Technology in the Banking Sector and the Importance of Modern Skills

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Abstract

This paper examines technology adoption and individual career progression of technically-skilled employees in the banking sector. We leverage detailed employer-employee data on individual worker skills to capture (i) the technical skills of each employee, (ii) firm-level technical capital, and (iii) a novel methodology to systematically measure vintages of technical skills, differentiating older technical skills (e.g., Fortran) from newer technical skills (e.g., Python). Banks dramatically increase their technology investments during the 2010s, with an average bank's technical capital growing by 84%. This increase is ubiquitous across bank size, deposits, and loan portfolio composition. At the individual level, we document a significant difference between employees with modern technical skills and those with outdated technical skills. Having modern technical skills in 2015 decreases the likelihood of adverse career outcomes (such as job separations accompanied by demotions) by 2020 by 2.7%. These effects are especially pronounced for older workers. For employees over 40, having modern technical skills reduces the probability of job separations with demotions by 3.9%. These results highlight the interaction between employee age and skill vintage, with important policy implications for workforce reskilling in the face of advancing new technologies.

Keywords: technological investment, reskilling, banking, modern skills, human capital, future of work

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1 Introduction

Advances in technology are major drivers of both firm performance and workforce changes. In recent years, technological advances including aumation and artificial intelligence (AI) have lead to changes in workforce composition (Babina et al., 2023), increases in firm valuations (Eisfeldt et al., 2023), and brings productivity improvements in certain tasks (Brynjolfsson et al., 2023). At the same time, technical skills can become over-hyped due to fads (Fedyk and Hodson, 2023b), and recent technological waves have potentially put at risk more high-skilled and even technically-skilled labor.[1] Our paper takes a granular look at investment into technically-skilled employees in an important knowledge economy sector—banking—and offers a novel perspective on the types of technical skills that insulate workers from displacement over time.

We document a ubiquitous increase in technical workforces across banks, where characteristics such as size and loan portfolio composition are associated with more technical workforces both at the beginning and the end of the sample, but all banks experience similar *changes* over time. Looking at individual employees, we find that an important predictor of their success is not so much the presence of technical skills as its *vintage*. Employees with older technical skills are much more likely to become obsolete (face job separations and demotions), while employees with new technical skills are insulated from these effects. Finally, we uncover an important interaction between the age (vintage) of technical skills and the age of the employee: the importance of modern skills is, empirically, far greater for older workers than for younger ones.

The setting we focus on—financial services, and specifically banking—has several advantages. First, finance is predominantly service-oriented and comprised of white-collar jobs, making it an ideal setting to capture displacement of white-collar workers in the mod-

[1] Much of the prior literature has focused on the effects of automation technologies, such as robotics, on menial labor and blue-collar workers in industries such as manufacturing (Acemoglu and Restrepo, 2020; Benmelech and Zator, 2022). Less is known about the impact of technology on high-skilled white-collar labor.

ern knowledge economy. Second, banks have been among the first sectors to adopt new technologies such as artificial intelligence (AI) within the workforce, making them an early adopter where we can observe more long-standing effects. Empirically, there is still limited systematic evidence on the effects of new technology waves on the banking sector. Crosman (2018) suggests that the majority of bankers, especially those beyond entry-level positions, are not worried about replacement, and Jakšič and Marinč (2018) posit that the intrinsic relationship nature of banking will make it difficult for human bankers to be completely replaced by technology. Kaya (2019) warns of the major impacts of technologies such as AI in banking but points out the difficulty of quantifying technology adoption within banks, and Seamans and Raj (2018) and Frank et al. (2019) further highlight the lack of readily available firm-level datasets.

We overcome previous data limitations by taking advantage of detailed employer-employee matched data, from which we can identify both: (i) a variety of technical skills and (ii) granular shifts in labor composition. Our primary dataset comes from Cognism, Inc., a firm specializing in client relationship management, which tracks individual companies and employees, offering granular information on approximately half a billion individual employees. Using these data, we are able to match more than half of all U.S. bank employees in 2020. We supplement this dataset with a second data captured back in 2015 and utilized in (Mukharlyamov, 2022). This allows us to track the *same* workers in both 2020 and 2015 and observe how individual workers' subsequent career progressions depend on their starting skills back in 2015.

We introduce two novel measures of technical skill: (i) its level (advanced coding, basic coding, and off-the-shelf software use) and (ii) its vintage (modern vs. outdated). For the first measure, we manually classify the most frequent skills into one of four categories: (i) not technical (this includes skills such as *management, teamwork*, and *PowerPoint*); (ii) using off-the-shelf software (e.g., *business intelligence tools* or *Microsoft Excel*); (iii) basic coding (e.g., skills in *Visual Basic .NET* or *linear regression*); and (iv) advanced coding (i.e., knowledge of *C++, Java, Python*, etc.). For the second measure (skill novelty), we leverage data from Google Trends to identify which skills are increasing in coverage and popularity, and which are on the decline. For each technical skill reported by employees in 2015, we compare Google searches for that skill during the years 2010–2015 against Google searches for that skill during the years 2004–2009, taking the relative increase. Skills in the top quartile of the distribution based on this increase are labeled as "modern technical skills," whereas skills in the bottom quartile are deemed to be "old technical skills." For example, Android, Cloud Computing, Git, jQuery, and SSRS are identified as modern technical skills based on our measure, while COBOL, HTML, Linux, Perl, and VBScript are identified as old technical skills.

Our measure of vintages of technical skills is new in the literature on technological change. The literature has examined which tasks are most susceptible to automation. A substantial body of work has examined skill-biased technological change (Autor et al., 1998; Acemoglu, 2011). Others have studied diffusion of various technologies (Bloom et al., forthcoming), identified high-value and breakthrough technologies (Kogan et al., 2017; Kelly et al., 2021), and measured the varying effects from technological change on workers of different skills, educational backgrounds, and seniority (Babina et al., 2023). Yet the vintage of employee skills—its novelty, or staleness—is an important aspect of labor resilience that has been understudied in the past. Our paper proposes a direct measure of skill vintage and find it to be an important determinant of employees' career outcomes, which interacts with other characteristics such as employee age.

Our first empirical contribution is to provide a characterization of technical employees across banks. We show that employees with technical skills tend to be younger (median birth year in 1982 among those with at least some advanced coding abilities, compared to 1979 for those with all non-technical sills). At the same time, technical employees are more educated, with 28.2% (4.7%) of employees with advanced coding skills holding masters (doctorate) degrees, compared to only 11.9% (3.8%) of those without technical skills. In terms of educational specialization, the vast majority (80.2%) of employees with advanced coding skills hold STEM degrees, with most having at least one degree in computer science (45.6%) or engineering (36.8%). Employees with advanced coding skills are also more likely to hold degrees from elite education institutions (top one hundred schools from the U.S. News & World Report), with 15.2% (6.2%) of them holding a bachelors (masters) degree from an elite institution, compared to 10.4% (1.6%) of employees without technical skills.

We supplement the descriptive analysis of banks' technical talent with time series trend of the share of technical workers in banks over the course of the decade. There is a monotonic increase in the share of technically-skilled employees hired in each year: for example, the share of employees with advanced coding skills rises from 5.5% of those hired up-to-2010 to 11.3% of the cohort hired in 2015 to 16.3% of those hired in 2019 onward. The difference from the first half of the decade (2015 and earlier) to the second half of the decade (2016 onward) is highlight statistically significant.

We next conduct a firm-level analysis to examine cross-sectional differences in the extent to which different banks invest in technical workforces. We document that larger banks have substantially higher shares of technically-skilled workers, and technical workforce is strongly related to banks' loan portfolio composition. For example, the median share of employees with advanced coding skills is 15.5% at the largest banks (with over $1 trillion in assets), halves to 7.2% in banks whose assets are between $100 billion and $1 trillion, declines dramatically to 2.5% in medium-sized banks with $10-100 billion in assets, and drops to a mere 1.6% (0%) in small banks with assets of $3–$10 billion (less than $3 billion). The pattern is similar if we use deposits per branch as a measure of bank size instead of total assets. In terms of loan portfolio composition, banks with higher shares of consumer loans tend to employee substantially more technical workforces. For example, the average (median) share of employees with advanced coding skills is 15.4% (2.5%) in the top quartile of banks based on household-facing loans, compared to 9.5%–11.8% (1.3%–1.8%) in the other four quartiles of banks. In terms of changes over time, the increase in technical talent is ubiquitous across bank size (asset), deposits per branch, and loan portfolio composition. Larger banks (and banks with more consumer-facing loans) tend to hire more technical workers, but this seems to be equally the case at the beginning of the decade and the end.

In the second part of our paper, we turn to the individual employee level data (including the point-in-time skills from the 2015 data snapshot) in order to understand how employees' existing skills impact their subsequent career progression. First, we document that modern technical skills reported on employees resumes as of 2015 are associated with better career progression from 2015 to 2020. the outcome variables we consider are promotions (increasing seniority by at least one or at least two ranks), overall employer changes, and voluntary versus involuntary employer changes (those accompanied by promotions vs. demotions). In general, technical employees in banks have slower promotions than business-oriented employees, since the latter are the core function of financial institutions. However, employees with *modern* technical skills do as well as business-oriented employees and much better than their counterparts with outdated technical skills.

Second, zooming in specifically involuntary separations (with demotions) of technically-skilled employees, we document an interesting complementarity between skill vintage and employee age. In the overall sample (not sliced by age), employees with modern technical skills (those in the top quartile of the distribution based on their average skill novelty) are 2.74% (1.19%) less likely to experience a job separation accompanied by a demotion of at least one rank (two ranks), compared to employees with middling-vintage technical skills. On the other hand, employees with the most outdated skills (the bottom quartile based on average skill novelty) are 0.50% (0.68%) more likely to experience job changes with demotions of at least one rank (two ranks) than employees with technical skills of middling vintage. This pattern is starker for older employees: for example, the top quartile of modern skill vintage is associated with a 1.43% reduction in job separations with demotions of at least one rank among employees under 33, 2.55% reduction among employees aged 33–40, and 3.92% reduction among employees aged over 40. We find similar effects when we focus the sample on those banks that have layoffs (e.g., headcount reduction of 10% of more).

The importance of skill novelty and its relationship with employee age is specific to technical skills. When we repeat the analysis with soft skills, we do not observe the same patterns. In fact, more modern soft skills are associated with worse career progressions, as they tend to be more vague concepts (e.g., customer experience and multi-tasking) than older-vintage soft skills (e.g., personnel management and public relations). There is also no clear interaction between social skill vintage and employee age in jointly determining career outcomes. The analysis of social skills serves as a useful counterpoint and placebo test for our key results on modern technical skills.

Our paper contributes a novel angle to the long-standing literature on skill-biased technological change (Autor et al., 1998; Acemoglu, 2011) and the emerging literature on how new technologies might impact high-skilled white collar workers, as opposed to the menial workers affected by prior waves of automation (Grennan and Michaely, 2019; Fedyk et al., 2022; Cao et al., 2024). Thanks to our measure of skill vintages, we are able to speak to the importance of upskilling even *within* a skill category (modern technical skills vs. outdated technical skills) and the complementarity between skill age and employee age. As a result, our approach and findings have important implications for policy regarding workforce upskilling in the face of firms' technology adoption: the most important aspect is to keep *technical* workers up to date on modern technology, while less time-sensitive skills such as social skills are less dependent on novelty.

The remainder of the paper proceeds as follows. We describe the data in Section 2. Section 3 describes our novel measures of skill levels and vintages. Section 4 presents descriptive statistics on technical employees in the financial services industry and analyzes how the composition of banks' human capital changed over time, including how investments in technology vary across banks. Section 5 presents out main empirical analysis relating employee-level career progressions to technical skills, skill novelty, and the interaction between skill vintage and employee age. Section 6 concludes.

2 Data

We provide a description of our matched employer-employee data, outline the steps we take to match these data to auxiliary datasets such as Call Reports, and detail additional datasets used in the analysis, including Google Trends data.

2.1 Individual Employee Data

We identify and track individual bank employees using two datasets: (i) a snapshot of resumes of bank employees in 2020 and (ii) a snapshot of LinkedIn profiles of bank employees in 2015. We use the former dataset to examine the changes in banks' hiring from 2010 to 2020. We use the latter dataset to investigate how individual-level outcomes in later years vary based on employees' skills back in 2015.

The 2020 dataset comes from a unique archive of approximately 490 million individual resumes provided by Cognism, a platform for sales leads and customer relationship management. Cognism compiles its dataset from third party partnerships, partner organizations, and publicly available online profiles.[2] The 2015 dataset was collected directly from LinkedIn back in 2015 following the procedure in Mukharlyamov (2022). We pair the two snapshots (from 2015 and 2020) by matching on identifiers such as the URL of each employee's online profile.

For each person in the data, we observe education and employment history, as well as self-reported skills, patents, publications, awards, certifications, and other information that the person chose to include on their resume. For each job reported by the person, we observe the name of the employer, job title and description, and start and end dates. Education and employment data are processed to identify granular information including types of degree and majors (for education records) and department and seniority (for employment records). The data also include the individual's gender and an approximate age derived from the individual's education history. Cognism has procedures to identify the relative seniority

[2] For more detail on the Cognism resume data, please refer to Fedyk and Hodson (2023b).

of each individual at each point in time (Fedyk et al., 2022; Fedyk and Hodson, 2023a; Babina et al., 2023; Fedyk et al., 2024). The seniority markers are identified from the job titles, using a machine learning model trained on 20,000 manually-classified job titles, and designate six categories corresponding to entry-level positions (level 1), single contributors (level 2), team leads (level 3), middle managers (level 5), heads of regional offices or specific divisions (level 5), and company-level leadership positions (level 6). The seniority markers allow us to measure individual-level outcomes such as demotions and promotions.

Our final sample is constructed as follows. We identify the 500 largest bank holding companies (BHCs) by assets as of 2020. We then look up the commercial banks (CBs) that are subsidiaries of these BHCs. To this end, we use Call Reports and identify CBs that report one of the Top-500 BHCs as their financial high holder. We supplement this classification with the pairing of CBs and BHCs in the FDIC's summary of deposits. For each bank, we identify various ways in which an employee could list that bank (either the BHC or a subsidiary CB) name on their resume, including abbreviations and subsidiaries. We retrieve from Cognism the resumes of people who reported working at the identified set of banks at any point from 2010 to 2020.[3] We then narrow down this sample to avoid false matches, since a company name does not always uniquely identify a bank, some banks in the U.S. have similar names, and Cognism might not assign different numeric IDs to organizations with the same name. In particular, we keep only those banks where the by-state distribution of deposits from the FDIC's summary of deposits resembles the by-state distribution of employees as reported in Cognism's data. Finally, each pair of resulting candidate matches is reviewed manually, correcting any erroneous matches. These steps leave us with 1,854,928 resumes of people (1,456,060 of them were employed at 479 BHCs in 2015; 1,147,849—at 446 BHCs in 2020).[4] This covers approximately 53% of all employees of these BHCs based

[3]We match company names listed in Cognism resumes to the banks by calculating the Levenshtein distance between every potential pair of names.

[4]The number of employees used in the regressions will be lower, because not all employees report skills or list educational majors—when a relevant variable is missing, we drop the observation from the corresponding analysis.

on employment numbers in the Call Reports.

The above matching is based on resumes as of 2020. Some resume information, such as job history and education, comes with date stamps. However, information on skills tends not to be dated. In order to investigate how subsequent career trajectories of banking employees vary with their skill portfolios, we match the 2020 resume dataset to the 2015 resume dataset, leading to a set of 235,979 individuals whose skills we got to observe back in 2015 (point-in-time using the 2015 dataset) and whose career trajectories we were then able to track to 2020 (using the 2020 dataset).

2.2 Other Data

We download financial information from the banks' Call Reports. Specifically, we consider banks' total assets, deposits per branch, the share of household-facing loans (calculated as the sum of residential real estate loans and consumer loans scaled by total loans), the share of nonresidential real estate loans (the share of loans secured by non-farm nonresidential properties; construction, land development, and other land loans; and loans secured by farmland scaled by total loans), and the share of commercial and industrial loans (commercial and industrial loans scaled by total loans). In order to evaluate the novelty of specific technical skills in the individual resume data, we access Google Trends data from 2004 to 2015. The Google Trends data end in 2015, since that is the point at which we measure ex ante employee skills to track subsequent career outcomes.

3 Technology Measures and Descriptive Statistics

In this section, we present our measures of technology at three levels: (i) technical classification of skills, (ii) technical classification of employees, and (iii) technical upskilling at banks (at the firm-level). We also introduce our measure of technology vintage in Subsection 3.2.

3.1 Classification of Technical Skills

We begin with the full list of self-reported skills that appear in the resumes of bank employees (a total of over 39,000 skills). We rank these skills in order of frequency and restrict our attention to those skills that appear in at least 100 individual resumes (a total of 1,033 individual skills). We manually categorize each of these 1,033 most frequent skills into four categories:

- **Non-technical skills.** This set covers 385 of the most frequent skills and includes terms such as *leadership, strategic planning,* and *advertising.*
- **Software use.** This set consists of 282 skills that indicate sufficient technical familiarity to use off-the-shelf software tools. For example, the skills *Dreamweaver, HP Quicktest Professional, web analytics, SAP,* and *Microsoft Excel* fall in this category.
- **Basic coding.** This set includes 318 skills that are technical but do not necessitate extensive knowledge of programming, such as data analysis (e.g, the skill *linear regression*) and assisted programming environments (e.g., the skill *visual basic .NET*).
- **Advanced coding.** This set consists of 48 actual programming languages, encompassing individual skills such as *C++, C,* and *Python.*

3.2 Technology Vintages

For each technical skill (i.e., skills in the "software use," "basic coding," and "advanced coding" categories), we also consider whether the skill is relatively new (e.g., *Python*) or older and potentially obsolete (e.g., *Fortran*).

We measure skill vintages using Google Trends. Specifically, we observe the incidence of Google searches corresponding to each skill in the 2015 dataset and divide the average incidence during the years 2010–2015 by the average incidence during the years 2004–2009. This gives a growth multiple for each skill. The novelty score of each skill is the percentile (from 0 to 1) of that skill's growth multiple in the distribution of growth multiples across all technical skills. Skills with no captured Google searches in 2004–2009 are assigned the top percentile. Finally, our discrete measure of "modern skills" is an indicator variable equal to one for skills in the top quartile of the distribution of novelty scores based on Google Trends, and zero otherwise. Similarly, the indicator "old skills" is equal to one for the bottom quartile of the distribution of novelty scores based on Google Trends, and zero otherwise.

The vintages of employees' technical skills proposed in this paper offer a novel measure in the literature. Much has been said about the importance of technical skills for firms and workers, and about the displacement of human labor with technology. However, there is little empirical investigation of the *interaction* between technology and potential displacement: how not all technical skills are the same, and even technically-skilled employees may be at risk of displacement—if their skills are outdated. We compute the vintages for the 670 technical skills in the data, as well as for soft skills, which we use as a placebo comparison set. The 2,840 soft skills are identified from the top 10,000 skills listed on individual 2015 resumes using generative AI (specifically, OpenAI's GPT4 model).[5]

Panel A of Table 1 shows the association between the novelty of the technical skills and employee age. Younger employees tend to have more modern technical skills. For example, employees under 25 have technical skills with an average novelty score of 0.51, compared to 0.49 for employees aged between 31 and 35 and 0.46 for those aged over 50. Panel B of Table 1 shows the association between the novelty of employees' technical skills and bank size. There is no strong association between bank size and the novelty of employees' technical skills.

3.3 Technical Employees

After classifying each skill as described above, we next classify each individual employee—based on the skills listed on that employee's profile.

[5]For the use of generative AI to tag data, see Eisfeldt et al. (2023) and Kakhbod et al. (2024), among others.

First, we assign each employee a binary classification for each type of technical skill. Specifically, $AdvancedCoding_i$ is an indicator variable equal to one if employee i has at least one advanced coding skill. Thus, someone who reports both *leadership* and *C++* would be classified as having advanced coding capability. Similarly, $BasicCoding_i$ is an indicator variable equal to one if employee i has at least one basic coding skill (e.g., *visual basic*). The indicator variable $Software_i$ is equal to one if employee i is able to use at least one off-the-shelf software, for example, the *Bloomberg* terminal.

Second, we consider the vintages of each employee's technical skills and construct two indicator variables. $ModernCoding_i$ is set to one if employee i has at least one coding skill (either basic or advanced) that is considered modern based on Google Trends. Similarly, $ModernSoftware_i$ is equal to one if employee i is able to use at least one modern off-the-shelf software tool.

Third, we construct technical skill variables that combine the advanced coding, basic coding, and software categories. $Coding_i$ is set to one for any employee i with *either* at least one advanced coding skill *or* at least one basic coding skill. *Tech Capital (a)* is the sum of the indicators $AdvancedCoding_i$, $BasicCoding_i$, and $Software_i$. *Tech Capital (b)* gives more weight to more advanced technical skills and ranges in value from 0 to 6, computed as follows: $AdvancedCoding_i \times 3 + BasicCoding_i \times 2 + Software_i$.

Finally, for each individual employee we also consider their college major (three indicators for whether the employee has a degree in STEM, Humanities, or Social Sciences), whether the employee has a college degree, whether the employee has at least one graduate degree (Masters, J.D., or Ph.D.), and whether the employee has any degree from a Top-100 University according to the US News & World Report. We also compute each employee's tenure and seniority (on a scale of six levels from entry-level to senior leadership) at the employee's current job at each point in time.

Table 2 presents the descriptive statistics of bank employees and their technical skills across age and educational attainment. Panel A shows the age profile of employees in each skill category. Technical employees tend to be younger than non-technical employees, with employees who know at least one advanced programming language being, on average, 3.5 years younger than employees with no technical skills at all.

Technically-skilled employees also tend to hold more technical and more advanced educational degrees. Panels B and C of Table 2 consider educational attainment, with breakdowns across degree types and majors, respectively. Employees with advanced coding capabilities are the most likely to hold both Doctorate and Masters degrees, as can be seen from Panel B. For example, the incidence of (non-MBA) Masters degrees is 28.2% among advanced coding employees, compared to 18.4% among employees with basic coding skills, 14.0% among employees who only use off-the-shelf software tools, and 11.9% among non-technical employees.

Technically-skilled employees are also more likely to hold degrees in technical fields, as shown in Panel C. Accounting for multiple majors, 80.2% of employees with advanced coding skills hold at least one STEM degree, compared to 32.7% of employees with basic coding skills, 15.0% of employees with only off-the-shelf software skills, and 9.4% of nontechnical employees. The majority of these STEM degrees are specifically in Computer Science (45.6% of advanced coding employees hold at least one degree with a C.S. major), followed by Engineering (36.8% of advanced coding employees hold at least one Engineering degree).

Finally, technical employees are more likely to graduate from prestigious institutions. Panel D of Table 2 shows that 20.8% of employees with advanced coding skills have at least one degree from an institution ranked in the top 100 by the U.S. News & World Report, compared to 17.6% of employees with basic coding skills, 14.2% of employees who use only off-the-shelf software, and 13.0% of non-technical employees.

3.4 Firm-level Measures of Banks' Technical Upskilling

To characterize technology adoption at the firm level, we consider all employees working at bank j in year t and compute the average value of each technical variable across those employees. For binary variables ($AdvancedCoding$, $BasicCoding$, $Software$, and $Coding$)

this corresponds to the proportion of employees at bank j at time t who have at least one skill from the corresponding category. For the variables *Tech capital (a)* and *Tech capital (b)*, the bank-level measure is the average of the employee-level measures.

Table 3 presents descriptive statistics of banks' technical human capital and other bank characteristics, measured in 2020. The bank-level variable *Tech Hiring Intensity* is computed as the number of tech-skilled employees (all employees with advanced coding, basic coding, or software skills) hired by the bank between 2016 and 2020, scaled by that bank's 2020 headcount. For an average bank, around 39% of all employees have at least some technical ability—either coding or software use. However, a much smaller share of bank employees, only 3%, have advanced coding skills. The mean *Tech Hiring Intensity* is 22%, meaning that for an average bank in the sample, almost a quarter of all employees in 2020 represent newly hired employees from 2016 to 2020 with at least some technical skills. In terms of educational backgrounds, the average bank has a majority of employees (77%) with business degrees, followed by humanities (21%). Only 12% hold STEM degrees.[6]

4 Banks' Technical Upskilling

We leverage our detailed data on individual bank employees' technical abilities to provide the first overview of technology investments in the banking sector. Below, we characterize the shift in the technical composition of bank employees from 2010 to 2020 and then show how this shift varies across bank characteristics such as size and loan portfolio.

4.1 Changes in Banks' Employee Composition

Table 4 examines technical abilities of individuals who are employed at the banks at the end of the sample period (2020) but were hired at different times. Panel A breaks down the workforce by joining year (annual cohorts). The results show that the incidence

[6] These numbers add up to more than 100%, because some employees hold multiple majors that can span several categories.

of technical skills among employees monotonically increases over time. For example, only 15.7% of all employees hired in 2010 or earlier had any coding ability (either advanced or basic), compared to 27.4% of those hired in 2015 and 35.2% of those hired in 2019 and later. As a result, *Technical Capital (a)* (the sum of the three technical abilities for each employee) almost doubles from 0.60 up-to-2010 to 1.15 in 2019-onward, with an even starker increase in *Technical Capital (b)*, which weighs more advanced technical skills more heavily. This increase in technical skill is accompanied by an increase in technical education: the fraction of employees who hold at least one degree in a STEM field rises from 20.5% of those joining in 2010 or earlier to 27.0% of those hired in 2015, and then to 30.0% of those hired since 2019. Interestingly, the rise in technical skills outpaces the rise in technical degrees, suggesting that even employees who do not have formal technical education, such as a B.A. in science or engineering, are becoming progressively more likely to have at least some coding abilities.

Panel B of Table 4 groups the joining dates into the earlier period (2015 or before) and the later period (2016 onward) and evaluates the statistical significance of the differences. Technical skills of employees hired from 2016 onward are significantly stronger than those of the employees hired in 2015 or earlier, along all dimensions. For example, the difference in coding abilities is 13.5% (a more than 50% relative increase over the baseline of 20.7% in the early sample). Similarly, an additional 16.9% of employees joining in the later half of the sample period have skills related to off-the-shelf software (a one-third relative increase over the baseline of 46.9% of employees having such skills in the first half of the sample period). Correspondingly, banks' technical capital increases significantly from pre-2016 to 2016 onward. *Technical Capital (a)* increases from an average of 0.75 to 1.01, while *Technical Capital (b)* increases from an average of 1.11 to 1.77. All of these changes are statistically significant at the 1% level.

4.2 Which Banks Invest in Technology?

While the banking sector in general has increased its technical workforce from 2010 to 2020, technical investments may be unevenly distributed across banks. We document substantial heterogeneity in the presence of technical employees across bank size (assets), deposits, and loan portfolio composition. However, the proportional *changes* in technical human capital is similar across different banks. Thus, all banks roughly doubled their technical human capital from 2010 to 2020, but larger banks had more technical workforces to begin with and hired more additional technical workers in absolute terms.

We begin by examining the heterogeneity in the *composition* of banks' technical workforces at the end of the sample period in 2020. Table 5 Panel A shows the composition across bank size. Larger banks have more technical employees. For example, among the six largest banks (those with over a trillian dollars in assets), the average has 67.3% of the workforce with at least some technical skills, compared to 57.7% in the average large bank (with assets between \$100 billion and \$1 trillion), 41.0% at the average mid-sized bank (\$10-100 billion in assets), 39.6% at the average small bank (\$3-10 billion in assets), and 34.9% at the average smallest bank (below \$3 billion in assets). The difference is even starker when we focus on the highest level of technical ability. The average share of employees with advanced coding skills declines from over 18.1% at the largest banks (with over \$1 trillion in assets) to only 2.0% at the smallest banks (below \$3 billion in assets).

Overall, large banks are substantially more likely to have technical human capital than small banks. This is consistent with prior evidence on specialized technological investments such as artificial intelligence concentrating in large firms Babina et al. (2023). Our novel classification of all technical talent (advanced coding, basic coding, and users of off-the-shelf tools) allows us to provide a more granular overview of varied investments by firm size. While large banks invest more in all types of technical expertise, the difference is most pronounced for the most advanced technical category, with a six-fold increase in the share of advanced coding employees from the smallest to the largest banks.

Panel B of Table 5 considers the fraction of deposits to the number of branches, documenting that banks with higher deposits-per-branch tend to have more technical workforces. Intuitively, technology enables banks to attract and manage the same amount of deposits using fewer branches. We slice banks into quintiles based on deposits per branch and document that the share of all employees who have have at least some technical skills grows from an average of 35.0% in the bottom quintile of banks by deposits to 50.1% in the top quintile. Similarly, the share of employees with advanced coding skills grows from 1.8% in the bottom quintile of banks based on deposits to 6.9% in the top quintile. Most of the increase is due to the top quintile of banks versus the rest.

Panels C, D, and E of Table 5 show that the share of technical employees also varies with banks' portfolio of loans, revealing an association between technical human capital and consumer-focused lending. We hypothesize that technology can be most helpful in unlocking efficiencies in the business of household-facing loans, such as mortgages and credit cards, with room for standardization, automation, and fewer human-to-human interactions between lenders and borrowers. Panel C examines the association between technical employees and the fraction of banks' loans that are household-facing. The least household-facing banks (those in the bottom quintile based on the share of loans that are household-facing) have the least technical workforce, with an average of 39.6% of employees with at least some technical skills and an average of 3.2% of employees with advanced coding skills. These technical skill levels increase only slightly as we move to the second, third, and fourth quintile of banks based on household-facing loans. However, the banks with the most household-facing loans (those in the top quintile) have substantially more technical workforces, with an average of 45.1% of employees reporting at least some technical skills and an average of 5.2% having advanced coding skills. Correspondingly, Panels D and E show that both nonresidential real estate loans (Panel D) and commercial and industrial loans (Panel E) are inversely related to technical workforces. These results are consistent with the notion that technology offers fewer gains when a lending process involves larger loans (compared to household lending) and more human-to-human interactions. Panel D shows that rank in the *bottom* quintile based on the share of nonresidential real estate loans having significantly more technical workers in general and higher shares of workers with advanced coding skills in particular. Panel E shows that commercial and industrial loan shares display a negative but very weak association with technical human capital.

Next, Table 6 examines the *changes* in technical skills of workers hired from up-to-2015 to 2016-onward, and how those changes vary across banks' assets, deposits-per-branch, and loan portfolio composition. Asterisks next to the 2016-onward values denote that the corresponding difference from up-to-2015 to 2016-onward is statistically significant. Panel A looks at bank size. The proportion of technical workers undergoes significant increases in all bank size buckets, with the share of employees with advanced coding degrees roughly doubling in each bank group (e.g., increasing from 10.3% to 19.9% for the largest banks with over $1 trillion in assets and increasing from 2.1% to 3.7% for the smallest banks with less than $3 billion in assets). *Technical capital (a)* increases from 0.87 to 1.27 in the largest banks and from 0.40 to 0.61 in the smallest banks. All of the skill increases are statistically significant at the 1% level. Banks' workforces are also becoming more educated across the board, with an increasing presence of Masters degrees in all bank sizes and increasing shares of degrees specifically from top-rated ("elite") institutions in the larger banks.

Table 6 Panels B, C, D, and E examine how changes in employee composition vary with the banks' shares of residential loans, nonresidential real estate loans, commercial and industrial loans, and consumer loans, respectively. The results show a ubiquitous increase in technical employees across all bank types. For example, the share of employees with advanced coding skills increases from 5.7% to 10.0% in the top quintile of banks based on the shares of commercial and industrial loans and from 9.9% to 21.2% in the bottom quintile of banks based on the share of commercial and industrial loans. Similarly, this share increases from 10.3% to 20.9% in the top quintile of banks based on the share of consumer loans, and from 4.1% to 8.0% in the bottom quintile. Finally, other skill indicators—the share of workers with at least one degree in a STEM field, the share of workers with Masters degrees, and the share of workers with degrees from elite institutions—also show ubiquitous increases across all bank loan types.

Overall, the main source of heterogeneity across banks is size (total assets): larger banks have more technically-skilled workforces, both at the beginning and the end of the sample period. As a result, the *relative* increase in technical workers is similar (roughly two-fold) across the board.

5 Technical Skills, Skill Vintages, and Employee Outcomes

We now examine how white-collar jobs at banks evolve with banks' investments in technology. We document that banks that transition towards more technical workforces (that is, invest in technology) tend to have more employee separations. Older workers are at greatest risk of job separations during technical transitions, but this effect is mitigated for older workers who have invested in more modern skills.

5.1 Employee Skills and Job Progression

We begin by examining how employees' career trajectories relate to the composition of their skill portfolios and especially the novelty of their skills. We estimate the following equation:

$$Y_i = \Sigma_k(\alpha_k \times HasTechSkill_{i,k} + \beta_k \times HasModernTechSkill_{i,k}) + \gamma \times \Omega_i + \epsilon_i, \quad (1)$$

where Y_i is an outcome variable of interest, k references the category of technical skill (software or coding), $HasTechSkill_{i,k}$ is an indicator variable equal to one if individual i has at least one skill of type k listed on their resume in 2015, and $HasModernTechSkill_{i,k}$ is an indicator variable equal to one if i has at least one skill of type k that falls in the top quartile of the novelty distribution measured using Google Trends. Ω_i are person-level control variables that include age, educational majors, maximal educational attainment, whether at least one of i's educational degrees was granted by an elite (i.e., Top-100) academic institution, the length of current employment at i's employer, and the seniority of i's position. The control variables are all measured as of 2015. Standard errors are clustered by bank.

Table 7 reports the results for different outcome variables Y_i. Columns 1 and 2 estimate Equation 1 using a probit model with the outcome being a promotion—that is, an indicator equal to one if the seniority of individual i increased by at least one level (column 1) or at least two levels (column 2). The dependent variable in column 3 is an indicator equal to one if i's employer firm changed from 2015 to 2020. Columns 4–7 examine employer changes in more detail. Columns 4 and 5 focus on employer changes accompanied by *increases* in seniority by at least one or two levels, respectively. These are likely to be voluntary separations on the individual employee's part. Columns 6 and 7 focus on transitions to a different employer accompanied by a *decrease* in seniority by at least one or two levels, respectively. These likely reflect involuntary separations or demotions.

The first two columns of Table 7 show that, in general, technically-skilled employees are less likely to experience internal promotions than business-oriented employees. But this differential is mitigated when technical employees have *modern* skills, whether software or coding. In columns 4 and 5, we see an analogous pattern for external promotions (job switches with seniority increases): job changes with promotions are more common for business employees and less common for technical bank employees, but this differential is entirely offset when the technical employees possess modern technical skills. Finally, columns 6 and 7 display some evidence for modern technical skills also mitigating the risk of involuntary separations (job changes with seniority declines), at least for technical employees with coding skills. Overall, the evidence in Table 7 highlights how for technically-skilled employees, the *vintage* of their skills—how modern their technical skills are—is a key driver of their career progressions.

5.2 Modern Technical Skills, Layoffs, and Older Workers

The previous subsection suggests that modern technical tests carry benefits for workers, increasing the likelihood of promotions and decreasing the likelihood of demotions relative to older technical skills. We now examine this result in more detail, including how modern skills insulate workers during layoffs and how the importance of modern skills may differ across employee age.

To study employees' vulnerability to being displaced, part of our analysis focuses on the banks that experienced a reduction in the number of full-time equivalent employees (as reported in Call Reports) between 2015 and 2020. We consider three reduction thresholds: banks where the total headcount dropped by more than 10% from 2015 to 2020 , banks where the total headcount dropped more than 2%, and banks that experienced any kind of reductions in headcount (change in headcount $\leq 0\%$). Table 8 begins by looking at all banks in Panel A, and then considers the three reduction threshold (at least 10%, at least 2%, and at least 0%) in Panels B, C, and D, respectively.

The analysis in Table 8 is conducted at the employee level and focuses specifically on employees who have at least one technical skill. We rank the employees in terms of the vintage of their skills (i.e., the average novelty score of the skills in that employee's portfolio). The variable *old_tech* is an indicator equal to one for employees in the bottom quartile of all employees based on average skill vintage. The variable *mod_tech* is an indicator equal to one for employees in the top quartile based on average skill vintage. The omitted category thus comprises employees in the middle two quartiles based on skill vintage.

In each column, we estimate the following specification:

$$Demotion_i = \alpha \times old\_tech_i + \beta \times mod\_tech_i + \gamma \times \Omega_i + \epsilon_i, \tag{2}$$

where $Demotion_i$ is a dummy variable equal to one if employee i experienced an employment separation that resulted in i having a position with a lower seniority rank in 2020 than in 2015. Columns 1–4 consider all cases where the rank decreased by at least one point, while Columns 5–8 consider only those cases where the rank decreased by at least two points. Ω_i captures person-level controls: educational majors, maximal degree attained, the presence of at least one degree from an elite (i.e., Top-100) academic institution, age, length of employment at the 2015 employer, and the employee's 2015 seniority level. Standard errors are clustered by bank.

We estimate regression 2 on all technical employees and then separately for three age groups: younger (up to 32 years old), middle (33–40 yeras old), and older (over 40 years old). The separate age groups enable us to see whether old and modern technical skills have differential effects on older versus younger workers.

Panel A of Table 8 examines the relationship between skill vintage and the probability of job separations with demotions across the full sample of banks. We first discuss the results for all employees with technical skills pulled together ("entire sample"). The coefficient on *old_tech* is positive but insignificant for demotions of at least one rank and a statistically significant (at the 5% level) 0.679 for demotions of at least two ranks, indicating that having older technical skills is modestly harmful. The coefficient on *mod_tech* is a strongly statistically significant -0.0274 (-0.0119) for demotions of at least one rank (at least two ranks), statistically significant at the 1% level. This means that technical employees with the most modern technical skills (top quartile) are 2.74% less likely to experience a demotion of at least one rank and 1.19% less likely to experience a demotion of at least two ranks. Each of these marginal effects accounts for more than a quarter of the unconditional probability of demotion (reported in the table footer).

Next, we look at the results in Panel A of Table 8 sliced by age. The results in the youngest group of employees are slightly weaker than in the full sample (e.g., modern skills lower the probability of demotion by one rank by 1.43% rather than 2.74%). The effect sizes for the middle group of employees is comparable to the full sample results (e.g., modern skills reduce the probability of demotion by at least one rank by 2.55%). And the strongest effects of modern technology are visible for the oldest group of employees. In this group, having skills in the highest quartile of modernity corresponds to a reduction in the likelihood of demotion by at least one point (at least two points) by 3.92% (2.01%), compared to the full-sample effects of 2.74% (1.19%).

Next, we examine what happens specifically during layoffs—starting with substantial layoffs (banks reducing their total headcount by 10% or more) in Panel B of Table 8. First, comparing the full-sample results in this panel against those in the previous panel, we see that outdated technical skills (*old_tech*) are more harmful to employees during layoffs than during regular times. Having technical skills that are in the bottom quartile based on novelty corresponds to a 2.26% (1.44%) higher likelihood of demotions by at least one rank (at least two ranks), both statistically significant at the 5% level. Second, these effects increase with age. The adverse effect of old skills is small (less than 1%) and statistically insignificant in the younger and middle age categories, and large and statistically significnat in the older category: for employees over 40 years of age, having technical skills in the bottom quartile of novelty is associated with a dramatic 5.67% (3.20%) increase in the likelihood of demotion by at least one rank (at least two ranks). The positive effects of modern technical skills (the coefficient on *mod_tech*) also increase with age, but they are sizable and significant only for demotions by at least one rank, not demotions by at least two ranks. Overall, the most striking result in Panel B of Table 8 is the adverse interaction between older age *and* older technical skills: for workers over 40 years old, having old technical skills substantially increases their likelihood of adverse career outcomes during bank layoffs, and having technical skills in the middle two quartiles is worse than having technical skills ranked in the top quartile.

Panel C of Table 8 expands the sample a bit, to any layoffs that cut at least 2% of the workforce (rather than requiring a full 10% headcount reduction). Looking at all technically-skilled employees (independent of age), we find a statistically insignificant harmful effect from old technical skills (*old_tech*) and a significant beneficial effect (reducing the propensity to experience job separation resulting in a demotion) from modern technical skills (*mod_tech*). As before, these effects increase with employee age. For employees over 40, having technical skills ranked in the bottom quartile of novelty (rather than middling-vintage skills) translates into a 2.34% (1.31%) increase in demotions by at least one rank (by at least two ranks), albeit statistically insignificant. In contrast, having skills in the top quartile of novelty lowers the likelihood of demotions by at least one rank (at least two ranks) by 4.55% (1.62%), significant at the 1% (10%) level.

Finally, for further robustness, Panel C of Table 8 repeats the analysis on all bank-years with negative workforce changes (i.e, any net change in the employee count $\leq$ 0%) and shows results that reinforce the patterns in Panels A–C. Modern technical skills (those in the top quartile of novelty based on Google Trends data) significantly predict lower incidence of separations with seniority drops in the full sample, and this result is stronger for older workers than for younger workers. Similarly, having technical skills in the bottom quartile of novelty is associated with higher incidence of demotions, and this worsens with age, although this coefficient is not always significant.

Overall, the results in Table 8 highlight an important interaction between employee age and the vintage of technical skills: possessing modern (rather than outdated) technical skills insulates technically-oriented workers from adverse career outcomes, including during bank layoffs or workforce reductions, and this effect is especially pronounced for older workers.

5.3 Placebo Test: Vintages of Soft Skills

We investigate how the results in Table 8 would change if instead of focusing on employees with technical skills, we considered employees with soft skills. This analysis serves two purposes. First, it can offer a placebo test of sorts to see whether the impact of modern vintages that we observe in 8 is specific to technical skills. Second, soft skills are important determinants of success of individual employees and firm performance (Heckman and Kautz, 2012), so examining how these skills evolve over time is interesting in and of itself.

Table 9 presents the results, where the sample consists of all employees who possess at least one of 2,840 skills identified as a "soft skill" by GPT4o. The outcome variables are demotions of at least one rank and demotions of at least two ranks. We look at employees of all age, and then separately for younger employees (up to 32 years old), medium employees (33–40 years old), and older employees (over 40 years old).

The results for soft skills are very different from those for technical skills. First and foremost, the effect of skill vintage is flipped: for soft skills it is the *older* soft skills that seem to insulate employees from adverse outcomes, whereas novel soft skills do not bring as much value. For example, in the full sample, employees with the most modern soft skills are 1.1% (0.7%) more likely to suffer demotions of at least one rank (at least two ranks) than employees with mid-range novelty soft skills. In contrast, employees in the bottom quartile of soft skills based on novelty are 3.55% (1.75%) *less* likely to suffer demotions of at least one rank (at least two ranks) than employees with soft skills of mid-ranging novelty. This is likely because novel soft skills tend to be more nebulous and less difficult to acquire. When we tag each soft skill with the difficulty of acquiring that skill (also using the GPT4o model), this difficulty measure displays a correlation of -0.66 with skill vintage (i.e., more modern soft skills are generally *easier* to acquire).

The second notable result in Table **??** is that there is no clear age pattern to the soft skill results. The coefficients are very similar for all employee age groups. For example, the reduction in job separations with demotions of at least one rank from having odler-vintage soft skills is 1.73% for the younger workers (32 years old or less), 1.20% for mid-range workers (33–40 years old), and 1.65% for older workers (over 40 years old). For soft skills, it seems, the most important point is to have old-school (hard-to-get) soft skills, and individual employees' age is less of a factor.

6 Conclusion

In this paper, we explore investments in technical talent in the banking sector, which offers a unique setting to examine the evolution of technical skills specifically among white-collar workers in a knowledge industry. Recent advances in technology, such as artificial intelligence, relate to knowledge-based and cognitive tasks, unlike previous technologies that focused on automating menial blue-collar jobs. As a result, recent years bear the potential of disruptive effects on workers with technical abilities.

We document an important novel aspect of technical skill: its vintage. Technical employees with outdated skills are more likely to suffer demotions and involuntary job separations that lead to lower-ranked positions in other firms. In contrast, modern technical skills insulate workers from displacement, leading to a significantly lower probability of adverse career outcomes such as demotions. Importantly, this effect is unevenly distributed across employee age: the adverse impact of outdated technical skills and the beneficial effect of modern technical skills are both much stronger for older workers (over 40 years old) than for younger workers. This highlights an intriguing complementarity between employee age and skill age (vintage): the role of upskilling is especially relevant for older employees who may be more vulnerable to obsolescence. This raises potential policy implications for the maintenance of a competitive workforce during the confluence of (i) an aging population in the U.S. (Caplan and Rabe, 2023) and (ii) the advent of new technologies such as artificial intelligence (Acemoglu et al., 2022; Goldfarb et al., 2023). The the face of these trends, it is especially important to ensure that the technical part of the workforce—including older workers—have the tools necessary to keep up with modern technologies.

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Table 1: This table presents the descriptive statistics of technical skills' novelty scores. The Google Trends-based measure of a technical skill's novelty is constructed in two steps. First, we calculate the growth from 2004–2012 to 2013–2021 in the incidence of Google searches corresponding to that skill. Second, the novelty score of each skill is the percentile (from 0 to 1) of that skill's growth in the distribution across all 670 technical skills. Panel A presents the average novelty scores of technical skills reported by individuals of various age groups in our data. Panel B presents the average novelty scores of technical skills reported by individuals employed at banks of different sizes.

Panel A: Employee age

Group	N (individuals)	Mean	St. Dev.	p25	Median	p75
..-25	11,983	0.508	0.106	0.465	0.546	0.555
26-30	27,623	0.500	0.114	0.448	0.532	0.560
31-35	31,056	0.486	0.126	0.410	0.507	0.560
36-40	29,230	0.478	0.133	0.399	0.481	0.556
41-50	36,887	0.472	0.138	0.388	0.472	0.554
51-60	15,405	0.462	0.136	0.380	0.472	0.549
61-..	4,162	0.460	0.131	0.380	0.472	0.549

Panel B: Bank size

Group	N (individuals)	Mean	St. Dev.	p25	Median	p75
1T+	92,235	0.479	0.130	0.403	0.490	0.557
100B-1T	42,516	0.488	0.127	0.413	0.507	0.556
10-100B	15,600	0.480	0.125	0.403	0.499	0.552
3-10B	4,363	0.491	0.126	0.415	0.517	0.552
3B-	1,632	0.497	0.128	0.430	0.536	0.555

Table 2: Summary statistics on technical workers at banks. Panel A considers age, Panel B looks at educational degree levels, Panel C considers educational specializations, and Panel D looks at educational degree prestige (whether the individual has at least one degree from a top-100 educational instutution based on the U.S. News & World Report.

Panel A: Employee age

	# obs	mean	sd	p25	p50	p75
Not technical	275,829	1977.1	11.6	1970	1979	1986
Software	244,161	1979.5	11.0	1973	1981	1988
Basic coding	125,264	1979.2	10.2	1973	1981	1987
Advanced coding	78,009	1980.6	10.3	1975	1982	1988

Panel B: Educational attainment

	# obs	Vocational	Associate	Bachelors	Masters (non-MBA)	MBA	Doctorate
Not technical	143,057	1.6%	7.2%	85.6%	11.9%	9.1%	3.8%
Software	145,645	1.8%	7.9%	86.0%	14.0%	10.8%	2.3%
Basic coding	79,953	1.9%	5.4%	87.1%	18.4%	10.7%	2.8%
Advanced coding	54,223	1.3%	2.9%	87.4%	28.2%	4.9%	4.7%

Panel C: Educational majors

					Within STEM:		
	# obs	Business	Humanities	STEM	Computer Science	Engineering	Other STEM
Not technical	135,749	74.4%	28.8%	9.4%	2.1%	2.5%	5.2%
Software	138,360	77.2%	22.9%	15.0%	5.0%	5.2%	5.8%
Basic coding	77,324	66.5%	22.8%	32.7%	15.2%	11.6%	9.7%
Advanced coding	53,444	34.3%	11.0%	80.2%	45.6%	36.8%	16.6%

Panel D: Degrees from prestigious institutions

	# obs	Top 100 (any)	Top 100 BA	Top 100 MBA	Top 100 MA	Top 100 Doctorate
Not technical	143,057	13.0%	10.4%	1.6%	1.6%	0.6%
Software	145,645	14.2%	11.2%	2.1%	1.9%	0.3%
Basic coding	79,953	17.6%	13.9%	2.3%	3.0%	0.6%
Advanced coding	54,223	20.8%	15.2%	0.9%	6.2%	1.34%

Table 3: This table presents the descriptive statistics for sample banks as of 2020. An employee has some technical skills if their resume features skills identified as software, basic coding, or advanced coding. Tech-Hiring Intensity is the number of tech-skilled employees hired by a bank between 2015 and 2020 scaled by that bank's 2020 headcount

	N	Mean	Std Dev	p25	p50	p75
Employees' technological skills	445	0.392	0.133	0.314	0.375	0.462
Software	445	0.376	0.129	0.300	0.361	0.444
Coding	445	0.118	0.089	0.067	0.097	0.147
Basic	445	0.114	0.087	0.065	0.095	0.143
Advanced	445	0.031	0.047	0.000	0.018	0.039
Tech capital (a)	445	0.521	0.238	0.383	0.474	0.606
Tech capital (b)	445	0.697	0.402	0.474	0.611	0.824
Tech-Hiring Intensity	445	0.221	0.114	0.156	0.208	0.277
Employee majors						
Business	445	0.773	0.092	0.729	0.783	0.821
Humanities	445	0.207	0.072	0.172	0.209	0.248
STEM	445	0.122	0.077	0.078	0.107	0.152
Computer Science	445	0.054	0.044	0.026	0.046	0.073
Engineering	445	0.029	0.037	0.006	0.019	0.037
Other STEM	445	0.049	0.041	0.026	0.047	0.063
Employee educational attainment						
Associate's	445	0.073	0.047	0.042	0.066	0.095
College	445	0.724	0.080	0.683	0.726	0.769
Master's / MBA	445	0.185	0.079	0.141	0.178	0.221
JD, MD, PhD	445	0.019	0.022	0.004	0.016	0.026
Employee degree types						
MBA	445	0.104	0.061	0.078	0.102	0.127
Master's	445	0.088	0.046	0.059	0.083	0.109
Elite institution	445	0.042	0.060	0.009	0.023	0.052
Employee age						
At job start	446	34.4	2.5	32.8	34.2	35.7
As of 2020	446	42.0	2.7	40.5	41.7	43.1
Bank size						
Assets ($B)	446	49.256	267.823	2.065	4.263	11.933
Deposits per branch ($B)	444	1.734	10.509	0.071	0.104	0.174
Compositions of the loans portfolio						
Consumer	446	0.059	0.129	0.004	0.016	0.049
Credit cards	446	0.012	0.076	0.000	0.000	0.001
Other revolving plans	446	0.004	0.021	0.000	0.001	0.002
Automobile loans	446	0.020	0.053	0.000	0.001	0.011
Other consumer loans	446	0.023	0.068	0.002	0.005	0.017
Real estate	446	0.685	0.201	0.604	0.723	0.827
Residential	446	0.297	0.141	0.212	0.306	0.382
Commercial	446	0.299	0.172	0.185	0.277	0.369
Construction & Land	446	0.020	0.044	0.000	0.002	0.020
Farmland	446	0.070	0.047	0.034	0.063	0.098
Commercial & Industrial	446	0.184	0.116	0.104	0.168	0.248

Table 4: This table reports personal characteristics from the resumes of 1,147,849 individuals employed in 2020 by 446 bank holding companies (BHCs) in the United States. Technical skills—classified into software, basic coding, and advanced coding—feed into Technical Capital scores. *Tech Capital (a)* counts the number of distinct categories of technical skill (advanced coding, basic coding, and software use) that an individual has, with *Tech Capital (a)* thus ranging from 0 to 3. *Tech Capital (b)* gives more points for more advanced categories—1 point for software, 2 points for basic coding, and 3 points for advanced coding—and therefore ranges from 0 to 6. College majors capture the area of undergraduate or postgraduate studies. Panel A presents means for 2020 employees within annual cohorts depending on when they joined their as-of-2020 employer. Panel B splits 2020 employees into two groups: those hired up to 2015 versus those hired from 2016 onward, reporting the differences in the two subsample means. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A

Subsample	≤ 2010	2011	2012	2013	2014	2015	2016	2017	2018	≥ 2019
Tech skills										
Software	0.395	0.463	0.482	0.510	0.537	0.572	0.602	0.639	0.653	0.650
Coding	0.157	0.207	0.205	0.238	0.256	0.274	0.303	0.343	0.361	0.352
Basic	0.151	0.201	0.198	0.231	0.248	0.267	0.295	0.332	0.348	0.337
Advanced	0.055	0.075	0.078	0.093	0.100	0.113	0.129	0.158	0.171	0.163
Tech capital (a)	0.602	0.740	0.758	0.834	0.885	0.952	1.026	1.130	1.173	1.150
Tech capital (b)	0.863	1.092	1.113	1.252	1.333	1.446	1.577	1.779	1.863	1.814
Major										
Business	0.710	0.684	0.690	0.679	0.675	0.665	0.664	0.659	0.663	0.667
Humanities	0.205	0.214	0.216	0.214	0.217	0.218	0.217	0.213	0.214	0.220
STEM	0.205	0.239	0.225	0.248	0.255	0.270	0.274	0.299	0.302	0.299
Computer Science	0.097	0.112	0.104	0.114	0.119	0.124	0.124	0.139	0.144	0.144
Engineering	0.063	0.087	0.079	0.096	0.100	0.115	0.118	0.133	0.133	0.130
Other STEM	0.067	0.072	0.071	0.072	0.074	0.072	0.075	0.078	0.078	0.079
Max degree										
Associate's	0.051	0.050	0.056	0.051	0.047	0.045	0.045	0.035	0.031	0.030
College	0.707	0.685	0.691	0.683	0.675	0.673	0.669	0.662	0.668	0.680
Master's / MBA	0.218	0.236	0.231	0.238	0.250	0.254	0.255	0.272	0.271	0.261
JD, MD, PhD	0.024	0.029	0.023	0.027	0.028	0.028	0.032	0.031	0.030	0.029
Type of degree										
MBA	0.128	0.129	0.125	0.120	0.122	0.117	0.113	0.111	0.106	0.103
Master's	0.101	0.119	0.117	0.131	0.143	0.152	0.160	0.180	0.183	0.176
Elite institution	0.061	0.059	0.056	0.057	0.060	0.061	0.064	0.071	0.076	0.080

Panel B

Subsample	**2015 or before**			**2016 or after**			Difference
	N	Mean	SD	*N*	Mean	SD	in Means
Tech Skills							
Software	235,127	0.469	0.499	193,680	0.638	0.481	0.169***
Coding	235,127	0.207	0.405	193,680	0.342	0.474	0.135***
Basic	235,127	0.200	0.400	193,680	0.330	0.470	0.130***
Advanced	235,127	0.079	0.269	193,680	0.157	0.364	0.078***
Tech capital (a)	235,127	0.748	0.913	193,680	1.125	1.008	0.376***
Tech capital (b)	235,127	1.106	1.664	193,680	1.768	1.998	0.662***
Major							
Business	262,063	0.689	0.463	362,050	0.663	0.473	-0.026***
Humanities	262,063	0.212	0.409	362,050	0.216	0.412	0.004 ***
STEM	262,063	0.234	0.423	362,050	0.296	0.456	0.062***
Computer Science	262,063	0.109	0.312	362,050	0.139	0.346	0.030***
Engineering	262,063	0.085	0.279	362,050	0.130	0.336	0.044***
Other STEM	262,063	0.070	0.256	362,050	0.078	0.268	0.008***
Max Degree							
Associate's	347,957	0.050	0.217	447,438	0.034	0.182	-0.015***
College	347,957	0.690	0.462	447,438	0.670	0.470	-0.020***
Master's / MBA	347,957	0.234	0.423	447,438	0.266	0.442	0.032***
JD, MD, PhD	347,957	0.026	0.159	447,438	0.030	0.171	0.004***
Type of Degree							
MBA	347,957	0.124	0.330	447,438	0.107	0.310	-0.017***
Master's	347,957	0.122	0.328	447,438	0.176	0.381	0.054***
Elite Institution	347,957	0.060	0.237	447,438	0.073	0.261	0.013***

Table 5: The table presents the distribution of technological skills listed on the resumes of people employed in 2020 by banks in our sample. The resume data are from Cognism; the financial data come from Call Reports and the Summary of Deposits. Headcount columns show the number of full-time equivalent employees reported in Call Reports, the number of employees present in the resume data, and the number of employees listing skills on their resumes. Among these skills, we identify technological skills and partition them into software skills, basic coding skills, and advanced coding skills. Composition of the workforce across bank size in assets (Panel A), deposits per branch (Panel B), share of household-facing loans (Panel C), share of nonresidential real estate loans (Panel D), and share of commercial and industrial loans (Panel E).

Category	N	Headcount			Bank-level fractions of employees with technological skills														
	of Banks	Call	Cognism		Some technological skills					Basic/advanced coding skills					Advanced coding skills				
		Reports	All	∃ skills	mean	sd	p25	p50	p75	mean	sd	p25	p50	p75	mean	sd	p25	p50	p75
Panel A: Assets																			
1T+	6	1,049,189	556,207	157,293	67.3	9.3	60.9	66.5	75.2	35.6	8.7	30.4	33.8	43.4	18.1	8.0	13.6	15.5	25.2
100B - 1T	21	648,219	349,510	101,381	57.7	12.2	46.5	56.2	69.0	26.6	10.8	18.2	20.9	34.3	10.4	6.0	5.9	7.2	15.6
10-100B	91	295,298	153,060	44,783	41.0	12.3	33.9	38.6	49.4	13.9	8.1	9.0	12.0	17.1	3.6	3.8	1.5	2.5	4.9
3-10B	140	100,997	44,633	13,587	39.6	10.7	32.3	38.9	45.9	11.0	6.8	7.1	9.2	13.9	2.2	3.3	0	1.6	2.8
3B-	186	63,401	30,283	9,332	34.9	12.6	28.6	34.4	42.7	8.8	7.2	4.3	7.9	11.8	2.0	3.9	0	0	2.9
Panel B: Deposits-per-branch																			
5th (top quintile)	89	1,526,105	839,344	238,443	50.1	15.9	40	49.3	61.6	20.3	13.0	11.1	17.1	27.6	6.9	7.6	1.3	4.9	10.1
4th	88	345,332	173,245	51,688	37.4	12.4	30.9	39.2	45.6	11.3	6.4	7.2	11.1	15.5	2.5	2.5	0	1.8	3.9
3rd	89	96,219	40,679	12,274	37.6	10.8	32	36.3	44.1	10.1	5.7	6.7	9.4	13.6	1.9	2.3	0	1.4	2.8
2nd	88	118,691	54,971	16,507	35.4	9.9	29.3	34.9	41.5	8.4	4.7	5.3	7.9	11.1	1.9	2.0	0	1.8	2.9
1st (bottom quintile)	88	57590.0	18,319	5,393	35.0	10.5	29.3	33.9	40	8.4	5.7	5	7.7	10.5	1.8	3.8	0	1.1	2.6
Panel C: Share of household-facing loans																			
5th (top quintile)	89	1,126,124	593,004	172,790	45.1	13.9	34.9	44.2	52.7	15.4	11.3	7.9	12.3	18.2	5.2	6.8	1.4	2.5	6.3
4th	89	405,634	206,938	60,136	38.6	11.1	30.7	36.8	45.9	11.0	8.0	6.8	9.4	14.7	2.7	3.8	0	1.8	4.0
3rd	89	315,679	162,468	45,456	36.7	12.6	30.3	37.2	43.5	10.8	6.5	7.2	10	14.3	2.2	3.4	0	1.8	2.8
2nd	89	139,545	58,959	17,011	35.7	10.8	31.2	33.9	39.8	9.5	7.0	5.9	8.3	12.4	1.8	2.4	0	1.3	2.5
1st (bottom quintile)	88	170,122	112,324	30,983	39.6	15.6	29.8	40.4	47.6	11.8	9.6	5.6	9.0	15.3	3.2	4.7	0	1.7	4.6
Panel D: Share of nonresidential real estate loans																			
5th (top quintile)	89	49301.0	20,069	5,865	36.1	12.5	29.7	34	42.5	8.4	6.4	3.8	7.7	11.1	1.7	2.5	0	0	2.8
4th	89	70,767	28,027	8,551	33.9	11.6	28.9	34.4	41.5	9.8	7.1	6.1	8.7	13.1	1.6	1.9	0	1.2	2.5
3rd	89	83,742	35,328	10,697	34.9	10.6	29.2	35.0	40.6	8.4	4.1	6.1	8.3	10.9	1.5	2.0	0	1.1	2.2
2nd	89	156,235	72,835	19,970	39.0	9.8	33.3	37.2	45.2	10.7	5.1	7.4	10.6	13.5	2.6	2.1	1.4	2.3	3.7
1st (bottom quintile)	88	1,797,059	977,434	281,293	52.0	12.9	43.0	49.5	62.3	21.3	12.0	13.8	18.2	27.1	7.8	7.8	2.3	5.6	10.2
Panel E: Share of commercial and industrial loans																			
5th (top quintile)	89	286,138	144,933	42,787	40.9	13.8	32.9	40.5	47.6	13.1	8.9	7.2	12.2	16.8	3.4	4.1	0.8	2.5	5.1
4th	89	539,304	282,204	80,830	38.9	11.4	32	37.3	44.4	12.0	7.6	7.7	10.2	14.9	2.8	3.3	0	1.9	3.8
3rd	89	860,222	433,726	124,943	36.0	14.1	29.2	35.2	44.1	10.2	7.4	6.7	8.8	13.0	2.3	4.1	0	1.5	3.3
2nd	89	210,842	119,622	32,643	37.1	12.4	30.8	36.0	43.1	9.9	8.2	4.7	9.1	12.5	2.6	4.4	0	1.3	3.0
1st (bottom quintile)	88	260,598	153,208	45,173	42.9	13.5	33.5	40.7	50.2	13.4	11.3	6.8	10.6	15.3	4.0	6.5	0	1.8	4.5

Table 6: Changes in employee composition from up-to-2015 to 2016-onward, for different type of banks. Panel A slices the sample based on bank size. Panels B, C, D, and E slice the sample based on the portion of residential real estate loans, nonresidential real estate loans, commercial real estate loans, and consumer loans, respectively. ***, **, and * indicate that the differences from up-to-2015 to 2016-onward are significant at the 1%, 5%, and 10%, respectively.

Panel A

Bank Size (2020)	**1T+**		**100B-1T**		**10-100B**		**3-10B**		**3B-**	
Job Start Year	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**
Technical skills										
Software	0.526	0.686***	0.465	0.642***	0.356	0.535***	0.311	0.492***	0.295	0.434***
Coding	0.252	0.399***	0.201	0.344***	0.116	0.217***	0.088	0.164***	0.083	0.140***
Basic	0.244	0.384***	0.195	0.334***	0.112	0.211***	0.086	0.159***	0.081	0.135***
Advanced	0.103	0.199***	0.071	0.149***	0.034	0.074***	0.020	0.045***	0.021	0.037***
Tech Capital (a)	0.873	1.269***	0.731	1.124***	0.502	0.820***	0.418	0.695***	0.397	0.606***
Tech Capital (b)	1.323	2.050***	1.069	1.756***	0.681	1.178***	0.544	0.943***	0.521	0.816***
Educational majors										
Business	0.663	0.648***	0.708	0.654***	0.725	0.709***	0.770	0.760*	0.786	0.780
Humanities	0.207	0.202***	0.216	0.231***	0.232	0.234	0.213	0.222*	0.195	0.216***
STEM	0.279	0.343***	0.209	0.288***	0.143	0.189***	0.114	0.135***	0.109	0.108
Computer Science	0.130	0.156***	0.105	0.145***	0.065	0.093***	0.050	0.066***	0.050	0.049
Engineering	0.113	0.166***	0.068	0.114***	0.033	0.058***	0.024	0.034***	0.020	0.022
Other STEM	0.076	0.086***	0.062	0.076***	0.056	0.061***	0.047	0.047	0.046	0.047
Maximal educational degree										
Business	0.040	0.024***	0.054	0.036***	0.070	0.055***	0.074	0.059***	0.080	0.070***
College	0.680	0.655***	0.686	0.662***	0.733	0.723***	0.727	0.725	0.750	0.736**
Master's / MBA	0.252	0.288***	0.235	0.270***	0.178	0.201***	0.179	0.197***	0.151	0.178***
JD, MD, PhD	0.028	0.033***	0.025	0.031***	0.019	0.020	0.020	0.019	0.018	0.016
Type of degree										
Associate's	0.126	0.105***	0.131	0.114***	0.104	0.098***	0.110	0.104*	0.088	0.095*
Master's	0.140	0.204***	0.115	0.174***	0.081	0.114***	0.078	0.104***	0.069	0.091***
Elite Institution	0.076	0.095***	0.048	0.061***	0.036	0.041***	0.047	0.049	0.031	0.034
Employee age										
At Job Start	30.554	33.664***	31.417	34.696***	31.797	35.695***	31.850	36.078***	31.714	36.301***
As of 2020	41.970	36.049***	42.939	37.050***	43.784	38.059***	43.568	38.464***	43.749	38.718***

Panel B

Residential real estate loan share (2020)	Top (most)		4th quintile		3rd quintile		2nd quintile		Bottom (least)	
Job Start Year:	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**
Technical skills										
Software	0.423	0.596***	0.495	0.656***	0.430	0.569***	0.507	0.667***	0.533	0.689***
Coding	0.169	0.274***	0.217	0.366***	0.187	0.270***	0.233	0.361***	0.259	0.422***
Basic	0.165	0.267***	0.210	0.352***	0.181	0.262***	0.224	0.349***	0.251	0.406***
Advanced	0.057	0.100***	0.087	0.181***	0.070	0.109***	0.093	0.166***	0.099	0.212***
Tech capital (a)	0.644	0.963***	0.791	1.188***	0.681	0.940***	0.825	1.182***	0.883	1.307***
Tech capital (b)	0.923	1.429***	1.174	1.902***	1.002	1.420***	1.235	1.863***	1.332	2.138***
Educational majors										
Business	0.694	0.662***	0.672	0.650***	0.698	0.699	0.710	0.697***	0.676	0.618***
Humanities	0.242	0.246*	0.201	0.203	0.205	0.218***	0.200	0.201	0.216	0.222**
STEM	0.181	0.239***	0.263	0.320***	0.217	0.244***	0.242	0.287***	0.257	0.355***
Computer Science	0.087	0.117***	0.126	0.152***	0.108	0.117***	0.110	0.127***	0.121	0.174***
Engineering	0.050	0.090***	0.106	0.151***	0.074	0.093***	0.096	0.133***	0.098	0.158***
Other STEM	0.061	0.067***	0.070	0.077***	0.064	0.071***	0.070	0.077***	0.073	0.091***
Maximal educational degree										
Associate's	0.065	0.052***	0.052	0.032***	0.065	0.050***	0.031	0.022***	0.038	0.023***
College	0.732	0.705***	0.689	0.678***	0.693	0.677***	0.657	0.644***	0.692	0.662***
Master's / MBA	0.183	0.215***	0.231	0.258***	0.219	0.247***	0.283	0.305***	0.241	0.280***
JD, MD, PhD	0.021	0.028***	0.028	0.031***	0.023	0.026***	0.029	0.030	0.028	0.035***
Type of degree										
MBA	0.105	0.100***	0.118	0.101***	0.121	0.117***	0.149	0.115***	0.117	0.100***
Master's	0.087	0.130***	0.126	0.176***	0.108	0.147***	0.150	0.210***	0.136	0.199***
Elite institution	0.044	0.047***	0.064	0.078***	0.049	0.064***	0.082	0.089***	0.063	0.083***
Employee age										
At job start	31.191	35.133***	30.335	33.778***	31.251	35.469***	31.227	34.146***	31.158	33.872***
As of 2020	43.078	37.580***	41.447	36.187***	43.276	37.854***	42.762	36.529***	42.147	36.140***
Largest banks in category	Wells Fargo Popular Bank New York Community Bank		JPMorgan Chase US Bank People's United Bank		Bank of America Truist Financial Fifth Third Bank		Citi Morgan Stanley Charles Schwab		Goldman Sachs Capital One State Street	

Panel C

Nonresidential real estate loan share (2020)	Top (most)		4th quintile		3rd quintile		2nd quintile		Bottom (least)	
Job Start Year:	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**	**$\leq$ 2015**	**$\geq$ 2016**
Tech skills										
Software	0.335	0.500***	0.438	0.606***	0.526	0.673***	0.572	0.716***	0.539	0.686***
Coding	0.111	0.187***	0.182	0.282***	0.248	0.377***	0.278	0.449***	0.262	0.401***
Basic	0.108	0.182***	0.178	0.274***	0.240	0.365***	0.268	0.429***	0.253	0.388***
Advanced	0.031	0.055***	0.063	0.098***	0.097	0.181***	0.129	0.252***	0.099	0.182***
Tech capital (a)	0.475	0.737***	0.678	0.978***	0.863	1.219***	0.969	1.397***	0.890	1.256***
Tech capital (b)	0.645	1.029***	0.981	1.448***	1.297	1.947***	1.494	2.330***	1.341	2.008***
Major										
Business	0.762	0.756**	0.714	0.688***	0.675	0.637***	0.654	0.636***	0.649	0.631***
Humanities	0.207	0.222***	0.226	0.234***	0.203	0.215***	0.204	0.196***	0.224	0.223
STEM	0.134	0.153***	0.186	0.233***	0.257	0.326***	0.302	0.371***	0.275	0.337***
Computer Science	0.059	0.074***	0.094	0.114***	0.127	0.159***	0.136	0.170***	0.132	0.158***
Engineering	0.030	0.039***	0.054	0.087***	0.100	0.143***	0.134	0.186***	0.104	0.152***
Other STEM	0.054	0.054	0.059	0.065***	0.068	0.083***	0.082	0.093***	0.075	0.084***
Max degree										
Associate's	0.075	0.059***	0.064	0.049***	0.048	0.031***	0.027	0.015***	0.033	0.025***
College	0.722	0.713***	0.705	0.685***	0.681	0.653***	0.679	0.663***	0.669	0.647***
Master's / MBA	0.184	0.208***	0.209	0.236***	0.246	0.285***	0.259	0.285***	0.269	0.297***
JD, MD, PhD	0.019	0.020	0.022	0.030***	0.025	0.031***	0.035	0.036	0.029	0.030**
Type of degree										
MBA	0.112	0.110	0.127	0.115***	0.126	0.111***	0.123	0.092***	0.129	0.109***
Master's	0.080	0.110***	0.094	0.138***	0.133	0.193***	0.151	0.215***	0.155	0.207***
Elite institution	0.037	0.041***	0.050	0.056***	0.058	0.073***	0.107	0.121***	0.056	0.067***
Age										
At job start	31.837	36.268***	31.407	35.092***	30.987	34.401***	30.236	32.690***	30.649	34.091***
As of 2020	44.152	38.638***	43.211	37.536***	42.380	36.763***	41.358	35.013***	41.644	36.473***
Largest banks in category	Truist Financial Ameriprise Bank Regions Bank		Wells Fargo PNC Fifth Third Bank		Bank of America US Bank BNY Mellon		JPMorgan Chase Goldman Sachs Morgan Stanley		Citi Charles Schwab USAA	

Panel D

Commercial & industrial loan share (2020)	**Top (most)**		**4th quintile**		**3rd quintile**		**2nd quintile**		**Bottom (least)**	
Job Start Year:	$\leq$ 2015	$\geq$ 2016	$\leq$ 2015	$\geq$ 2016	$\leq$ 2015	$\geq$ 2016	$\leq$ 2015	$\geq$ 2016	$\leq$ 2015	$\geq$ 2016
Tech skills										
Software	0.443	0.585***	0.383	0.561***	0.497	0.670***	0.556	0.714***	0.491	0.661***
Coding	0.191	0.272***	0.155	0.269***	0.225	0.373***	0.278	0.452***	0.202	0.351***
Basic	0.184	0.263***	0.151	0.261***	0.218	0.360***	0.269	0.434***	0.194	0.339***
Advanced	0.072	0.108***	0.049	0.098***	0.086	0.175***	0.113	0.241***	0.081	0.164***
Tech capital (a)	0.700	0.956***	0.582	0.920***	0.802	1.205***	0.937	1.388***	0.766	1.164***
Tech capital (b)	1.028	1.436***	0.831	1.377***	1.192	1.915***	1.431	2.303***	1.121	1.830***
Major										
Business	0.709	0.707	0.723	0.694***	0.670	0.639***	0.654	0.621***	0.701	0.667***
Humanities	0.208	0.219***	0.218	0.234***	0.213	0.209*	0.200	0.204	0.223	0.220
STEM	0.208	0.235***	0.175	0.224***	0.253	0.327***	0.313	0.388***	0.211	0.284***
Computer Science	0.104	0.115***	0.078	0.106***	0.122	0.156***	0.139	0.176***	0.102	0.138***
Engineering	0.070	0.089***	0.054	0.085***	0.096	0.154***	0.136	0.189***	0.070	0.117***
Other STEM	0.061	0.067***	0.060	0.066***	0.070	0.076***	0.084	0.100***	0.065	0.079***
Max degree										
Associate's	0.061	0.048***	0.067	0.048***	0.051	0.032***	0.034	0.018***	0.035	0.028***
College	0.693	0.686***	0.706	0.691***	0.702	0.674***	0.644	0.638*	0.702	0.663***
Master's / MBA	0.223	0.240***	0.205	0.236***	0.221	0.261***	0.290	0.310***	0.235	0.278***
JD, MD, PhD	0.023	0.026***	0.022	0.025***	0.025	0.033***	0.032	0.033	0.027	0.031***
Type of degree										
MBA	0.127	0.113***	0.120	0.113***	0.117	0.105***	0.133	0.099***	0.122	0.105***
Master's	0.107	0.143***	0.095	0.137***	0.117	0.175***	0.174	0.234***	0.125	0.191***
Elite institution	0.052	0.065***	0.042	0.051***	0.061	0.074***	0.085	0.109***	0.069	0.069
Age										
At job start	31.513	35.163***	31.496	35.326***	30.577	34.002***	30.311	33.243***	31.327	34.434***
As of 2020	43.375	37.543***	43.518	37.685***	41.921	36.420***	40.924	35.558***	43.077	36.810***
Largest banks in category	Bank of America PNC American Express		US Bank Truist Financial WeBanco		JPMorgan Chase Wells Fargo Capital One		Citi Goldman Sachs BNY Mellon		Morgan Stanley Fifth Third Bank USAA	

Panel E

Consumer loan share (2020)	**Top (most)**		**4th quintile**		**3rd quintile**		**2nd quintile**		**Bottom (least)**	
Job Start Year:	$\leq$ 2015	$\geq$ 2016	$\leq$ 2015	$\geq$ 2016	$\leq$ 2015	$\geq$ 2016	$\leq$ 2015	$\geq$ 2016	$\leq$ 2015	$\geq$ 2016
Tech skills										
Software	0.554	0.702***	0.483	0.646***	0.469	0.633***	0.491	0.664***	0.376	0.550***
Coding	0.274	0.430***	0.210	0.355***	0.215	0.322***	0.220	0.381***	0.131	0.230***
Basic	0.265	0.416***	0.203	0.341***	0.208	0.312***	0.212	0.364***	0.126	0.223***
Advanced	0.103	0.209***	0.082	0.170***	0.080	0.133***	0.099	0.199***	0.041	0.080***
Tech capital (a)	0.923	1.328***	0.768	1.158***	0.758	1.077***	0.802	1.227***	0.543	0.852***
Tech capital (b)	1.395	2.163***	1.134	1.840***	1.127	1.654***	1.212	1.989***	0.751	1.235***
Major										
Business	0.637	0.595***	0.678	0.655***	0.680	0.664***	0.710	0.677***	0.761	0.743***
Humanities	0.224	0.225	0.204	0.208	0.218	0.225***	0.207	0.210	0.208	0.213**
STEM	0.289	0.375***	0.253	0.310***	0.231	0.281***	0.236	0.310***	0.142	0.182***
Computer Science	0.139	0.179***	0.122	0.147***	0.114	0.136***	0.104	0.142***	0.065	0.086***
Engineering	0.112	0.171***	0.099	0.143***	0.080	0.117***	0.094	0.141***	0.039	0.063***
Other STEM	0.076	0.092***	0.069	0.076***	0.067	0.074***	0.074	0.089***	0.052	0.057***
Max degree										
Associate's	0.038	0.026***	0.055	0.035***	0.057	0.042***	0.036	0.024***	0.059	0.042***
College	0.667	0.643***	0.691	0.675***	0.701	0.674***	0.675	0.663***	0.717	0.699***
Master's / MBA	0.267	0.299***	0.228	0.259***	0.218	0.253***	0.257	0.280***	0.203	0.236***
JD, MD, PhD	0.028	0.032***	0.026	0.031***	0.023	0.030***	0.032	0.034*	0.021	0.023**
Type of degree										
MBA	0.125	0.104***	0.120	0.104***	0.121	0.115***	0.135	0.096***	0.118	0.113***
Master's	0.157	0.215***	0.120	0.173***	0.109	0.157***	0.136	0.203***	0.093	0.135***
Elite institution	0.054	0.074***	0.060	0.075***	0.052	0.062***	0.114	0.126***	0.041	0.044***
Age										
At job start	30.567	33.876***	30.611	34.002***	31.067	34.959***	31.213	33.389***	31.884	35.721***
As of 2020	41.404	36.239***	41.836	36.415***	43.001	37.366***	43.053	35.704***	43.774	38.076***
Largest banks in category	Citi Capital One USAA		JPMorgan Chase US Bank Truist Financial		Bank of America Wells Fargo Fifth Third Bank		Goldman Sachs Morgan Stanley BNY Mellon		Charles Schwab State Street Northern Trust	

Table 7: Employee job changes and modern technical skills. The table estimates probit regressions of job changes, with the outcome variable being one- and two-points increases in seniority in columns 1 and 2, change of employer in column 3, one- and two-point *increases* in seniority coupled with a change in employer (likely voluntary departures) in columns 4 and 5, and one- and two-point *drops* in seniority coupled with a change in employer (likely involuntary departures) in columns 6 and 7.

VARIABLES	(1) senbump_1p	(2) senbump_2p	(3) job_chng	(4) jobchng_senbump_1p	(5) jobchng_senbump_2p	(6) jobchng_sendrop_1p	(7) jobchng_sendrop_2p
modern_software_75p	0.007200	0.006530	0.0149*	0.0115*	0.00771*	0.00933**	-0.000909
	[0.00541]	[0.00443]	[0.00819]	[0.00605]	[0.00454]	[0.00469]	[0.00290]
software_15	-0.00968*	-0.00705**	-0.0286***	-0.0165***	-0.00868***	0.003050	0.000420
	[0.00535]	[0.00330]	[0.00920]	[0.00474]	[0.00284]	[0.00196]	[0.00147]
modern_coding_75p	0.0292**	0.009580	0.0126***	0.0149**	0.006700	-0.0221***	-0.0130***
	[0.0120]	[0.00668]	[0.00464]	[0.00604]	[0.00414]	[0.00630]	[0.00368]
coding_15	-0.0161**	-0.00921**	-0.008690	-0.0126***	-0.00967***	0.0155***	0.0119***
	[0.00689]	[0.00465]	[0.0107]	[0.00336]	[0.00283]	[0.00541]	[0.00356]
business	0.0348***	0.0170***	0.006150	0.0239***	0.0137***	-0.0155***	-0.00788***
	[0.00489]	[0.00481]	[0.00604]	[0.00257]	[0.00273]	[0.00312]	[0.00211]
humanities	0.005970	0.003920	-0.003200	0.001100	0.002170	0.001150	0.001280
	[0.00471]	[0.00546]	[0.00479]	[0.00302]	[0.00267]	[0.00288]	[0.00209]
stem	0.006920	0.003540	0.000294	0.002940	0.001220	-0.002160	0.000671
	[0.00430]	[0.00394]	[0.00876]	[0.00282]	[0.00276]	[0.00614]	[0.00311]
max_college	0.0922***	0.0608***	-0.0357*	0.0516***	0.0326***	-0.0358***	-0.00696*
	[0.0101]	[0.00972]	[0.0184]	[0.0108]	[0.00754]	[0.00827]	[0.00369]
max_grad_degree	0.128***	0.0800***	-0.025000	0.0756***	0.0444***	-0.0439***	-0.0122***
	[0.0106]	[0.00870]	[0.0172]	[0.00975]	[0.00684]	[0.00888]	[0.00426]
elite_degree	0.0641***	0.0587***	0.0660***	0.0485***	0.0353***	-0.0126***	0.000319
	[0.00534]	[0.00471]	[0.00935]	[0.00520]	[0.00459]	[0.00381]	[0.00244]
age_15	0.000560*	0.000225	-0.000267	0.000488**	0.000246**	-0.000711***	-0.000253**
	[0.000301]	[0.000169]	[0.000440]	[0.000208]	[0.000113]	[0.000152]	[0.000101]
tenure	0.000236	0.000215	0.000456	0.000194	0.000035	0.000966**	0.000534
	[0.000418]	[0.000375]	[0.00109]	[0.000354]	[0.000350]	[0.000405]	[0.000424]
seniority_2015	-0.0848***	-0.0609***	-0.0108***	-0.0446***	-0.0333***	0.0752***	0.0429***
	[0.00405]	[0.00307]	[0.00334]	[0.00153]	[0.00129]	[0.00258]	[0.00200]
Constant	0.317***	0.178***	0.655***	0.162***	0.0955***	-0.0255***	-0.0506***
	[0.0201]	[0.0168]	[0.0183]	[0.0141]	[0.00939]	[0.00858]	[0.00468]
Observations	70,301	70,301	70,301	70,301	70,301	70,301	70,301
Adjusted R-squared	0.069	0.071	0.003	0.031	0.035	0.103	0.076
LHS mean	0.241	0.104	0.580	0.132	0.059	0.107	0.045

Table 8: This table examines the relationship between employees' adverse job loss (change changes accompanied by demotions) and employees' modern and old technical skills. Panel A considers all bank-years. Panel B focuses on bank-years with large layoffs (workforce reductions of 10% of more). Panel B focuses on bank-years with either large or mid-sized layoffs (workforce reductions of 2% or more). Panel D focuses on bank-years with *any* layoffs (any negative workforce changes). The regressions are run at the employee level, focusing on employees that have at least some technical skills. The variable *old_tech* is an indicator variable identifying employees in the bottom 25% based on the novelty of their technical skills, while *mod_tech* is an indicator variable capturing employees in the top 25% based on the novelty of their technical skills.

Panel A: Full sample

	LHS = jobchng_sendrop_1p				**LHS = jobchng_sendrop_2p**			
Variable	**Entire sample**	**Youngest**	**Med: 32-39**	**Oldest**	**Entire sample**	**Youngest**	**Med: 32-39**	**Oldest**
old_tech	0.00502	-0.00132	0.0039	0.011	0.00679**	0.00876***	0.00712*	0.00695
	[0.00482]	[0.00445]	[0.00405]	[0.00504]	[0.00333]	[0.00325]	[0.00409]	[0.00547]
mod_tech	-0.0274***	-0.0143***	-0.0255***	-0.0392***	-0.0119***	-0.00471*	-0.0100**	-0.0201***
	[0.00277]	[0.00332]	[0.00571]	[0.00511]	[0.00182]	[0.00230]	[0.00385]	[0.00429]
business	-0.0197***	-0.0206**	-0.0181**	-0.0245**	-0.00950**	-0.00887**	-0.00643*	-0.0159**
	[0.00304]	[0.00851]	[0.00821]	[0.00947]	[0.00302]	[0.00501]	[0.00499]	[0.00510]
humanities	0.00581	-0.000291	0.0126**	0.00458	0.00306	-0.0014	0.00967**	0.0014
	[0.00416]	[0.00831]	[0.00546]	[0.0106]	[0.00368]	[0.00501]	[0.00406]	[0.00795]
stem	-0.00407	-0.00906	-0.00645	-0.0108	-0.000792	-0.00063	-0.00455*	0.0005
	[0.00729]	[0.00902]	[0.0106]	[0.0103]	[0.00359]	[0.00501]	[0.00243]	[0.00561]
max_college	-0.0235*	0.0127	-0.0650**	-0.0199	-0.00565	-0.00116	-0.0175	-0.0175
	[0.0135]	[0.0172]	[0.0304]	[0.0236]	[0.00564]	[0.00708]	[0.0101]	[0.0181]
max_grad_degree	-0.0238**	-0.0149*	-0.0313	-0.0296	-0.00616*	-0.00300	0.000745	-0.0123
	[0.0118]	[0.0139]	[0.0213]	[0.0213]	[0.00563]	[0.00820]	[0.0121]	[0.0213]
elite_degree	-0.0112	-0.00593	0.00777	-0.0128	0.00632*	0.00407	0.0166**	-0.00439
	[0.00399]	[0.00772]	[0.0213]	[0.00876]	[0.00366]	[0.00406]	[0.00676]	[0.00491]
age_15	-0.00105***	-0.00405***	-0.00233***	-0.00125**	-0.000692***	-0.00230***	-0.00130**	-0.000845*
	[0.00248]	[0.000584]	[0.000420]	[0.000508]	[0.000134]	[0.000420]	[0.000612]	[0.000461]
tenure	0.00178**	-0.000765	0.00129	0.00198*	0.000795*	-0.000198*	0.000631	0.00122*
	[0.00206]	[0.00139]	[0.00166]	[0.000812]	[0.000681]	[0.00123]	[0.000546]	[0.00168]
seniority_2015	0.0784***	0.0973***	0.0785***	0.0727**	0.0432***	0.0506**	0.0425***	0.0437
	[0.00535]	[0.00748]	[0.00450]	[0.00868]	[0.00250]	[0.00271]	[0.00300]	[0.00767]
Constant	-0.0230**	-0.00759	-0.114***	-0.0329	-0.0339**	-0.00148	-0.0148*	-0.103**
	[0.0122]	[0.0221]	[0.0517]	[0.0313]	[0.00147]	[0.0182]	[0.0180]	[0.0214]
Observations	41,043	13,709	13,717	13,617	41,043	13,709	13,717	13,617
Adjusted R-squared	0.119	0.175	0.112	0.086	0.086	0.083	0.123	0.079
LHS mean	0.098	0.065	0.097	0.133	0.040	0.024	0.039	0.058

Panel B: Bank-years with headcount change from '15 to '20 $\leq$ -10%

	LHS = jobchng_sendrop_1p				LHS = jobchng_sendrop_2p			
Subsample: Headcount change from '15 to '20 $\leq$ -10%	**Entire sample** (1)	**Youngest** (2)	**Med: 33–40** (3)	**Oldest** (4)	**Entire sample** (5)	**Youngest** (6)	**Med: 33–40** (7)	**Oldest** (8)
old_tech	0.0226**	0.00858	0.00662	0.0567***	0.0144**	0.00972	0.00682	0.0320***
	[0.0101]	[0.0139]	[0.0139]	[0.0166]	[0.00710]	[0.00652]	[0.0132]	[0.00794]
mod_tech	-0.0258***	-0.0209***	-0.0305***	-0.0510***	-0.00563*	0.00247	-0.0121	-0.0155
	[0.00713]	[0.00723]	[0.0121]	[0.0119]	[0.00310]	[0.00386]	[0.0121]	[0.0148]
business	-0.0116***	-0.0113	-0.0358**	-0.00743	-0.00276*	-0.0112	-0.00556	-0.0105
	[0.00411]	[0.00836]	[0.0137]	[0.00876]	[0.00464]	[0.00710]	[0.00721]	[0.0156]
humanities	0.0167**	0.00298	0.0355**	0.00793	0.0139**	-0.00394	0.0291*	0.0137
	[0.00910]	[0.00778]	[0.0135]	[0.0138]	[0.00608]	[0.00687]	[0.0145]	[0.00907]
stem	-0.0169**	-0.00636	-0.0222*	-0.0165**	-0.00294**	-0.00054	-0.0154*	0.0154*
	[0.00717]	[0.00629]	[0.0195]	[0.00746]	[0.00352]	[0.00556]	[0.00868]	[0.00887]
max_college	-0.0216	-0.0620**	-0.0339	0.0373	0.00908	-0.0477	0.0107	0.0719***
	[0.0134]	[0.0356]	[0.0464]	[0.0855]	[0.00856]	[0.00978]	[0.0107]	[0.0107]
max_grad_degree	-0.0223	-0.0593*	0.0466	-0.0285	0.0309*	0.0351**	0.0402**	0.0156
	[0.0278]	[0.0347]	[0.0513]	[0.0764]	[0.0113]	[0.0328]	[0.0133]	[0.0156]
elite_degree	-0.00365	-0.0105	-0.0201	0.0108	-0.00435	0.00242	0.0180	0.0167
	[0.0108]	[0.00861]	[0.0201]	[0.00885]	[0.0105]	[0.00890]	[0.0167]	[0.0116]
age_15	-0.00163***	-0.00488***	-0.00495***	0.00143	-0.000986***	-0.00346***	-0.000690	0.00126
	[0.00202]	[0.00231]	[0.00231]	[0.00148]	[0.00324]	[0.00123]	[0.00168]	[0.00216]
tenure	0.00462**	-0.00327	0.00287	-0.00276*	0.00426***	0.00100	0.000692	0.00149**
	[0.00301]	[0.00307]	[0.00340]	[0.00177]	[0.00268]	[0.00234]	[0.00267]	[0.00224]
seniority_2015	0.0821***	0.105***	0.0719**	0.0811***	0.0461**	0.0539**	0.0439**	0.0480***
	[0.00670]	[0.00874]	[0.00874]	[0.00574]	[0.00341]	[0.00685]	[0.00704]	[0.00544]
Constant	-0.0196	0.0888**	0.112	-0.219*	-0.0603***	0.0698*	-0.0887	-0.228***
	[0.0292]	[0.0436]	[0.112]	[0.110]	[0.0173]	[0.0388]	[0.0822]	[0.0462]
Observations	6,281	2,368	2,381	2,072	6,281	2,368	2,381	2,072
Adjusted R-squared	0.108	0.177	0.079	0.086	0.077	0.110	0.066	0.068
LHS mean	0.128	0.098	0.122	0.168	0.056	0.039	0.053	0.078

Panel C: Bank-years with headcount change from '15 to '20 $\leq$ -2%

	LHS = jobchng_sendrop_1p				LHS = jobchng_sendrop_2p			
Subsample: Headcount change from '15 to '20 $\leq$ -2%	**Entire sample** (1)	**Youngest** (2)	**Med: 33–40** (3)	**Oldest** (4)	**Entire sample** (5)	**Youngest** (6)	**Med: 33–40** (7)	**Oldest** (8)
old_tech	0.011	0.00522	0.00417	0.0234	0.00841	0.0100***	0.00365	0.0131
	[0.0103]	[0.00616]	[0.0208]	[0.00648]	[0.00362]	[0.00301]	[0.0110]	[0.00820]
mod_tech	-0.0266***	-0.0173**	-0.0148	-0.0455***	-0.00915***	-0.0000601	-0.0106	-0.0162*
	[0.00360]	[0.00465]	[0.0103]	[0.00992]	[0.00312]	[0.00301]	[0.0110]	[0.00820]
business	-0.0128***	-0.00898*	-0.0123**	-0.0183	-0.00399	-0.00385	-0.00867	-0.00349
	[0.00261]	[0.00711]	[0.00763]	[0.00813]	[0.00270]	[0.00475]	[0.00566]	[0.00619]
humanities	0.0159***	0.0128	0.0222**	0.00917	0.0145***	0.00454	0.0199**	0.0156**
	[0.00478]	[0.00915]	[0.0108]	[0.00939]	[0.00402]	[0.00690]	[0.00800]	[0.00730]
stem	-0.00928**	0.00528	-0.0179**	-0.00538	-0.00311*	-0.00152	-0.00332	-0.0111*
	[0.00496]	[0.00868]	[0.00975]	[0.00538]	[0.00222]	[0.00597]	[0.00455]	[0.00559]
max_college	-0.0288*	-0.0624**	-0.0650**	0.0327	-0.0112	-0.0307**	0.0108*	0.0256
	[0.0162]	[0.0197]	[0.0327]	[0.0425]	[0.00755]	[0.0128]	[0.00547]	[0.0193]
max_grad_degree	-0.0259**	-0.0120	-0.0186	-0.0237*	0.00682	0.0141*	0.0168**	0.0116
	[0.0124]	[0.0202]	[0.0350]	[0.0350]	[0.00682]	[0.0141]	[0.00953]	[0.0145]
elite_degree	0.00498	0.00262	0.00531	-0.00356	0.00618	0.0108*	7.51E-03	-0.00234
	[0.00624]	[0.00853]	[0.0132]	[0.00873]	[0.00459]	[0.00504]	[0.00890]	[0.00604]
age_15	-0.00150***	-0.00536***	-0.00395***	-0.000819	-0.000973***	-0.00310***	-0.000729	0.000566
	[0.000212]	[0.000615]	[0.00171]	[0.000218]	[0.000494]	[0.00141]	[0.00122]	[0.000767]
tenure	1.90E-03	-0.00351**	0.00510**	0.00154**	-0.00545***	0.00031	0.00301	0.00137
	[0.00114]	[0.00141]	[0.00323]	[0.000764]	[0.00104]	[0.00221]	[0.00458]	[0.00214]
seniority_2015	0.0756***	0.0973***	0.0687***	0.0724***	0.0420**	0.0514***	0.0388***	0.0422***
	[0.00597]	[0.00727]	[0.00592]	[0.00720]	[0.00391]	[0.00316]	[0.00458]	[0.00410]
Constant	-0.00783	0.0655***	0.0788	-0.131*	-0.0373***	0.0525***	-0.0604	-0.131**
	[0.0512]	[0.0225]	[0.0788]	[0.0884]	[0.0168]	[0.0510]	[0.0822]	[0.0572]
Observations	13,096	4,608	4,285	4,203	13,096	4,608	4,285	4,203
Adjusted R-squared	0.110	0.174	0.089	0.086	0.078	0.121	0.065	0.064
LHS mean	0.095	0.072	0.093	0.123	0.040	0.027	0.039	0.054

Panel D: Bank-years with headcount change from '15 to '20 $\leq$ 0%

	LHS = jobchng_sendrop_1p				LHS = jobchng_sendrop_2p			
Subsample: Headcount change from '15 to '20 $\leq$ 0%	**Entire sample** (1)	**Youngest** (2)	**Med: 33–40** (3)	**Oldest** (4)	**Entire sample** (5)	**Youngest** (6)	**Med: 33–40** (7)	**Oldest** (8)
old_tech	0.00825	-0.00198	0.00373	0.0243*	0.0106**	0.0135***	0.0066	0.0153
	[0.00714]	[0.00669]	[0.0139]	[0.00658]	[0.00432]	[0.00359]	[0.00489]	[0.00983]
mod_tech	-0.0301***	-0.0218***	-0.0186**	-0.0448***	-0.0107***	-0.00383	-0.00886*	-0.0165**
	[0.00361]	[0.00409]	[0.00902]	[0.00565]	[0.00273]	[0.00275]	[0.00327]	[0.00438]
business	-0.0160***	-0.0287**	-0.0259***	-0.00444	-0.00507***	-0.0124**	-0.00521*	-0.00642
	[0.00313]	[0.0121]	[0.00514]	[0.0119]	[0.00217]	[0.00605]	[0.00392]	[0.00459]
humanities	0.0144***	-0.0112	0.0239***	0.0253*	0.0116***	-0.00686	0.0223***	0.0167**
	[0.00373]	[0.0142]	[0.00772]	[0.0151]	[0.00261]	[0.00741]	[0.00509]	[0.00429]
stem	0.000493	-0.00503	-0.00950	-0.0198**	-0.00325	0.0102**	0.00327	0.0100
	[0.0115]	[0.00962]	[0.0127]	[0.0198]	[0.00558]	[0.00555]	[0.00432]	[0.0100]
max_college	-0.0121	0.00232	0.00377	-0.0367*	-0.00809	-0.00927	-0.00915*	-0.0206
	[0.0161]	[0.0160]	[0.0144]	[0.0108]	[0.00892]	[0.0174]	[0.00953]	[0.0100]
max_grad_degree	-0.0112	0.0195	0.0239	-0.0484	-0.0110	0.0281	0.0252***	-0.0402
	[0.0137]	[0.0208]	[0.0325]	[0.0105]	[0.0105]	[0.0178]	[0.00561]	[0.0383]
elite_degree	0.00485	0.00422	0.0252**	-0.0179	0.00826*	0.0295***	-0.0135	-0.00814
	[0.00447]	[0.00578]	[0.0180]	[0.00522]	[0.00522]	[0.00416]	[0.00510]	[0.00631]
age_15	-0.00147***	-0.00515***	-0.00283***	0.00126*	-0.000766***	-0.00336***	-0.00215*	0.00123*
	[0.000143]	[0.000470]	[0.00159]	[0.000151]	[0.000334]	[0.00112]	[0.00121]	[0.000690]
tenure	0.00295***	0.00110	0.00430**	0.00420**	0.00127	0.00138**	0.00147**	0.00112*
	[0.00103]	[0.00124]	[0.00140]	[0.00110]	[0.00106]	[0.00103]	[0.00117]	[0.00112]
seniority_2015	0.0816***	0.103***	0.0758***	0.0774***	0.0466***	0.0576***	0.0420***	0.0485***
	[0.00607]	[0.00588]	[0.00669]	[0.00693]	[0.00413]	[0.00468]	[0.00413]	[0.00557]
Constant	-0.0329	0.0419*	-0.105	0.0488*	-0.0137**	0.0172	-0.076	-0.144*
	[0.0198]	[0.0175]	[0.0906]	[0.0148]	[0.0166]	[0.0732]	[0.0103]	[0.0320]
Observations	20,792	7,222	6,874	6,696	20,792	7,222	6,874	6,696
Adjusted R-squared	0.116	0.182	0.097	0.088	0.123	0.130	0.070	0.069
LHS mean	0.110	0.082	0.111	0.140	0.048	0.034	0.046	0.056

Table 9: This table examines the relationship between employees' adverse job loss (change changes accompanied by demotions) and employees' modern and old soft skills. The regressions are run at the employee level, focusing on employees that have at least some soft skills. The variable old_soft is an indicator variable identifying employees in the bottom 25% based on the novelty of their soft skills, while mod_soft is an indicator variable capturing employees in the top 25% based on the novelty of their soft skills.

	LHS = jobchng_sendrop_1p				LHS = jobchng_sendrop_2p			
Variable	**Entire sample**	**Youngest**	**Med: 33-41**	**Oldest**	**Entire sample**	**Youngest**	**Med: 33-41**	**Oldest**
old_soft	-0.0155***	-0.0173***	-0.0120*	-0.0165***	-0.00608**	-0.0034	-0.0058	-0.0070
	[0.00283]	[0.00594]	[0.00689]	[0.00629]	[0.00283]	[0.00353]	[0.00446]	[0.00454]
mod_soft	0.0122***	0.00975***	0.0124***	0.0148*	0.0028	0.0023	-0.0006	0.0068
	[0.00230]	[0.00324]	[0.00370]	[0.00776]	[0.00181]	[0.00259]	[0.00280]	[0.00439]
business	-0.0128***	-0.0114*	-0.0215***	-0.0081	-0.00434**	-0.0048	-0.0056	-0.0056
	[0.00341]	[0.00580]	[0.00584]	[0.00958]	[0.00214]	[0.00376]	[0.00560]	[0.00599]
humanities	0.0045	0.0049	0.0035	0.0047	0.0024	-0.0016	0.0066	0.0019
	[0.00403]	[0.00479]	[0.00595]	[0.00963]	[0.00276]	[0.00409]	[0.00511]	[0.00660]
stem	-0.0028	-0.0048	-0.0086	0.0040	-0.0035	-0.0071	-0.0018	-0.0028
	[0.00652]	[0.00807]	[0.00703]	[0.0127]	[0.00280]	[0.00435]	[0.00484]	[0.00545]
max_college	-0.0323***	-0.0209	-0.0490***	-0.0258	-0.0062	-0.0077	-0.0089	-0.0048
	[0.00974]	[0.0127]	[0.0181]	[0.0171]	[0.00391]	[0.00811]	[0.00700]	[0.0125]
max_grad_degree	-0.0382***	-0.0124	-0.0377*	-0.0476***	-0.0109**	0.0028	-0.0020	-0.0232*
	[0.0104]	[0.0141]	[0.0194]	[0.0177]	[0.00423]	[0.0105]	[0.00762]	[0.0125]
elite_degree	-0.0168***	-0.0118	-0.0006	-0.0339***	-0.00588***	-0.0031	0.0058	-0.0209***
	[0.00499]	[0.00985]	[0.0110]	[0.0108]	[0.00197]	[0.00480]	[0.00760]	[0.00552]
age_15	-0.000813***	-0.00369***	-0.00213**	0.00124***	-0.000245**	-0.00249***	-0.00114*	0.00112***
	[0.000198]	[0.000729]	[0.000888]	[0.000420]	[0.000113]	[0.000579]	[0.000662]	[0.000268]
tenure	0.000970**	-0.0002	0.0010	0.000924**	0.0003	-0.0014	-0.0005	0.0006
	[0.000423]	[0.00153]	[0.00111]	[0.000418]	[0.000435]	[0.000857]	[0.000564]	[0.000492]
seniority_2015	0.0776***	0.0945***	0.0766***	0.0713***	0.0431***	0.0469***	0.0424***	0.0449***
	[0.00237]	[0.00371]	[0.00304]	[0.00328]	[0.00183]	[0.00315]	[0.00232]	[0.00230]
Constant	-0.0272**	0.0144	0.0367	-0.113***	-0.0511***	0.0132	-0.0192	-0.120***
	[0.0113]	[0.0241]	[0.0318]	[0.0222]	[0.00463]	[0.0159]	[0.0252]	[0.0161]
Observations	49,293	16,499	17,217	15,577	49,293	16,499	17,217	15,577
Adjusted R-squared	0.105	0.151	0.097	0.074	0.077	0.108	0.071	0.060
LHS mean	0.108	0.074	0.109	0.142	0.044	0.024	0.042	0.065