			0.001***	0.000*		
			(0.000)	(0.000)		
$ScaledNo.of Links$					564.694***	314.647***
					(68.350)	(89.892)
Obs.	3,240	1,647	3,240	1,647	3,240	1,647
Controls	Y	Y	Y	Y	Y	Y
R^2	0.119	0.074	0.099	0.034	0.222	0.038