# Technology Shocks, Human Capital, and Financial Decisions

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**Abstract**

Broad technological change is hard for workers to interpret: a new technology can displace some tasks, complement others, and revalue skill bundles. How do workers assess the risk to their human capital while the transformation is still unfolding? I study layoffs in which AI is changing the need for certain kinds of work. Such layoffs give stayers, the workers who remain at the firm, a local signal: they see which roles the firm cuts. Linking coded layoff announcements to employment histories, household records, and deed and mortgage records, I compare stayers in the same layoff by how heavily the layoff cut their roles relative to the firm's normal turnover. After AI layoffs, high-exposure stayers, those in the roles the layoff cut most, start 71 percent more short training programs in the year of the layoff if they are under 40, and over the following year reduce first-home purchases by 16 percent if they are renters and home equity borrowing by 19 percent if they are homeowners with ample equity, compared with low-exposure coworkers. These gaps do not appear after other layoffs. I build a standard life-cycle model of housing and mortgages and incorporate the risk that technology replaces workers' jobs. The calibrated model generates about four fifths of the post-layoff purchase gap in the data, and almost all of this gap comes from the change in stayers' beliefs about whether AI can replace their work. A counterfactual decomposition shows that AI layoffs lower total homeownership by 1.3 percentage points. Households respond to technological change before it reaches their own jobs.

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# 1 Introduction

Artificial intelligence is changing how firms organize tasks, allocate workers and value skills (Acemoglu et al., 2022; Hampole et al., 2025). The effects differ across workers. AI substitutes for workers in some tasks and complements them in others (Brynjolfsson et al., 2025; Noy and Zhang, 2023; Dell'Acqua et al., 2026), and how exposed a job is to AI varies across tasks, occupations and employers (Webb, 2019; Felten et al., 2021; Acemoglu et al., 2022; Hampole et al., 2025). Yet how individual workers interpret this transformation is not well understood. This paper asks how workers infer the risk to their human capital while these changes are still unfolding, and whether that inference affects their financial decisions.

Answering this question requires observing when workers receive news about this risk and how they respond. Layoffs at the worker's own firm provide such a setting. When a firm cuts workers whose tasks AI can now perform, the workers who remain see which roles the firm cut and whether their own is among them. Remaining workers (stayers) whose roles the firm cut most learn that their human capital may also be at risk, while coworkers in the same layoff whose roles the firm cut less have much less reason to draw this conclusion. I measure the response in three decisions. The first is training. Stayers who expect their human capital to be worth less can acquire new skills. Workers retrain when a new technology changes their jobs (Dauth et al., 2021; Battisti et al., 2023), and retraining raises their later earnings (Hyman, 2018; Hyman et al., 2025). The second is buying a first home. A purchase ties a large and illiquid share of the household's wealth to a single house in its current location (Cocco, 2005; Davidoff, 2006) and is costly to reverse (Chetty and Szeidl, 2007; Dixit and Pindyck, 1994), so a renter who has become less sure of future earnings has reason to postpone it. The third is new home equity borrowing. An owner who has become less sure of future earnings is less willing to take on leverage, because the commitment payments on new debt rely on those earnings (Mian and Sufi, 2011; Bhutta and Keys, 2016; DeFusco, 2018).

The main finding is that stayers change how they invest in training and housing before their own earnings change, and that they do so after AI layoffs but not after other layoffs. I compare stayers in the roles the layoff over-cut (high-exposure stayers) with their coworkers in the same layoff. After AI layoffs, high-exposure stayers start more training programs and take on fewer housing commitments than their coworkers: renters buy fewer first homes, and owners take on less new home equity borrowing. After industry downturns, firm contractions and layoffs due to other technologies, the differences between high-exposure stayers and their coworkers in short programs, purchases and borrowing are not statistically significant. The response therefore reflects what an AI layoff reveals

about how AI has revalued the stayers' human capital, not the layoff itself.

The evidence comes from a catalog of 4,987 layoffs linked to worker, household and property records. I collect layoffs from WARN notices (2016–2025) and the layoffs.fyi tracker (2022–2025), gather the firm's statements and press coverage for each, and code the reasons for the layoff against a written codebook. Each layoff with a stated reason belongs to one of three types, set by its primary and secondary reasons (Figure 1). In a *technology transformation*, a new technology does the work of the workers cut, or the firm spends the resources the layoff frees on a new technology, either AI or another technology. An *industry downturn* is caused by a shock common to the firm's industry or the economy, and a *firm contraction* by a reason specific to the firm. The layoffs are linked to Revelio Labs worker profiles, which record positions, skills and education, and each worker is linked to an InfoUSA household and to the CoreLogic deeds and mortgages that name the worker as buyer or borrower.

The empirical design compares stayers in the same layoff who share an age band (five bands), a seniority band (four bands) and a job category (seven categories), a group I call a matched cell; the only difference between them is how much the layoff over-cut their roles. A layoff over-cuts a role when the role's share of the layoff's departures exceeds its share of the firm's departures in the same months a year earlier, so the over-cut roles are the work the layoff removed beyond the firm's normal turnover. Workers in the same role perform similar tasks and use similar skills, so the over-cut roles describe the work the layoff cut. Within each cell, I compare stayers whose roles the layoff over-cut more than the median coworker's (high-exposure stayers) with their coworkers. Two stayers in a cell work at the same firm and face the same announcement, stock price and interest rates, so information about the firm as a whole affects both alike. Stayers in the roles a firm cuts may also expect to be cut in a later round, whatever the reason for the layoff. In industry downturns and firm contractions, the firm cuts these roles because the demand for what it produces has fallen, not because the work in these roles has become less valuable, so these layoffs carry the same risk of a later round but little news about the value of the stayers' human capital. I therefore estimate the same comparison for each type of layoff and compare the gap after AI layoffs with the gap after other layoffs. Focusing on stayers also separates what workers learn from changes in their income. Workers who lose their jobs learn about the value of their human capital at the same time as they lose income and liquidity (Jacobson et al., 1993; Ganong and Noel, 2019). Stayers keep their jobs and their income, so a change in their decisions reflects a change in their beliefs rather than a loss of income.

Workers cut in AI layoffs fare worse than workers cut in firm contractions who held the same role, seniority and pay. They take 0.38 months longer to find a new job, against

2.4 months after firm contractions; their new jobs pay 2.7 log points less relative to their old ones; and they are 1.4 percentage points more likely to take a lower-seniority position and 3.3 percentage points more likely to change job title (Table 2). The additional losses of workers cut in industry downturns or in layoffs due to other technologies are smaller and not statistically significant. Other employers value the workers cut in AI layoffs less, so stayers who do the same work have reason to reassess the value of their own human capital.

The estimates are large relative to the coworkers' rates. In the year of the layoff, high-exposure stayers under 40 are 0.25 percentage points more likely than their coworkers to start a short training program, such as a course, certificate or bootcamp, against a base rate of 0.36 percent, or 71 percent of that rate (Table 3). Over the 12 months after the layoff, high-exposure renters record 0.44 fewer quarters with a home purchase per 100 renters than their coworkers, net of their own purchase rates before the layoff, or 16 percent of the coworkers' rate. High-exposure owners with a combined loan-to-value ratio below 0.6 record 0.27 fewer quarters with new home equity borrowing per 100 owners, or 19 percent of their coworkers' rate (Table 4).

The housing response is specific to AI layoffs. In the year before the layoff, the differences between high-exposure stayers and their coworkers in purchases and borrowing are small and not statistically significant. When AI layoffs are pooled with all other layoffs of 2023–24, the gap at AI layoffs is more negative by 0.60 for purchases and 0.38 for borrowing, so the gap is not explained by a shock to workers in these roles in these years, or to the housing and credit markets where they live, which would have appeared at the other layoffs as well (Table 5). The purchase gap rises with how heavily the layoff over-cut the stayer's role, and holds when age, tenure and household demographics are controlled for. At layoffs that mention AI without citing it as a reason, the estimates are positive and not statistically significant. The gap holds under checks on each step of the record linkage and when I drop one AI layoff at a time.

The purchase gap comes from stayers who work in the five leading technology hubs, and it is larger among stayers under 40 and in households without children (Table 6). It holds among stayers who are still at the firm four quarters later, so it does not reflect realized job loss. It is larger when the workers cut from the stayer's role had similar outcomes after the layoff, so that the layoff gives stayers more precise information, and among stayers who update their profiles, a sign of job search (Table 7). Together, the evidence is consistent with stayers interpreting an AI layoff at their own firm as information about the value of their human capital: they stay at the firm, invest in new skills and postpone housing commitments that must be paid from future income.

The last part of the paper asks what this learning implies for homeownership and

welfare. I build a life-cycle model of housing tenure, mortgages and home equity borrowing in the tradition of Cocco (2005) and Kaplan et al. (2020). Households are uncertain whether a new technology can replace their work and learn about it from layoffs at their employer, because stayers whose work can be replaced are more likely to be high-exposure stayers. They can retrain so that their work can no longer be replaced. I calibrate the model to the stayers and to AI, setting the share of workers whose work AI can replace to 19 percent, the share of U.S. workers with more than half of their tasks exposed to large language models (Eloundou et al., 2024), and targeting the purchase gap and the rate of retraining. The calibrated model generates about four fifths of the post-layoff purchase gap in the data, and almost all of this gap comes from the change in stayers' beliefs about whether AI can replace their work. In the calibrated economy, AI layoffs lower homeownership by 1.3 percentage points and cost households 2.75 percent of consumption, 8.0 percent for the workers whose work AI can replace and 1.4 percent for the others. Most of this cost is the expected loss of earnings. Of three policies financed within the economy, only mortgage relief for owners who are cut raises welfare, by 0.02 percent; wage insurance lowers it by 0.07 percent and a training subsidy by 0.22 percent.

**Related literature.** The paper relates to three literatures. The first studies how technology changes the demand for tasks and skills (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2019, 2022; Deming and Noray, 2020), and more recent work measures which jobs are exposed to AI and how AI affects labor demand and productivity (Webb, 2019; Felten et al., 2021; Acemoglu et al., 2022; Brynjolfsson et al., 2025; Noy and Zhang, 2023; Dell'Acqua et al., 2026; Hampole et al., 2025). This work measures how exposed jobs are to AI in general. I study what workers learn when an AI layoff at their own firm cuts particular roles, and how they respond before their earnings change. This requires classifying layoffs by the reasons in the firm's statements and press coverage, the firm's own account of the layoff (Farber and Hallock, 2009), and checking that account against the later careers of the workers cut. The classification separates layoffs in which technology replaces work, or in which the firm cuts workers to fund technology, from layoffs caused by downturns or by reasons specific to the firm. The evidence on the workers cut relates to work on the costs of displacement (Jacobson et al., 1993), on the occupation-specific nature of human capital (Kambourov and Manovskii, 2009), and on the share of displaced workers' losses that technological change accounts for (Braxton and Taska, 2023).

The second literature studies how labor-income risk shapes housing and portfolio decisions. Housing is a large, illiquid asset that crowds out households' holdings of stocks (Cocco, 2005), households whose income covaries more with local house prices buy less housing (Davidoff, 2006), and the value of owning as a hedge against future housing

costs shapes how house price risk affects housing demand and returns (Han, 2010, 2013). Consumption commitments such as housing amplify aversion to moderate income risk (Chetty and Szeidl, 2007), and job insecurity reduces homeownership (Lepinteur et al., 2026). In this work, and in quantitative life-cycle models of housing (Berger et al., 2018; Kaplan et al., 2020), labor-income risk is a known property of the income process, such as its variance, its left tail (Guvenen et al., 2014; Catherine, 2022) or the risk of losing a job. Here the risk is a change in the value of a worker's human capital, which the worker must infer from a dated event while still employed. Closest to this paper, Alfaro and Park (2025) study how uncertainty about an employer affects its employees' spending and saving, and Gomes et al. (2024) and Berg et al. (2026) relate workers' exposure to robots and AI, measured by industry or occupation, to their stock holdings; Ahammer et al. (2025) study the health of workers who remain after a layoff. Here exposure is specific to each layoff and differs among coworkers, and the outcomes are housing commitments rather than liquid assets. The borrowing result also relates to work on how home equity borrowing responds to housing collateral (DeFusco, 2018): high-exposure stayers forgo new borrowing that otherwise similar coworkers take up.

The third literature studies how personal experience affects beliefs and financial decisions (Malmendier and Nagel, 2011, 2016; Koudijs and Voth, 2016; Kuchler and Zafar, 2019; D'Acunto et al., 2021), including in housing (Bailey et al., 2018; Kuchler et al., 2023). Most of this work concerns beliefs about aggregate outcomes such as stock returns, inflation or house prices. Here the experience is seeing coworkers who do the same work lose their jobs, and the belief concerns the value of the worker's human capital. Coding the content of each layoff allows the same comparison across layoff types. After layoffs due to other technologies and layoffs that mention AI without citing it as a reason, the estimates are smaller than after AI layoffs and not statistically significant, so the response reflects what the layoff reveals about how AI has revalued the worker's human capital, not the fact that a layoff occurred.

**Roadmap.** Section 2 describes the layoff catalog, the codebook and the linked data. Section 3 presents the within-layoff design. Section 4 reports what happens to the workers cut and how stayers respond in training and in housing, and tests whether the housing response comes from AI revaluing the stayers' human capital. Section 5 examines who responds and through which channels. Section 6 builds and calibrates the model, measures the effects of the technology on homeownership and welfare, and runs counterfactuals. Section 7 concludes.

## 2 Data and Measurement

The analysis links four sources. A catalog of layoffs, each coded for the reasons the firm and the press give for it, supplies the layoffs and their types. Revelio Labs worker profiles supply the workers cut and the stayers, with their roles, positions and education. InfoUSA household records place each worker in a household, and CoreLogic deed and mortgage records supply the purchases and home equity borrowing in the worker's name. Appendix Figure A1 summarizes how the sources are combined.

### 2.1 The layoff catalog

The catalog combines two sources. The first is the notices that employers file under the Worker Adjustment and Retraining Notification (WARN) Act, which requires advance notice of large layoffs and plant closings. WARN notices are an administrative record, but they are filed site by site and say little about why the layoff occurs. I use the notices of a balanced panel of 11 states for 2016–2021 and of all states from 2022. The second source is layoffs.fyi, a tracker of announced layoffs, mostly at technology firms, that begins in 2022 and links each entry to the press coverage or company statement that reports it. The catalog leaves out 2020, when closures due to COVID-19 dominate WARN filings.

For each record I collect the firm's statements about the layoff and the press coverage of it. Repeated announcements of the same layoff are collapsed into one, WARN filings that are site-level parts of an announced layoff are replaced by the announcement, and filings by the same firm in quick succession are merged into one layoff. The 5,662 records of the two sources give 4,987 layoffs for 2016–2025, of which 4,793 are matched to a company in Revelio.

### 2.2 Coding each layoff

Each layoff is coded against a written codebook with four questions (Appendix Figure A2). The first records the reasons the material gives for the cut: a primary reason, the one the headline or the firm's statement puts first, and a secondary reason when a distinct second one is stated. Every stated reason receives one code, assigned by ordered steps that make the codes mutually exclusive. A reason is a technology if a named technology does work the workers cut did, or if the firm moves resources from the activities it cuts toward building or using that technology. It is a shock common to the industry or the economy if the material describes a pressure that affects firms other than this one, and otherwise it is specific to the firm. The second question asks, for layoffs with a technology reason, whether the material describes the tasks the technology now performs or only asserts a

gain in efficiency. The third records whether the firm and the press give the same reason, and the fourth the scope of the cuts: the whole firm, whole sites, part of one site, or units across the firm.

Each layoff is coded independently by two coders, both the large language model Claude Opus, from the collected material. The 1,075 layoffs on which they differ on the primary reason, on whether the firm and the press give the same reason, or on the scope of the cuts are adjudicated under written rules, and a separate pair of coders records whether automation or software is mentioned among the stated reasons. Before adjudication, the two coders agree on the primary reason for 90.8 percent of layoffs (Appendix Table A2). Appendix Figure A3 follows one layoff through the codebook. When Intuit cut 1,800 workers in July 2024, its chief executive wrote that the firm would "increase investments in priority focus areas of AI and generative AI," and the press reported the cut as a shift toward AI. Both coders give AI as the primary reason, because the firm moves the resources the layoff frees toward AI.

### 2.3 Three types of layoff

The reasons assign each layoff to one of three types (Figure 1). A layoff is a *technology transformation* if its primary or secondary reason is a new technology that takes over the work of the workers cut or receives the resources the layoff frees. I split these layoffs into AI layoffs, in which the technology is AI of any kind (machine learning, generative AI, chatbots or AI agents; most announcements say only "AI"), and layoffs due to other technologies, in which it is software, automation, robotics or another production technology, or in which automation or software is mentioned among the stated reasons. Among the remaining layoffs, an *industry downturn* is a layoff whose primary reason is a shock common to the firm's industry or the economy, such as falling industry demand, an economy-wide slowdown or a policy aimed at the industry. A *firm contraction* is a layoff whose primary reason is specific to the firm, such as cost cutting, lost demand for its own products, a strategic exit, financial distress or a change of ownership. The catalog contains 75 AI layoffs, 217 layoffs due to other technologies, 860 industry downturns and 2,895 firm contractions; the remaining 940 layoffs state no reason and are not classified. The two coders assign the same type to 93.9 percent of layoffs ($\kappa = 0.90$) and agree on whether a layoff is an AI layoff for 99.9 percent ($\kappa = 0.96$).

The types differ in what stayers can infer from the layoff about the value of particular work. In a technology transformation, the firm states which work a technology now does, or which work it gives up to pay for one. Because other firms can adopt the same technology, the firm's statement is also informative about the value of that work at other employers. In an industry downturn, the firm cuts workers because demand has fallen

across the industry or the economy, and in a firm contraction it cuts workers because of its own circumstances. In neither type does the firm state which kinds of work have lost value. Of the 75 AI layoffs, the firm moves the resources the layoff frees toward AI in 55, as at Intuit, and AI takes over the work of the workers cut in 11. In both kinds of AI layoff, stayers in the roles the firm cut observe that the firm values that work less than its investment in AI. A layoff whose material mentions AI without citing it as a reason is assigned the type of its stated reasons; Panel D of Table 5 uses these layoffs as a comparison.

Appendix Figure A4 shows the catalog by year, type and source. AI layoffs appear from 2022, with 3 that year, 18 in 2023, 19 in 2024 and 35 in 2025. Appendix Figure A5 shows the industries of the 4,772 layoffs whose firm has a Revelio industry code. Information technology services is the largest industry, with 17 percent of these layoffs, followed by health care with 9 percent, and the 15 largest industries account for 78 percent. AI layoffs are concentrated in technology: 46 of the 75 are in information technology services and 10 in digital commerce services.

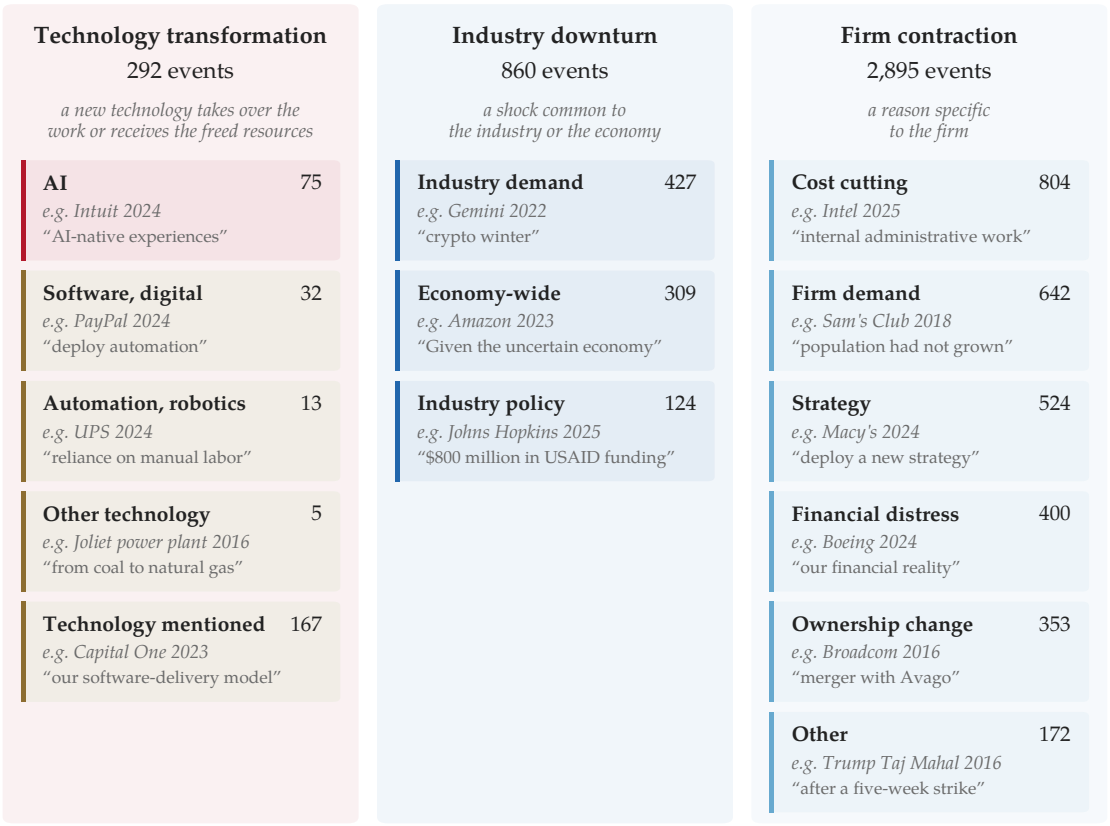
### 2.4 Workers cut and stayers

Revelio Labs builds worker histories from online professional profiles. For each worker it reports a sequence of positions, each with the employer, start and end month, job title, location, a standardized role, a seniority level from 1 (entry level) to 7 (senior executive) and a modeled salary. It also reports education records, degree and non-degree programs with their start years. Revelio models a salary from the title, employer, seniority and location of the position, so it measures the pay of the job rather than of the worker. Positions and education records are observed through mid-2026.

The *workers cut* in a layoff are the workers whose position at the firm ends between a month before and three months after the layoff date. The *stayers* are the firm's workers on the layoff date who have held their position for at least a year, whose position continues at least 92 days past the layoff, and whose Revelio profile is active. Workers who move to another position at the firm within 92 days are excluded. Because some firms cut workers in several rounds, a stayer's window ends before the firm's next layoff of at least 50 workers, so that each stayer's outcomes follow one layoff.

### 2.5 Layoff exposure

Workers in the same occupation perform similar tasks and use similar skills, and much of their human capital is specific to the occupation (Acemoglu and Autor, 2011; Gathmann and Schönberg, 2010; Kambourov and Manovskii, 2009). I therefore measure what a layoff




## Figure 1. Three Types of Layoff

*Notes:* Each layoff is assigned a primary reason and, where one is stated, a secondary reason from the firm statements and press coverage collected for it, and the reasons determine its type. A layoff is a Technology transformation if its primary or secondary reason is a new technology that takes over the work of the workers cut or receives the resources the layoff frees. It is a Technology transformation: AI if that technology is AI, and a Technology transformation: Other technology if it is another technology (software and digital processes, automation and robotics, or another production technology) or if automation or software is mentioned among the stated reasons. Among the remaining layoffs, an Industry downturn is a layoff whose primary reason is a shock common to the firm's industry or the economy: falling industry demand (including demand lost to other firms' technology), economy-wide conditions or policy aimed at the industry. A Firm contraction is a layoff whose primary reason is specific to the firm: cost cutting, lost demand for the firm's own products, a strategic exit or refocus, financial distress, a change of ownership, or another firm-specific event. Numbers are layoffs in the cleaned catalog. In the Technology transformation panel, a layoff is counted under the technology named as its reason (the primary reason if it is a technology, otherwise the secondary reason), or under Technology mentioned if automation or software is mentioned among the stated reasons but no technology is the primary or secondary reason; the other panels count layoffs by primary reason. Quotes are from the firm statement or press coverage of each example. Layoffs with no stated reason are not classified.

tells a stayer about the value of the stayer's human capital by how heavily the layoff cut the stayer's role, one of 50 Revelio roles, which group job titles into kinds of work close to occupations (Appendix Table A3). The workers cut in a layoff include workers who would have left in any case, so the measure compares the layoff's departures with the firm's normal turnover. For layoff $e$ and role $r$, let $s^L_{er}$ be the share of the layoff's departures that come from role $r$, and $s^B_{er}$ the share of the firm's departures that come from role $r$ in the same window a year earlier. The layoff *over-cuts* role $r$ if $s^L_{er} > s^B_{er}$, and the amount by which it over-cuts the role is

$$\text{Overcut}_{er} = \left(s^L_{er} - s^B_{er}\right)^+, \tag{1}$$

which is zero for a role the layoff did not over-cut. A stayer $i$ in role $r(i)$ is a *high-exposure stayer* if the layoff over-cut the stayer's role by more than it over-cut the role of the median stayer in the same cell,

$$\text{HighExp}_i = \mathbf{1}\Big[\,\text{Overcut}_{e(i)r(i)} > \underset{j \in c(i)}{\text{median}}\,\text{Overcut}_{e(j)r(j)}\Big], \tag{2}$$

and a *low-exposure stayer* otherwise. A cell $c(i)$ groups the stayers of one layoff who are in the same age band (under 30, 30s, 40s, 50s, 60 and over), seniority band (Revelio levels 1–2, 3–4, 5 and 6–7) and job category, one of 7 Revelio job categories. A layoff over-cuts the roles of 48 percent of its stayers, and 53 percent of stayers are in cells where the median stayer's role is not over-cut, so that there a high-exposure stayer is a stayer whose role the layoff over-cut. In the other cells, a high-exposure stayer's role is over-cut by more than the median coworker's. The measure differs from measures of AI exposure, which assign one value to each occupation (Webb, 2019; Felten et al., 2021; Eloundou et al., 2024): layoff exposure is specific to each layoff and differs among coworkers at the same firm.

### 2.6 Households and property records

InfoUSA compiles household records from public and commercial sources. For each household and year it reports the residential address, length of residence, household size, the presence of children, marital status and a modeled household income. Each Revelio worker is linked, in the year before the layoff, to the InfoUSA person with the same first and last name and an agreeing middle initial who ranks first on birth year and on distance from the worker's job.

CoreLogic deed records report each recorded transfer of residential property, with the names and mailing address of the buyers and the address of the property. A purchase is a deed that names the stayer as a buyer, by first and last name with middle initials

agreeing when both are recorded, and that is tied to the stayer's home: either the stayer's InfoUSA home is the purchased property within three years of the sale, or the buyer's mailing address is the stayer's home. Requiring the address as well as the name keeps out purchases by namesakes. CoreLogic mortgage records report each lien recorded against a property, with its type, amount and borrowers. New home equity borrowing is a home equity line of credit or home equity loan that names the stayer as a borrower, recorded on the stayer's home or on a property the stayer bought. Deeds and mortgages are complete through mid-2025.

A stayer is a homeowner if named among the owners of the stayer's home in the county assessor roll in the year before the layoff, and a renter otherwise. For owners, the combined loan-to-value ratio (CLTV) at the end of that year divides the debt on the home by its CoreLogic market value. Debt is the latest first lien recorded since the owner moved in plus junior liens recorded in the previous five years, at their original amounts.

### 2.7 Outcomes and samples

For the workers cut, the new job is the first position that starts within 12 months of leaving, at a firm other than the layoff firm and its parent. The outcomes are the months from leaving to the new job, the change in log salary, whether the new job has a lower seniority level, and whether it is in a different one of 150 finer Revelio roles, a change of job title. For stayers, the training outcome is the start of a program in the education records, dated by year. Short programs are courses, certificates, bootcamps, professional and executive education and other non-degree programs of up to a year; degree programs are associate, bachelor's, master's, MBA and doctoral programs. The housing outcomes are counted by quarter: a quarter with a purchase deed naming the stayer as buyer, and a quarter with new home equity borrowing. Section 3 nets out each stayer's own rate before the layoff from these counts.

The analysis sample has 1,855,022 stayers at 1,508 layoffs dated 2016–2024. AI layoffs begin in 2022, so industry downturns and firm contractions enter from 2022 as well, while layoffs due to other technologies enter from 2016. Each outcome uses the stayers for whom the decision is relevant and who are observed for the whole window. The training sample has 309,130 stayers under 40 at 1,043 layoffs, observed from three years before through one year after the layoff year. The purchase sample has 271,643 renters at 1,071 layoffs, and the borrowing sample 118,011 owners with a CLTV below 0.6 at 941 layoffs, both observed through 12 months after the layoff. Owners with a CLTV below 0.6 have ample equity, so new home equity borrowing is for them a choice rather than a constraint. The sample of workers cut has the 488,228 workers who find a new job within 12 months of leaving, at 2,945 layoffs dated 2016–2024, 38 of them AI layoffs; unlike the stayer samples, it includes

industry downturns and firm contractions before 2022.

Table 1 describes the layoffs and the stayers. The median layoff announces 121 workers cut. Per layoff, Revelio records a median of 150 workers cut and 414 stayers, and a median of 82 stayers meet the rules of the analysis sample. The stayers are well-paid, mid-career workers: the mean modeled salary is $146,800, 70 percent are under 40, 37 percent are women, and the median stayer has held the position for 2.9 years. Sixty-four percent are married and a third have children at home. Fifty-three percent own their home, the mean market value of these homes is $738,000, and the median CLTV is 0.68. Over the 24 months before the layoff, owners with a CLTV below 0.6 record new home equity borrowing in 1.10 quarters per 100 owners per year. Over the 12 months after the layoff, renters record a purchase in 2.42 quarters per 100 renters.

# 3 Empirical Design

## 3.1 The comparison within a layoff

I compare high- and low-exposure stayers in the same layoff. After a layoff, everyone who remains at the firm may revise what they expect about the firm's prospects, its stock price and the value of employees' equity, and about workloads and promotion chances. The layoff also occurs at one point in the interest-rate cycle. Two stayers in the same cell share all of this. They work at the same firm, were kept in the same layoff, are of similar age and seniority and hold the same kind of job, and they differ in how heavily the layoff over-cut their roles. The comparison removes any effect the layoff has on all of its stayers alike and keeps the effect that differs with how heavily the layoff cut the stayer's role. If all stayers at an AI layoff buy and borrow less, the comparison removes that decline as well, so the estimates measure how stayers respond to information about their own role, not the total effect of the layoff on those who remain.

The design uses stayers because they keep their jobs. The workers cut learn about the value of their human capital at the same time as they lose earnings and liquidity, and this loss alone would delay a purchase. Stayers keep their income, so a change in their purchases and borrowing after the layoff reflects what they learned from it.

Stayers whose role the firm cut may expect to be next in any layoff, so I estimate the high-exposure gap, the difference between high-exposure stayers and their coworkers in the same cell, separately for each type of layoff. The comparison across types tests whether the gap is larger when the firm cuts work that a new technology takes over, or cuts work to pay for a new technology. Relative to firm contractions, the benchmark, industry downturns show whether the gap also appears after any shock common to other firms, and layoffs due to other technologies show whether it appears after any new technology.

**Table 1. Summary Statistics**

| | Mean | SD | P25 | Median | P75 | Obs. |
|---|---|---|---|---|---|---|
| *Panel A. Layoffs* (layoffs.fyi and WARN notices; one observation per layoff) | | | | | | |
| Announced layoffs | 397 | 1,368 | 63 | 121 | 293 | 1,318 |
| Workers cut (Revelio) | 799 | 2,680 | 63 | 150 | 415 | 1,508 |
| Stayers at the layoff firm (Revelio) | 4,828 | 25,090 | 151 | 414 | 1,527 | 1,508 |
| Stayers in the analysis sample | 1,230 | 5,426 | 18 | 82 | 431 | 1,508 |
| Year of the layoff | 2022.7 | 1.4 | 2022 | 2023 | 2024 | 1,508 |
| Type of layoff (share of events) | | | | | | |
| Technology transformation | | | | | | |
| AI | 0.02 | 0.15 | 0 | 0 | 0 | 1,508 |
| Other technology | 0.10 | 0.30 | 0 | 0 | 0 | 1,508 |
| Industry downturn | 0.26 | 0.44 | 0 | 0 | 1 | 1,508 |
| Firm contraction | 0.62 | 0.49 | 0 | 1 | 1 | 1,508 |
| *Panel B. Worker profiles and education records* (Revelio; stayers) | | | | | | |
| Under 40 | 0.70 | 0.46 | 0 | 1 | 1 | 1,855,022 |
| Female | 0.37 | 0.48 | 0 | 0 | 1 | 1,855,022 |
| Salary ($000) | 146.8 | 77.4 | 85.2 | 146.6 | 192.9 | 1,855,022 |
| Seniority (1–7) | 3.16 | 1.56 | 2.00 | 3.00 | 5.00 | 1,855,022 |
| Years in the position | 4.7 | 5.1 | 1.8 | 2.9 | 5.4 | 1,855,022 |
| Over-cut of own role | 0.006 | 0.015 | 0.000 | 0.000 | 0.006 | 1,855,022 |
| Short programs per year, under 40 (per 100) | 0.68 | 5.00 | 0 | 0 | 0 | 1,273,888 |
| *Panel C. Household records* (InfoUSA; stayers, year before the layoff) | | | | | | |
| Ethnicity (share) | | | | | | |
| White | 0.59 | 0.49 | 0 | 1 | 1 | 1,692,430 |
| Black | 0.05 | 0.22 | 0 | 0 | 0 | 1,692,430 |
| Hispanic | 0.12 | 0.33 | 0 | 0 | 0 | 1,692,430 |
| Asian | 0.23 | 0.42 | 0 | 0 | 0 | 1,692,430 |
| Married | 0.64 | 0.48 | 0 | 1 | 1 | 1,855,022 |
| Children in the household | 0.33 | 0.47 | 0 | 0 | 1 | 1,855,022 |
| Household size | 2.0 | 1.2 | 1.0 | 2.0 | 3.0 | 1,855,022 |
| Household income ($000, modeled) | 131 | 114 | 49 | 100 | 170 | 1,855,022 |
| Length of residence (years) | 10.8 | 10.7 | 2.0 | 7.0 | 16.0 | 1,855,022 |
| *Panel D. Property, deed and mortgage records* (CoreLogic; stayers) | | | | | | |
| Homeowner | 0.53 | 0.50 | 0 | 1 | 1 | 1,855,022 |
| Owners in the year before the layoff | | | | | | |
| Home market value ($000) | 738 | 569 | 334 | 568 | 949 | 965,754 |
| Combined loan-to-value ratio | 0.72 | 0.52 | 0.44 | 0.68 | 0.89 | 965,754 |
| Home equity borrowing, CLTV $< 0.6$ (per 100) | 1.10 | 7.54 | 0.00 | 0.00 | 0.00 | 124,682 |
| Renters in the year before the layoff | | | | | | |
| Purchases, 12 months after the layoff (per 100) | 2.42 | 15.47 | 0.00 | 0.00 | 0.00 | 279,328 |

*Notes:* This table reports summary statistics for the analysis sample of Section 2.7; the samples of Figures 3–5 further require that a stayer be observed for the whole window. Panel A describes the 1,508 layoffs (2016–2024); workers cut and stayers at the layoff firm are Revelio workers who leave the firm in the layoff window and who remain, and types follow Figure 1, with Industry downturn and Firm contraction layoffs dated 2022 or later. Panels B–D describe the stayers of the analysis sample. The over-cut of own role is the share of the layoff's departures in the stayer's role (one of 50 Revelio roles) minus that share among the firm's departures in the same window a year earlier, set to zero if negative (equation (1)). Short training programs are per year over the three years before the layoff. Panel C is measured in InfoUSA in the year before the layoff; ethnicity is name-based and income is modeled. In Panel D, homeowners are named as owners of their home in the assessor roll in the year before the layoff; market value is winsorized at the 95th percentile; new home equity borrowing (home equity lines of credit and loans in the stayer's name) is per year over the 24 months before the layoff; purchases are quarters with a deed naming the stayer as buyer. Percentiles of indicator variables are 0 or 1.

### 3.2 Estimating equations

Within the layoffs of each type, I estimate

$$Y_{it} = \beta_t \, \text{HighExp}_i + X_i' \gamma_t + \alpha_{c(i),t} + \varepsilon_{it}, \tag{3}$$

where $Y_{it}$ is an outcome of stayer $i$ at time $t$ relative to the layoff, measured relative to the stayer's own level before the layoff; $\text{HighExp}_i$ is the indicator for high-exposure stayers in equation (2); $\alpha_{c(i),t}$ are fixed effects for cells of layoff $\times$ age band $\times$ seniority band $\times$ job category; $X_i$ contains log salary, seniority and a female indicator; and $\varepsilon_{it}$ is the error. The coefficient $\beta_t$ is the difference in $Y_{it}$ between high-exposure stayers and their coworkers in the same cell. Because each outcome is measured relative to the stayer's own level before the layoff, a stable difference between high-exposure stayers and their coworkers does not enter $\beta_t$.

**Housing.** For renters and for owners with a CLTV below 0.6, $t$ is the number of months $h$ since the layoff, and $Y_{ih}$ is the number of quarters in the first $h$ months with a purchase deed naming the stayer as buyer or with new home equity borrowing recorded in the stayer's name, per 100 stayers, minus the stayer's own number over the 24 months before the layoff, scaled to the length of the window.[1] Table 4 reports $\beta_h$ at 6 and 12 months, and the 12-month estimate is the main estimate. Figures 4 and 5 also plot $\beta_h$ for the 6 and 12 months before the layoff. The path equals zero at the layoff date, so a stable difference in rates does not appear as a slope, while a difference in trends before the layoff does.

**Training.** For stayers under 40, $t$ is the year $k$ relative to the layoff year, and $Y_{ik} = y_{ik} - y_{i,-1}$, where $y_{ik}$ equals 100 if stayer $i$ starts a program of a given kind in year $k$, so the year before the layoff is the reference. Figure 3 plots $\beta_k$ for short programs from three years before to one year after the layoff year, and Table 3 reports $\beta_0$ for short programs and degree programs.

**Comparisons across types.** To test whether the high-exposure gap at AI layoffs differs from the gap at other layoffs, I pool AI layoffs with a set of comparison layoffs and estimate, at 12 months,

$$Y_i = \beta \, \text{HighExp}_i + \lambda \, \text{HighExp}_i \times \text{AI}_e + X_i' \gamma + \alpha_{c(i)} + \varepsilon_i, \tag{4}$$

where $\text{AI}_e$ equals one if stayer $i$'s layoff $e$ is an AI layoff. Cells lie within a layoff, so they absorb the main effect of an AI layoff, and $\lambda$ is the difference between the high-exposure gap at AI layoffs and the gap at the comparison layoffs.

[1] Let $N_i(a, b)$ be the number of quarters between months $a$ and $b$ relative to the layoff with an event; a quarter with several events counts once. Then $Y_{ih} = 100 \times [N_i(1, h) - (h/24)\, N_i(-24, -1)]$ for $h > 0$, and $Y_{ih} = -100 \times [N_i(h, -1) - (|h|/24)\, N_i(-24, -1)]$ for the months $h < 0$ before the layoff.

**Workers cut.** For a worker $i$ cut in layoff $e(i)$, I estimate

$$y_i = \sum_g \beta_g \, \mathbf{1}[\text{type}_{e(i)} = g] + \gamma \log w_i + \alpha_{c(i)} + \varepsilon_i, \tag{5}$$

where $y_i$ is an outcome of the new job, $g$ indexes AI layoffs, layoffs due to other technologies and industry downturns, with firm contractions omitted, $\log w_i$ is the worker's log salary before the layoff, and $\alpha_{c(i)}$ are fixed effects for cells of role (50 Revelio roles) $\times$ seniority $\times$ salary quintile $\times$ half-year of leaving. The coefficient $\beta_g$ compares workers cut in layoffs of type $g$ with workers cut in firm contractions who held the same kind of job at the same rank and pay and left at the same time. If the firm cuts work whose market value has fallen, the workers cut should take longer to find new jobs and take jobs with lower pay or seniority.

### 3.3 Identifying assumption and threats

The identifying assumption is that, within a cell, the housing outcomes of high- and low-exposure stayers would have changed by the same amount in the absence of the layoff. Because each outcome nets out the stayer's own rate before the layoff, the assumption concerns changes rather than levels: high-exposure stayers may buy or borrow more or less often than their coworkers, as long as the difference would have stayed the same. For the comparisons across types, the assumption is that, apart from what stayers learn at an AI layoff about the value of the work the firm cuts, the gap at AI layoffs would equal the gap at the comparison layoffs. Table 5 addresses the threats to these assumptions at AI layoffs, one panel at a time.

**Differences between stayers.** Stayers in the roles the firm cut may differ from their coworkers in ways that also affect housing decisions. Before the layoff, high-exposure stayers resemble their coworkers: their mean age, salary, seniority, marital status, household income and homeownership, and their rates of training, home purchases and home equity borrowing, are close to those of low-exposure stayers (Appendix Table A1). Panel B replaces the outcome with the number of quarters with an event in the 12 months before the layoff minus the number in the 12 months before that, a placebo for diverging trends. It also adds controls for years in the position, for household demographics, and for both.

**Shocks in the years of AI layoffs.** Nearly all AI layoffs in the housing samples fall in 2023 and 2024, years of high mortgage rates and of cuts across the technology sector. A shock in those years to workers in the roles cut in AI layoffs, or to the housing markets where they live, would remain after the comparison within a layoff. The same shock would also affect high-exposure stayers at other layoffs of those years. Panel A pools AI layoffs with all other layoffs of 2023–24, and with the layoffs of each other type, and reports $\lambda$

from equation (4).

**Intensity.** If stayers respond to information about their own work, the response should be larger when the layoff over-cut their role by more. Panel C replaces $\text{HighExp}_i$ with indicators for the quartiles of $\text{Overcut}_{e(i)r(i)}$ within cells.

**The word "AI."** Stated layoff reasons are the firm's account as relayed by the press (Farber and Hallock, 2009), and firms may describe layoffs as driven by AI to show investors that they are becoming more efficient. Stayers may then react to the word rather than to what the firm does. Panel D estimates the gap at layoffs whose stated reasons mention AI without citing it as the primary or secondary reason. A cost cut presented as an AI layoff would be coded as one, and the outcomes of the workers cut (Table 2) address that case because they do not depend on how the firm describes the layoff: if AI layoffs were cost cuts described as AI layoffs, the workers cut would fare like workers cut in firm contractions.

**Record linkage.** The links from layoffs to Revelio companies, from workers to households and from households to deeds and loans use names and addresses. Errors that differ between high- and low-exposure stayers could produce a gap. Panel E checks each step. It keeps layoffs whose count of workers cut in Revelio is within a factor of 1.25 of the announced count; keeps stayers whose household is in the state where they work and whose full name is shared by at most 50 persons in InfoUSA; and counts only purchases followed by a move to the property and only borrowing recorded on the stayer's home.

**Credit supply.** Lenders may tighten credit to employees of a firm that cuts workers. A lender sees the applicant's employer and job, which stayers in a cell share, but is unlikely to know which roles the employer cut. Credit supply that responds to the layoff is therefore largely removed by the comparison within a cell, and the borrowing sample is restricted to owners with ample equity, for whom collateral constraints are least likely to bind.

**Selection into staying.** The firm chooses whom to keep. If it keeps the high-exposure workers it values most, these stayers learn that the firm values them, which should make them more willing to buy. If instead high-exposure stayers expect to be cut in the next round, the decline in their purchases and borrowing may reflect what they expect for their own job at the firm. Section 5 estimates the response among stayers who are still at the firm two and four quarters after the layoff (Table 7, Panel A).

### 3.4 Inference

Standard errors are clustered by firm, so that repeated layoffs at the same firm are not treated as independent. The housing estimates at AI layoffs are based on 30 layoffs for purchases and 27 for borrowing, and a single layoff with many stayers can have a large effect on an estimate. Panel F of Table 5 drops each AI layoff in turn and reports the

estimates closest to and farthest from zero.

# 4 Results

After AI layoffs, the workers cut find worse jobs than comparable displaced workers, and the stayers in the roles the layoff over-cut start more training programs and take on fewer housing commitments than their coworkers in the same layoff. The section first uses the later careers of the workers cut to test whether other employers value the workers cut less after AI layoffs. It then compares stayers within the same layoff, first in the training programs they start and then in their housing commitments, and ends with checks on whether the housing response can be attributed to the AI layoff.

## 4.1 Outcomes of the workers cut

Stayers can learn from a layoff that their own human capital is worth less only if other employers also value the workers cut less. The later careers of the workers cut measure this directly. If a new technology now does their work, or the firm cut them to fund its investment in the technology, other employers should also value their work less, and they should take longer to find comparable jobs. If the firm cut them for a reason specific to the firm, they should fare like other displaced workers.

Figure 2 and Table 2 compare workers cut in each type of layoff with workers cut in firm contractions. Each worker cut is compared with workers cut in firm contractions in the same cell, which groups workers by role (50 Revelio roles), seniority, salary quintile and half-year of leaving, and the regression also controls for log salary before the layoff. The sample is the 488,228 workers cut at 2,945 layoffs who start a job at another firm within 12 months of leaving, 21,826 of them at 38 AI layoffs. Workers cut in firm contractions take 2.44 months on average to start the new job, and it pays 4.34 log points less than the job they left. Of these workers, 26.7 percent take a position at a lower seniority level and 64.3 percent change job title, measured as a move to a different one of 150 finer Revelio roles, such as software engineer and data analyst.

Workers cut in AI layoffs fare worse on all four outcomes. They take 0.38 months longer to find a new job (s.e. 0.08), about a sixth longer than workers cut in firm contractions. Their new jobs pay 2.65 log points less relative to their old ones (s.e. 1.24), which adds about 60 percent to the average pay loss after firm contractions. They are 1.41 percentage points more likely to take a lower-seniority position (s.e. 0.56) and 3.25 percentage points more likely to change job title (s.e. 0.95). Compared with workers cut in firm contractions who held the same role, seniority and pay and left at the same time, they find new jobs more slowly, at lower pay and seniority, and more often with a different job title. This is

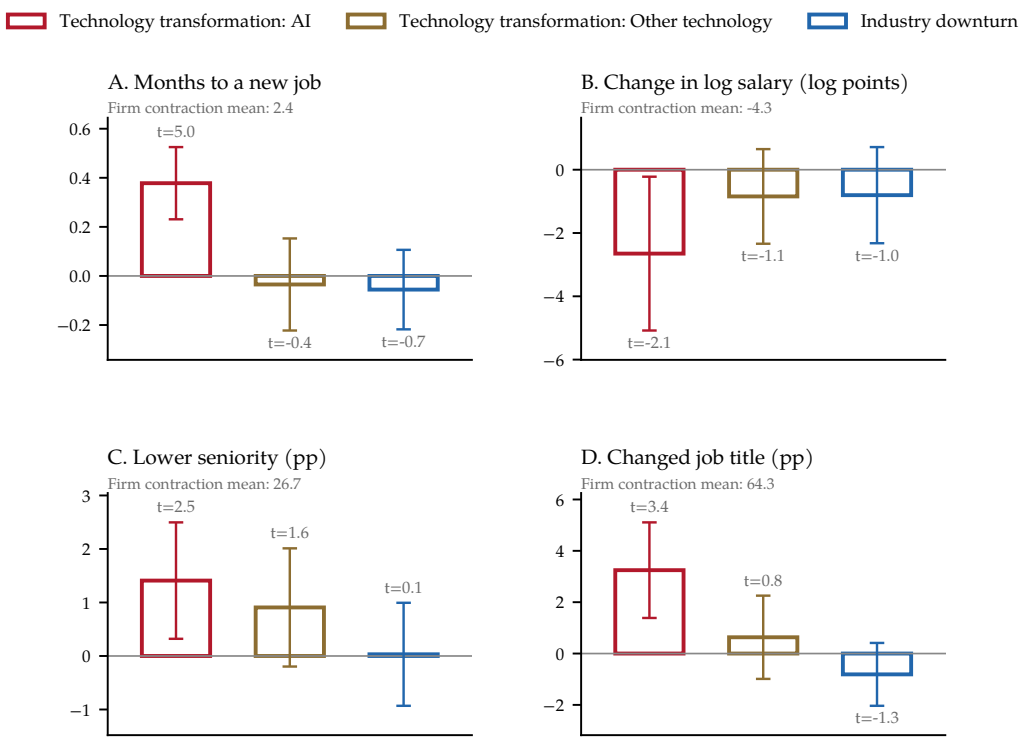



**Figure 2. Outcomes of the Workers Cut, by Type of Layoff**

*Notes:* This figure compares workers cut at each type of layoff with workers cut at Firm contraction layoffs. The sample includes the 488,228 workers cut at 2,945 layoffs who find a new job within 12 months of leaving (21,826 at 38 AI layoffs); a new job is the first position that starts within 12 months of leaving, at a firm other than the layoff firm and its parent. Each bar plots $\beta_g$ from

$$y_i = \sum_g \beta_g \mathbf{1}[\text{type}_{e(i)} = g] + \gamma \log w_i + \alpha_{c(i)} + \varepsilon_i,$$

where $g$ indexes the three types shown, $\log w_i$ is the worker's log salary before the layoff, and $\alpha_{c(i)}$ are fixed effects for cells of role (50 Revelio roles) $\times$ seniority $\times$ salary quintile $\times$ half-year of leaving, so that each worker is compared with workers cut at Firm contraction layoffs in the same role, seniority and pay range at the same time. Outcomes: (A) months from leaving to the start of the new job; (B) log salary of the new job minus log salary before the layoff, times 100; (C) the new job has a lower Revelio seniority level than the job before the layoff, on Revelio's scale from 1 (entry level) to 7 (senior executive); (D) the new job has a different job title, measured as a different one of 150 finer Revelio roles, such as software engineer and data analyst. The mean for workers cut at Firm contraction layoffs is shown in each panel. Technology transformation: AI layoffs name AI as the primary or a secondary reason; Other technology layoffs name another technology as the primary or a secondary reason or mention automation or software among the stated reasons. Whiskers show 95 percent confidence intervals clustered by firm; numbers next to the bars are $t$ statistics.

## Table 2. Outcomes of the Workers Cut

| | Months to new job (1) | Δ log salary (2) | Lower seniority (3) | Switched job title (4) |
|---|---|---|---|---|
| Technology transformation | | | | |
| AI | 0.38*** | −2.65** | 1.41** | 3.25*** |
| | (0.08) | (1.24) | (0.56) | (0.95) |
| Other technology | −0.03 | −0.84 | 0.91 | 0.63 |
| | (0.10) | (0.76) | (0.56) | (0.83) |
| Industry downturn | −0.06 | −0.80 | 0.03 | −0.81 |
| | (0.08) | (0.77) | (0.49) | (0.62) |
| Log salary | Yes | Yes | Yes | Yes |
| Cell FE | Yes | Yes | Yes | Yes |
| Workers cut | 488,228 | 488,228 | 488,228 | 488,228 |
| Layoffs | 2,945 | 2,945 | 2,945 | 2,945 |
| AI layoffs | 38 | 38 | 38 | 38 |
| $R^2$ | 0.064 | 0.192 | 0.288 | 0.173 |
| Firm contraction mean | 2.44 | −4.34 | 26.73 | 64.32 |

*Notes:* This table reports the estimates of Figure 2. Each column regresses an outcome of the workers cut on indicators for the type of layoff,

$$y_i = \sum_g \beta_g \mathbf{1}[\text{type}_{e(i)} = g] + \gamma \log w_i + \alpha_{c(i)} + \varepsilon_i,$$

with Firm contraction as the omitted type; $\log w_i$ is the worker's log salary before the layoff and $\alpha_{c(i)}$ are fixed effects for cells of role (50 Revelio roles) × seniority × salary quintile × half-year of leaving. The sample is the workers cut who find a new job, the first position that starts within 12 months of leaving at a firm other than the layoff firm and its parent. Outcomes: (1) months from leaving to the new job, (2) log salary of the new job minus log salary before the layoff, times 100, (3) a lower Revelio seniority level than before the layoff, and (4) a different job title, measured as a different one of 150 finer Revelio roles, such as software engineer and data analyst. Columns (3) and (4) are in percentage points. Technology transformation: AI layoffs name AI as the primary or a secondary reason; Other technology layoffs name another technology as the primary or a secondary reason or mention automation or software among the stated reasons. *Cell FE* are the fixed effects $\alpha_{c(i)}$. *Firm contraction mean* is the mean of the outcome among the workers cut in firm contractions, the omitted type. $R^2$ is that of the full regression, including the cell fixed effects. Standard errors clustered by firm are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the pattern one would expect if the market value of the work they did has fallen, and it is consistent with evidence that technological change accounts for a large part of the losses of displaced workers (Braxton and Taska, 2023).

For workers cut in layoffs due to other technologies and in industry downturns, none of the eight estimates relative to workers cut in firm contractions is statistically significant. They take about as long to find a new job ($-0.03$ and $-0.06$ months, s.e. 0.10 and 0.08), and their additional pay losses, $-0.84$ and $-0.80$ log points (s.e. 0.76 and 0.77), are about a third of the additional loss after AI layoffs. AI layoffs are thus the only type after which the workers cut find worse jobs than comparable displaced workers, and so the only type from which high-exposure stayers can learn that their own human capital is worth less.

### 4.2 Training of stayers

If high-exposure stayers conclude from a layoff that their human capital is worth less, one response is to acquire new skills. Figure 3 plots, by year relative to the layoff, the difference in short training programs started between high-exposure stayers under 40 and their coworkers in the same cell, measured as a change from the year before the layoff. Short programs are courses, certificates, bootcamps, professional and executive education and other non-degree programs of up to a year. As in all stayer estimates, a cell groups the stayers of one layoff with the same age band, seniority band and job category, and high-exposure stayers are those whose role the layoff over-cut by more than the median coworker's (Section 2.5). The sample is 309,130 stayers under 40 at 1,043 layoffs, 17,547 of them at 26 AI layoffs. Table 3 reports the estimates for the year of the layoff, for short programs and degree programs, separately by type of layoff.

In the year of an AI layoff, high-exposure stayers are 0.25 percentage points more likely than their coworkers to start a short program (s.e. 0.07), against a rate of 0.36 percent among low-exposure stayers in the year before the layoff. In the years before the layoff the difference is small and not statistically significant (0.15 and $-0.03$ in years $-3$ and $-2$, s.e. 0.20 and 0.11), so the increase begins with the layoff. In the year after, the gap in short programs is smaller, 0.09 percentage points (s.e. 0.04). Degree programs do not respond in the year of the layoff: the estimate is $-0.07$ (s.e. 0.15), against a base of 0.67 percent. High-exposure stayers thus respond to an AI layoff with short programs, which take less time and money than a degree.

After the other types of layoff, the estimates for short programs in columns (2) to (4) of Table 3 range from 0.06 to 0.12, and none is statistically significant. The increase in short programs is thus specific to AI layoffs, the layoffs after which the workers cut find worse jobs.

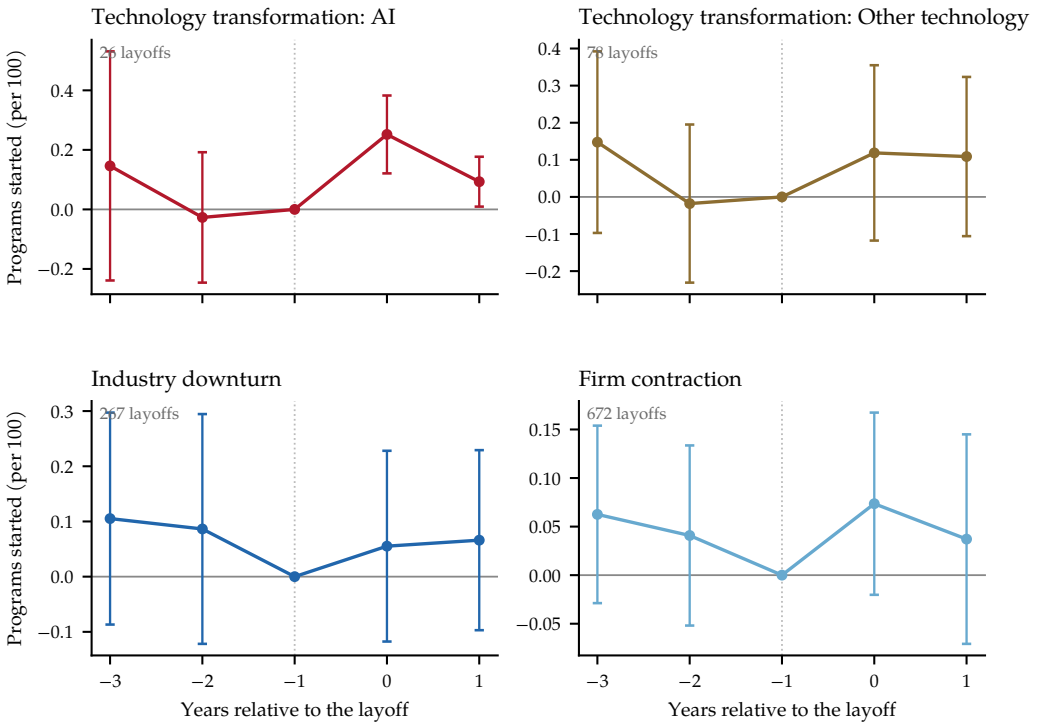



**Figure 3. Short Training Programs of Stayers under 40, by Type of Layoff**

*Notes:* This figure plots, by year relative to the layoff, the difference in short training programs started between high-exposure stayers under 40 and their coworkers in the same layoff. The sample includes 309,130 stayers under 40 observed from year −3 through year 1, at 1,043 layoffs. Each point plots $\beta_k$ from $y_{ik} - y_{i,-1} = \beta_k \, \text{HighExp}_i + X_i'\gamma_k + \alpha_{c(i),k} + \varepsilon_{ik}$, where $y_{ik}$ equals 100 if stayer $i$ starts a short program (a course, certificate, bootcamp, professional or executive education or other non-degree program of up to a year) in year $k$ relative to the layoff year (Revelio dates education records by year). Year −1 is the reference and equals zero. $\text{HighExp}_i$ equals one for high-exposure stayers, whose role the layoff over-cut by more than the role of the median stayer in their cell, and zero otherwise; a layoff over-cuts a role when the role's share of the layoff's departures exceeds its share of the firm's departures in the same window a year earlier (equations (1) and (2)). $\alpha_{c(i)}$ are fixed effects for cells of layoff × age band × seniority band × job category, so that each stayer is compared with coworkers of the same age, seniority and broad job in the same layoff, and $X_i$ contains log salary, seniority and a female indicator. Stayers are workers at the layoff firm on the layoff date, with at least a year of tenure, whose position continues at least 92 days past the layoff and whose Revelio profile is active; workers who move to another position at the firm within 92 days are excluded, and each stayer's window ends before the firm's next layoff of at least 50 workers. Technology transformation: AI layoffs name AI as the primary or a secondary reason; Other technology layoffs name another technology as the primary or a secondary reason or mention automation or software among the stated reasons. Industry downturn and Firm contraction panels use layoffs dated 2022 or later. Whiskers show 95 percent confidence intervals clustered by firm.

**Table 3. Training Programs of Stayers under 40 in the Year of the Layoff**

| | Short programs | | | | Degree programs | | | |
|---|---|---|---|---|---|---|---|---|
| | AI | Other technology | Industry downturn | Firm contraction | AI | Other technology | Industry downturn | Firm contraction |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| High exposure | 0.25*** | 0.12 | 0.06 | 0.07 | −0.07 | 0.19 | −0.04 | 0.07 |
| | (0.07) | (0.12) | (0.09) | (0.05) | (0.15) | (0.17) | (0.14) | (0.08) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cell FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stayers | 17,547 | 29,125 | 46,051 | 216,407 | 17,547 | 29,125 | 46,051 | 216,407 |
| Layoffs | 26 | 78 | 267 | 672 | 26 | 78 | 267 | 672 |
| $R^2$ | 0.030 | 0.034 | 0.073 | 0.034 | 0.027 | 0.032 | 0.053 | 0.025 |
| Low-exposure mean | 0.36 | 0.32 | 0.50 | 0.63 | 0.67 | 1.05 | 1.01 | 1.99 |

*Notes:* Each column reports $\beta_0$ from

$$y_{i0} - y_{i,-1} = \beta_0 \,\mathrm{HighExp}_i + X_i'\gamma_0 + \alpha_{c(i),0} + \varepsilon_{i0},$$

estimated on the stayers of one type of layoff, where $y_{ik}$ equals 100 if stayer $i$ starts a program of the kind in the column in year $k$ relative to the layoff year (Revelio education records), so that $k = 0$ is the year of the layoff. Short programs, the outcome of Figure 3, are courses, certificates, bootcamps, professional and executive education, and other non-degree programs of up to a year. Of the short programs that stayers under 40 start from year $-3$ through year 1, 52 percent are offered by universities and colleges, mostly certificates, extension and executive education, 12 percent by bootcamps and workforce training programs such as General Assembly, Flatiron School or Year Up, and 6 percent by online platforms such as Coursera and Udacity. Among the 56 percent of records that report a field, the main fields are business, management, finance and marketing (27 percent), computer science, software, information technology and data science (25 percent), engineering (10 percent) and health (8 percent). Degree programs are associate, bachelor's, master's, MBA and doctoral programs. The sample, $\mathrm{HighExp}_i$ and cells are those of Figure 3: stayers under 40 observed from year $-3$ through year 1. *Low-exposure mean* is the share of low-exposure stayers, per 100, who start a program of the kind in the column in the year before the layoff. Controls are log salary, seniority and a female indicator. Cell FE are fixed effects for cells of layoff × age band × seniority band × job category. $R^2$ is that of the full regression, including the cell fixed effects. Standard errors clustered by firm are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### 4.3 Housing commitments of stayers

The housing outcomes count events in the months after the layoff, net of each stayer's own rate before it. For first-home purchases, the outcome over the first $h$ months is the number of quarters with a deed naming the stayer as buyer, per 100 stayers, minus $h/24$ times the same number over the 24 months before the layoff. Home equity borrowing is counted the same way, with quarters in which a new home equity line of credit or home equity loan is recorded in the stayer's name. Subtracting the stayer's own pre-layoff rate removes a stable difference between high-exposure stayers and their coworkers. I express magnitudes in percent of the count among low-exposure stayers at AI layoffs over the 12 months after the layoff (last row of each panel of Table 4).

**First-home purchases.** Figure 4 plots the difference between high-exposure renters and their coworkers, at six-month intervals from 12 months before the layoff to 12 months after, with the layoff date as the reference. Renters are stayers who did not own a home in the year before the layoff. The sample is 271,643 renters at 1,071 layoffs. Panel A of Table 4 reports the estimates at 6 and 12 months for each type of layoff.

Before an AI layoff, the differences in purchases between high-exposure renters and their coworkers are small and not statistically significant: the estimates at 12 and 6 months before the layoff are $-0.06$ (s.e. 0.05) and $-0.15$ (s.e. 0.13). After the layoff, high-exposure renters buy less often than their coworkers, and the gap grows at about the same pace through the year. Over the first 6 months, high-exposure renters record 0.21 fewer quarters with a purchase per 100 renters than their coworkers (s.e. 0.08), and over the first 12 months 0.44 fewer (s.e. 0.08). Low-exposure renters at AI layoffs record 2.68 quarters with a purchase per 100 over the 12 months after the layoff, so high-exposure renters make 16 percent fewer first-home purchases than their coworkers over this period. The estimate is based on 29,411 renters at 30 AI layoffs.

After the other types of layoff, none of the estimates is statistically significant. After layoffs due to other technologies and industry downturns, the estimates are $-0.18$ and $-0.16$ at 6 months and 0.17 in both cases at 12 months, and after firm contractions they are 0.07 at both horizons. The estimates after layoffs due to other technologies and industry downturns are less precise than those for AI layoffs, but at 12 months each of the three 95 percent confidence intervals excludes the AI estimate of $-0.44$.

**Home equity borrowing.** Figure 5 shows the same comparison for owners with a CLTV below 0.6 in the year before the layoff. These households have ample equity, so new home equity borrowing is a choice rather than a constraint. The sample is 118,011 owners at 941 layoffs, and Panel B of Table 4 reports the estimates at 6 and 12 months.

Home equity borrowing shows the same pattern. Before an AI layoff, the estimates are 0.05 and 0.07 (s.e. 0.10 for both). After it, high-exposure owners record 0.13 fewer

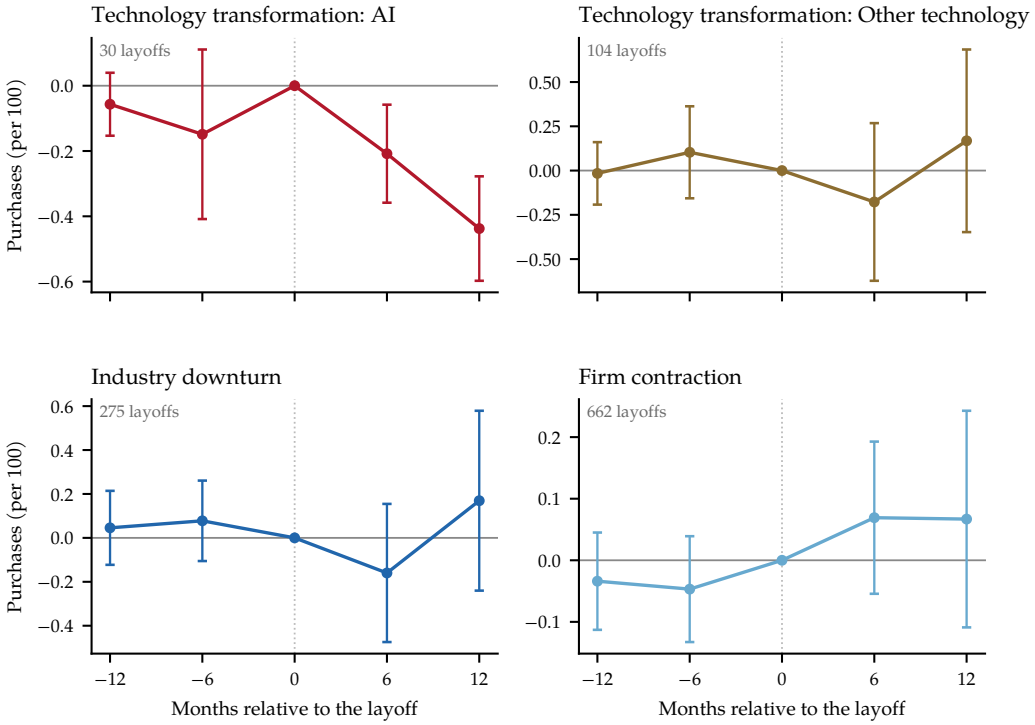



**Figure 4. First-Home Purchases of Renters, by Type of Layoff**

*Notes:* This figure plots the cumulative difference in home purchases between high-exposure renters and their coworkers in the same layoff. The sample includes 271,643 stayers who did not own a home in the year before the layoff and are observed through month 12, at 1,071 layoffs. Each point plots $\beta_h$ from $Y_{ih} = \beta_h \, \text{HighExp}_i + X_i' \gamma_h + \alpha_{c(i),h} + \varepsilon_{ih}$, where $Y_{ih}$ is the cumulative number of quarters with a residential purchase deed naming the stayer as buyer, per 100 stayers, in excess of the stayer's own rate over the 24 months before the layoff: for $h > 0$ the number in the first $h$ months after the layoff minus $h/24$ times the number in the 24 months before it, and for $h < 0$ minus the same excess over the $|h|$ months before the layoff (quarters with at least one purchase count once). The layoff date is the reference and equals zero, so a stable difference in rates between high-exposure stayers and their coworkers does not appear as a slope. $\text{HighExp}_i$ equals one for high-exposure stayers, whose role the layoff over-cut by more than the role of the median stayer in their cell, and zero otherwise; a layoff over-cuts a role when the role's share of the layoff's departures exceeds its share of the firm's departures in the same window a year earlier (equations (1) and (2)). $\alpha_{c(i)}$ are fixed effects for cells of layoff $\times$ age band $\times$ seniority band $\times$ job category, so that each stayer is compared with coworkers of the same age, seniority and broad job in the same layoff, and $X_i$ contains log salary, seniority and a female indicator. Stayers are workers at the layoff firm on the layoff date, with at least a year of tenure, whose position continues at least 92 days past the layoff and whose Revelio profile is active; workers who move to another position at the firm within 92 days are excluded, and each stayer's window ends before the firm's next layoff of at least 50 workers. Technology transformation: AI layoffs name AI as the primary or a secondary reason; Other technology layoffs name another technology as the primary or a secondary reason or mention automation or software among the stated reasons. Industry downturn and Firm contraction panels use layoffs dated 2022 or later. Whiskers show 95 percent confidence intervals clustered by firm.

## Table 4. First-Home Purchases and Home Equity Borrowing of Stayers

| | 6 months after the layoff | | | | 12 months after the layoff | | | |
|---|---|---|---|---|---|---|---|---|
| | AI | Other technology | Industry downturn | Firm contraction | AI | Other technology | Industry downturn | Firm contraction |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Panel A. First-home purchases, renters* | | | | | | | | |
| High exposure | −0.21*** | −0.18 | −0.16 | 0.07 | −0.44*** | 0.17 | 0.17 | 0.07 |
| | (0.08) | (0.23) | (0.16) | (0.06) | (0.08) | (0.26) | (0.21) | (0.09) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cell FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stayers | 29,411 | 25,660 | 36,965 | 179,607 | 29,411 | 25,660 | 36,965 | 179,607 |
| Layoffs | 30 | 104 | 275 | 662 | 30 | 104 | 275 | 662 |
| $R^2$ | 0.025 | 0.073 | 0.106 | 0.065 | 0.032 | 0.080 | 0.102 | 0.066 |
| Low-exposure mean | 1.59 | 1.55 | 1.59 | 1.19 | 2.68 | 2.85 | 2.64 | 2.14 |
| *Panel B. Home equity borrowing, owners with CLTV < 0.6* | | | | | | | | |
| High exposure | −0.13** | −0.21 | 0.20 | 0.03 | −0.27*** | −0.05 | 0.34 | 0.09 |
| | (0.07) | (0.21) | (0.16) | (0.08) | (0.04) | (0.23) | (0.24) | (0.13) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cell FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stayers | 23,538 | 9,775 | 15,925 | 68,773 | 23,538 | 9,775 | 15,925 | 68,773 |
| Layoffs | 27 | 94 | 240 | 580 | 27 | 94 | 240 | 580 |
| $R^2$ | 0.023 | 0.146 | 0.133 | 0.095 | 0.027 | 0.142 | 0.137 | 0.098 |
| Low-exposure mean | 0.80 | 0.89 | 0.62 | 0.68 | 1.39 | 1.48 | 1.20 | 1.29 |

*Notes:* Each column reports $\beta_h$ from

$$Y_{ih} = \beta_h \, \text{HighExp}_i + X_i' \gamma_h + \alpha_{c(i),h} + \varepsilon_{ih},$$

estimated on the stayers of one type of layoff, where $Y_{ih}$ is the number of quarters in the first $h$ months after the layoff with a purchase deed naming stayer $i$ as buyer (Panel A) or with new home equity borrowing, a home equity line of credit or loan recorded in the stayer's name (Panel B), per 100 stayers, minus $h/24$ times the same number over the 24 months before the layoff. These are the estimates behind Figures 4 and 5. Panel A uses renters, stayers who did not own a home in the year before the layoff; Panel B uses owners with a combined loan-to-value ratio below 0.6 in that year. Both samples are observed through month 12, so the 6- and 12-month estimates use the same stayers. *Low-exposure mean* is the number of quarters with the event in the first $h$ months after the layoff per 100 low-exposure stayers, the base for the percent magnitudes in the text. Controls are log salary, seniority and a female indicator. Cell FE are fixed effects for cells of layoff × age band × seniority band × job category. $R^2$ is that of the full regression, including the cell fixed effects. Standard errors clustered by firm are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

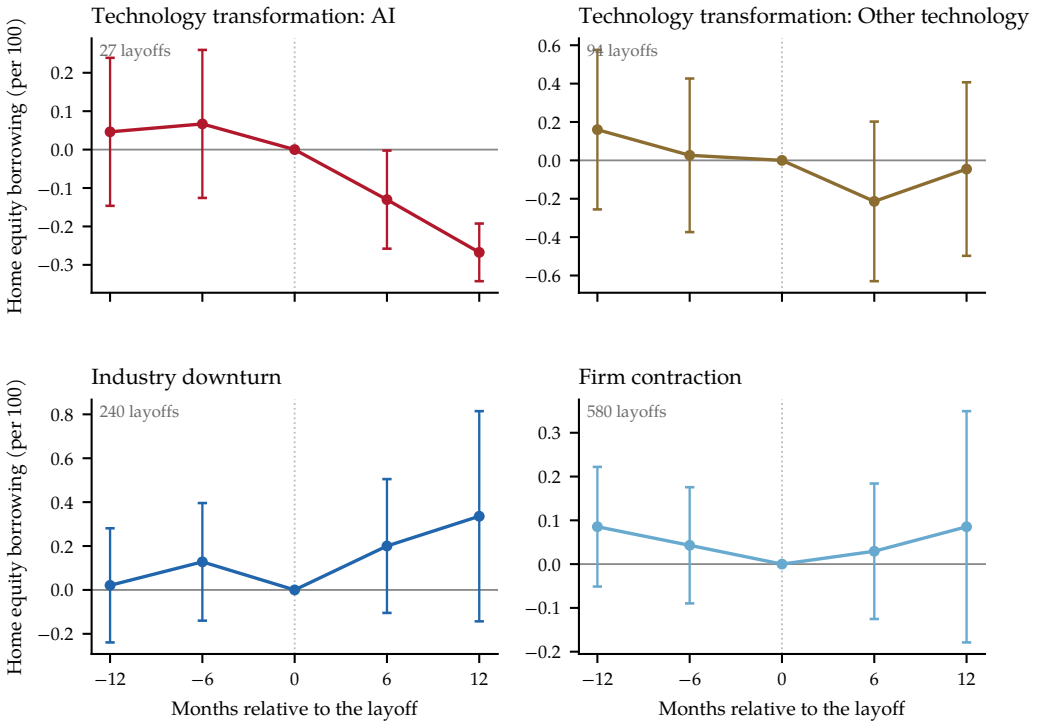



**Figure 5. Home Equity Borrowing of Owners, by Type of Layoff**

*Notes:* This figure plots the cumulative difference in home equity borrowing between high-exposure homeowners and their coworkers in the same layoff. The sample includes 118,011 stayers who owned a home with a combined loan-to-value ratio below 0.6 in the year before the layoff and are observed through month 12, at 941 layoffs. Each point plots $\beta_h$ from $Y_{ih} = \beta_h \, \text{HighExp}_i + X_i'\gamma_h + \alpha_{c(i),h} + \varepsilon_{ih}$, where $Y_{ih}$ is the cumulative number of quarters with new home equity borrowing (a home equity line of credit or home equity loan recorded in the stayer's name), per 100 stayers, in excess of the stayer's own rate over the 24 months before the layoff: for $h > 0$ the number in the first $h$ months after the layoff minus $h/24$ times the number in the 24 months before it, and for $h < 0$ minus the same excess over the $|h|$ months before the layoff (quarters with at least one new loan count once). The layoff date is the reference and equals zero, so a stable difference in rates between high-exposure stayers and their coworkers does not appear as a slope. $\text{HighExp}_i$ equals one for high-exposure stayers, whose role the layoff over-cut by more than the role of the median stayer in their cell, and zero otherwise; a layoff over-cuts a role when the role's share of the layoff's departures exceeds its share of the firm's departures in the same window a year earlier (equations (1) and (2)). $\alpha_{c(i)}$ are fixed effects for cells of layoff $\times$ age band $\times$ seniority band $\times$ job category, so that each stayer is compared with coworkers of the same age, seniority and broad job in the same layoff, and $X_i$ contains log salary, seniority and a female indicator. Stayers are workers at the layoff firm on the layoff date, with at least a year of tenure, whose position continues at least 92 days past the layoff and whose Revelio profile is active; workers who move to another position at the firm within 92 days are excluded, and each stayer's window ends before the firm's next layoff of at least 50 workers. Technology transformation: AI layoffs name AI as the primary or a secondary reason; Other technology layoffs name another technology as the primary or a secondary reason or mention automation or software among the stated reasons. Industry downturn and Firm contraction panels use layoffs dated 2022 or later. Whiskers show 95 percent confidence intervals clustered by firm.

quarters with new home equity borrowing per 100 owners over the first 6 months (s.e. 0.07) and 0.27 fewer over the first 12 months (s.e. 0.04). Low-exposure owners at AI layoffs record 1.39 such quarters per 100 over the 12 months after the layoff, so high-exposure owners take on 19 percent less new home equity borrowing than their coworkers over this period. The estimate is based on 23,538 owners at 27 AI layoffs. After the other types, the 12-month estimates are $-0.05$ for layoffs due to other technologies, 0.34 for industry downturns and 0.09 for firm contractions, none of them statistically significant.

The two outcomes are parts of one response. High-exposure renters postpone buying a first home, and owners with ample equity take on less new borrowing against the home they have. A purchase commits the household to a down payment and to mortgage payments for a fixed level of housing, and new home equity borrowing adds payments that must come out of the same future income. In the year after an AI layoff, high-exposure stayers take on fewer of both commitments than coworkers of the same age, seniority and job category in the same layoff.

### 4.4 Identification checks

The comparison within a layoff removes everything that affects all stayers of the layoff alike. The remaining concern is a difference between high- and low-exposure stayers that coincides with AI layoffs but is not caused by them. Table 5 examines the main such differences for the 12-month estimates of Table 4. Panel A pools AI layoffs with a set of comparison layoffs and reports the difference between the high-exposure gap at AI layoffs and the gap at the comparison layoffs. Panels B–F report the gap at AI layoffs under an alternative outcome, specification or sample.

**AI layoffs versus other layoffs (Panel A).** Nearly all AI layoffs in the housing samples are dated 2023 or 2024, years of high mortgage rates and large layoffs in the technology sector. If workers in the roles that AI layoffs cut were buying and borrowing less in these years for other reasons, the gap at AI layoffs would reflect the period rather than the layoff. Pooled with all other layoffs of 2023–24, the difference between the gap at AI layoffs and the gap at the other layoffs is $-0.60$ for purchases (s.e. 0.11) and $-0.38$ for borrowing (s.e. 0.12). Both differences exceed the baseline estimates in absolute value, so at the other layoffs of these years high-exposure stayers buy and borrow, if anything, slightly more than their coworkers. A shock to workers in these roles in these years, or to the housing and credit markets where they live, would also have lowered purchases and borrowing by high-exposure stayers at the other layoffs of these years. Against each type separately, the purchase difference is $-0.59$ relative to layoffs due to other technologies (s.e. 0.27), $-0.63$ relative to industry downturns (s.e. 0.23) and $-0.52$ relative to firm contractions (s.e. 0.12). The borrowing difference is $-0.61$ relative to industry downturns (s.e. 0.25) and $-0.36$

## Table 5. Identification Checks

| | First-home purchases Renters | | Home equity borrowing Owners with CLTV $< 0.6$ | |
|---|---|---|---|---|
| | Estimate | Stayers (layoffs) | Estimate | Stayers (layoffs) |
| Baseline: AI layoffs (Table 4) | −0.44*** | 29,411 (30) | −0.27*** | 23,538 (27) |
| | (0.08) | | (0.04) | |
| *Panel A. AI layoffs versus other layoffs* | | | | |
| AI minus all other layoffs of 2023–24 | −0.60*** | 219,777 (712) | −0.38*** | 105,841 (648) |
| | (0.11) | | (0.12) | |
| AI minus Other technology | −0.59** | 55,071 (134) | −0.23 | 33,313 (121) |
| | (0.27) | | (0.24) | |
| AI minus Industry downturn | −0.63*** | 66,376 (305) | −0.61** | 39,463 (267) |
| | (0.23) | | (0.25) | |
| AI minus Firm contraction | −0.52*** | 209,018 (692) | −0.36*** | 92,311 (607) |
| | (0.12) | | (0.14) | |
| *Panel B. Pre-layoff placebo and additional controls* | | | | |
| Placebo: months −12 to −1 against −24 to −13 | 0.11 | 29,411 (30) | −0.09 | 23,538 (27) |
| | (0.10) | | (0.20) | |
| Controls for years in the position | −0.47*** | 29,411 (30) | −0.29*** | 23,538 (27) |
| | (0.09) | | (0.04) | |
| Controls for household demographics (InfoUSA) | −0.43*** | 29,411 (30) | −0.28*** | 23,538 (27) |
| | (0.09) | | (0.04) | |
| Controls for both | −0.45*** | 29,411 (30) | −0.30*** | 23,538 (27) |
| | (0.09) | | (0.04) | |
| *Panel C. Quartiles of over-cut, relative to the bottom quartile* | | | | |
| Second quartile | −0.25 | 29,411 (30) | 0.19 | 23,538 (27) |
| | (0.22) | | (0.30) | |
| Third quartile | −0.70** | 29,411 (30) | −0.05 | 23,538 (27) |
| | (0.29) | | (0.18) | |
| Top quartile | −0.70*** | 29,411 (30) | −0.18* | 23,538 (27) |
| | (0.17) | | (0.10) | |
| *Panel D. Layoffs that mention AI without citing it as a reason* | | | | |
| AI-mentioned layoffs | 0.27 | 26,094 (48) | 0.06 | 12,860 (43) |
| | (0.22) | | (0.24) | |

## Table 5. Identification Checks (Continued)

| | First-home purchases Renters | | Home equity borrowing Owners with CLTV $< 0.6$ | |
|---|---|---|---|---|
| | Estimate | Stayers (layoffs) | Estimate | Stayers (layoffs) |
| *Panel E. Record linkage* | | | | |
| Layoffs: Revelio count near announced count | $-0.44^{***}$ | 21,336 (14) | $-0.29^{***}$ | 17,501 (13) |
| | (0.09) | | (0.03) | |
| Households: same state, uncommon name | $-0.39^{***}$ | 20,200 (29) | $-0.41^{***}$ | 19,162 (27) |
| | (0.11) | | (0.10) | |
| Deeds and loans: move at purchase, own home | $-0.33^{**}$ | 29,411 (30) | $-0.35^{***}$ | 23,538 (27) |
| | (0.13) | | (0.06) | |
| *Panel F. Dropping one AI layoff at a time* | | | | |
| Closest to zero | $-0.33^{***}$ | 16,094 (29) | $-0.24^{***}$ | 12,938 (26) |
| | (0.12) | | (0.07) | |
| Farthest from zero | $-0.49^{***}$ | 24,221 (29) | $-0.28^{***}$ | 23,315 (26) |
| | (0.07) | | (0.03) | |

*Notes:* This table checks the AI estimates of Table 4 at 12 months. Unless a row says otherwise, each estimate is $\beta$ from

$$Y_i = \beta \,\mathrm{HighExp}_i + X_i'\gamma + \alpha_{c(i)} + \varepsilon_i,$$

with the outcome, sample, cells and controls of Table 4: $Y_i$ is the number of quarters in the 12 months after the layoff with a purchase deed naming the stayer as buyer (renters) or with new home equity borrowing (owners with a combined loan-to-value ratio below 0.6), per 100 stayers, minus half that number over the 24 months before. Panel A pools AI layoffs with the layoffs named in the row, adds $\lambda\,\mathrm{HighExp}_i \times \mathrm{AI}_e$ (equation (4)), and reports $\lambda$; cells are within a layoff, so they absorb the AI main effect. Panel B uses as the outcome the number of quarters in months $-12$ to $-1$ minus that number in months $-24$ to $-13$, or adds controls for years in the position, InfoUSA household demographics in the year before the layoff (ethnicity, married, children, household size, log income and length of residence, with indicators for missing values), or both. Panel C replaces $\mathrm{HighExp}_i$ with indicators for the quartiles of $\mathrm{Overcut}_{e(i)r(i)}$ within cells, where tied stayers take their average rank. Panel D estimates the baseline on layoffs whose stated reasons mention AI but do not name it as the primary or secondary reason. Panel E checks each step of the record linkage: it keeps layoffs whose count of workers cut in Revelio is within a factor of 1.25 of the announced count; keeps stayers whose InfoUSA household is in the state of their work location and whose first name, middle initial and last name are shared by at most 50 persons in InfoUSA; and counts only purchases followed by a move to the property and only borrowing recorded on the stayer's home. Panel F drops each AI layoff in turn and reports the estimates closest to and farthest from zero. *Stayers (layoffs)* gives the number of stayers and, in parentheses, of layoffs in the sample of the estimate. Standard errors clustered by firm are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

relative to firm contractions (s.e. 0.14); relative to layoffs due to other technologies it is $-0.23$ and not statistically significant (s.e. 0.24).

**Pre-layoff placebo and additional controls (Panel B).** The placebo replaces the outcome with the number of quarters with an event in months $-12$ to $-1$ minus that number in months $-24$ to $-13$. It is 0.11 for purchases (s.e. 0.10) and $-0.09$ for borrowing (s.e. 0.20), and neither is statistically significant, so in the year before an AI layoff the purchases and borrowing of high-exposure stayers show no significant trend relative to those of their coworkers. A control for years in the position, which captures differences in career stage within cells, gives $-0.47$ and $-0.29$. Controls for household demographics in InfoUSA (ethnicity, marital status, children, household size, income and length of residence) give $-0.43$ and $-0.28$, and both sets together give $-0.45$ and $-0.30$, with standard errors close to those of the baseline.

**Quartiles of over-cut (Panel C).** If stayers respond to what they learn from the layoff about their own role, the gap should be larger the more the layoff over-cut the stayer's role. Panel C replaces the median split with quartiles of $\text{Overcut}_{e(i)r(i)}$ within cells. For purchases, relative to the bottom quartile, the gap is $-0.25$ in the second quartile (s.e. 0.22) and $-0.70$ in the third and top quartiles (s.e. 0.29 and 0.17), so it rises through the third quartile and is flat above it. For borrowing the gradient is weaker: only the top quartile differs from the bottom at the 10 percent level, by $-0.18$ (s.e. 0.10), smaller in absolute value than the baseline estimate from the median split.

**Layoffs that mention AI without citing it as a reason (Panel D).** Stayers may respond to the mention of AI in the announcement rather than to the firm's use of AI. Panel D estimates the gap at the 48 layoffs whose stated reasons mention AI but do not name it as the primary or a secondary reason (43 in the borrowing sample). The estimates are 0.27 for purchases (s.e. 0.22) and 0.06 for borrowing (s.e. 0.24), both positive and not statistically significant.

**Record linkage (Panel E).** The outcomes of each stayer depend on three record links: from the layoff to the Revelio profiles of its workers, from each profile to an InfoUSA household, and from the worker to the CoreLogic deeds and loans that name them. Panel E makes each link stricter in turn. Keeping the 14 AI layoffs (13 for borrowing) whose count of workers cut in Revelio is within a factor of 1.25 of the announced count gives $-0.44$ (s.e. 0.09) and $-0.29$ (s.e. 0.03). Keeping stayers whose household is in the state of their work location and whose first name, middle initial and last name are shared by at most 50 persons in InfoUSA, for whom a namesake is unlikely to be linked in their place, gives $-0.39$ (s.e. 0.11) and $-0.41$ (s.e. 0.10). Counting only purchases followed by a move to the property, and only borrowing recorded on the stayer's own home, gives $-0.33$ (s.e. 0.13) and $-0.35$ (s.e. 0.06). All six estimates are negative and statistically significant,

between $-0.33$ and $-0.44$ for purchases and between $-0.29$ and $-0.41$ for borrowing.

**Dropping one AI layoff at a time (Panel F).** The estimates are based on 30 and 27 AI layoffs, and a few large layoffs account for many of the stayers. When each AI layoff is dropped in turn, the purchase estimate ranges from $-0.33$ (s.e. 0.12) to $-0.49$ (s.e. 0.07), and the borrowing estimate from $-0.24$ (s.e. 0.07) to $-0.28$ (s.e. 0.03). The estimates closest to zero come from dropping a layoff that contributes 13,317 of the 29,411 renters and one that contributes 10,600 of the 23,538 owners, and both remain significant at the 1 percent level.

The responses of stayers match the outcomes of the workers cut. After AI layoffs, the workers cut find worse jobs than comparable displaced workers, and high-exposure stayers start training programs and take on fewer housing commitments. After industry downturns and layoffs due to other technologies, the outcomes of the workers cut do not differ significantly from those of workers cut in firm contractions, and after all three types, the differences between high- and low-exposure stayers in purchases and borrowing are not statistically significant. Within an AI layoff, the response comes from the stayers whose roles the layoff over-cut, and for purchases it grows with how heavily the layoff over-cut the role. When the layoff mentions AI without citing it as a reason, the estimates are positive and not statistically significant. Stayers respond to what they learn from the layoff about the value of work like their own, while they still hold their jobs.

# 5 Heterogeneity and Channels

Section 4 shows that after AI layoffs, high-exposure stayers start more training programs, make fewer first-home purchases and take on less new home equity borrowing. These responses are consistent with stayers learning from the layoff that their human capital is worth less. The same reductions could instead come from realized job loss, if high-exposure stayers leave the firm soon after the layoff, or from a shortage of liquid funds. This section uses two kinds of evidence to distinguish these explanations. The first is which stayers reduce purchases and borrowing the most: a stayer who comes to expect lower future earnings should postpone a purchase most when waiting is cheap and the purchase commits much of that income. The second is how the reductions vary with what happens after the layoff: whether the stayer keeps the job, how dispersed the salary losses of the workers cut from the stayer's role are, and whether the stayer looks for other work.

## 5.1 Heterogeneity

Table 6 estimates the AI results of Table 4 at 12 months within subgroups of stayers, with the same outcomes, samples, cells and controls. Each subgroup includes stayers from most

of the AI layoffs: 23 to 29 of the 30 layoffs in the purchase sample and 21 to 27 of the 27 layoffs in the borrowing sample.

**Children (Panel A).** Households without children account for the reduction in purchases. High-exposure renters without children record 0.61 fewer quarters with a purchase per 100 renters than their low-exposure coworkers (s.e. 0.11), while the estimate for renters with children is 0.01 (s.e. 0.15). A household with children often buys because it needs more space or a particular school district, and these needs set the timing of the purchase. A household without children can wait at little cost, so it can postpone the purchase when it expects lower future earnings. Among owners, the borrowing estimates are similar with and without children, $-0.34$ (s.e. 0.21) and $-0.21$ (s.e. 0.18), and neither is statistically significant.

**Women and men (Panel B).** The estimates show no consistent difference between women and men. High-exposure men reduce purchases by 0.59 quarters per 100 renters (s.e. 0.25), and women by 0.20, which is not statistically significant (s.e. 0.34). For borrowing, the order reverses: $-0.43$ (s.e. 0.31) for women and $-0.22$ (s.e. 0.14) for men, neither statistically significant. The estimates for women are imprecise in both samples. Men make up 63 percent of the renters in Panel B, and their purchase estimate is within one standard error of the full-sample estimate of $-0.44$.

**Age (Panel C).** The point estimate for purchases is larger among younger stayers: $-0.50$ (s.e. 0.09) for renters under 40, against $-0.28$ (s.e. 0.15) for renters 40 and over. Younger workers have most of their earnings ahead of them, so a fall in the value of their human capital lowers more of their future income, and a first home bought at these ages commits them to payments over most of their working lives. For borrowing, the estimates for the two age groups are similar, $-0.24$ (s.e. 0.13) under 40 and $-0.30$ (s.e. 0.09) at 40 and over. Owners 40 and over make up about half of the borrowing sample, so the reduction in borrowing also occurs among workers well into their careers.

**Tech hubs (Panel D).** Tech hubs are the five metropolitan areas that Atkinson et al. (2019) identify as the leading innovation centers (Boston, San Francisco, San Jose, Seattle and San Diego), assigned by the stayer's work location. High-exposure renters in these hubs reduce purchases by 1.08 quarters per 100 renters (s.e. 0.30), more than twice the full-sample estimate, while elsewhere the estimate is $-0.07$ (s.e. 0.23) and not statistically significant. The hubs are among the most expensive housing markets in the country. A first home there requires a large mortgage relative to earnings, so a purchase commits more of the household's future income, and the same change in expected income matters more for the decision. Home equity borrowing does not require paying the local price of a home, and the reduction in borrowing is nearly the same in and outside the hubs: $-0.27$ (s.e. 0.07) and $-0.26$ (s.e. 0.06).

## Table 6. Heterogeneity of the Housing Response

| | First-home purchases, renters | | Home equity borrowing, CLTV $< 0.6$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A. Children in the household* | | | | |
| | *With children* | *Without children* | *With children* | *Without children* |
| High exposure | 0.01 | $-0.61^{***}$ | $-0.34$ | $-0.21$ |
| | (0.15) | (0.11) | (0.21) | (0.18) |
| Stayers | 8,029 | 21,097 | 10,500 | 12,815 |
| Layoffs | 27 | 29 | 25 | 26 |
| $R^2$ | 0.073 | 0.038 | 0.050 | 0.043 |
| Low-exposure mean | 2.06 | 2.91 | 1.57 | 1.25 |
| *Panel B. Women and men* | | | | |
| | *Women* | *Men* | *Women* | *Men* |
| High exposure | $-0.20$ | $-0.59^{**}$ | $-0.43$ | $-0.22$ |
| | (0.34) | (0.25) | (0.31) | (0.14) |
| Stayers | 10,683 | 18,433 | 6,799 | 16,490 |
| Layoffs | 25 | 29 | 24 | 27 |
| $R^2$ | 0.065 | 0.039 | 0.067 | 0.036 |
| Low-exposure mean | 2.16 | 2.97 | 1.29 | 1.43 |
| *Panel C. Age* | | | | |
| | *Under 40* | *40 and over* | *Under 40* | *40 and over* |
| High exposure | $-0.50^{***}$ | $-0.28^{*}$ | $-0.24^{*}$ | $-0.30^{***}$ |
| | (0.09) | (0.15) | (0.13) | (0.09) |
| Stayers | 20,722 | 8,689 | 11,131 | 12,407 |
| Layoffs | 29 | 23 | 26 | 21 |
| $R^2$ | 0.028 | 0.044 | 0.028 | 0.027 |
| Low-exposure mean | 3.01 | 1.84 | 1.33 | 1.45 |
| *Panel D. Tech hubs* | | | | |
| | *Tech hubs* | *Elsewhere* | *Tech hubs* | *Elsewhere* |
| High exposure | $-1.08^{***}$ | $-0.07$ | $-0.27^{***}$ | $-0.26^{***}$ |
| | (0.30) | (0.23) | (0.07) | (0.06) |
| Stayers | 12,873 | 16,295 | 10,990 | 12,329 |
| Layoffs | 28 | 29 | 22 | 27 |
| $R^2$ | 0.044 | 0.052 | 0.036 | 0.045 |
| Low-exposure mean | 3.53 | 1.94 | 1.22 | 1.57 |
| Controls | Yes | Yes | Yes | Yes |
| Cell FE | Yes | Yes | Yes | Yes |

*Notes:* This table estimates the AI results of Table 4 at 12 months within subgroups of stayers. Each column reports $\beta$, estimated within the subgroup in its header, from

$$Y_i = \beta \, \text{HighExp}_i + X_i'\gamma + \alpha_{c(i)} + \varepsilon_i,$$

with the outcome and sample of Table 4. Children are measured in the InfoUSA household in the year before the layoff. Age is measured in the year before the layoff. Tech hubs are the five metropolitan areas that Atkinson et al. (2019) identify as the leading innovation centers (Boston, San Francisco, San Jose, Seattle and San Diego), by the stayer's work location. *Low-exposure mean* is the number of quarters with the event in the 12 months after the layoff per 100 low-exposure stayers in the subgroup. Controls are log salary, seniority and a female indicator. Cell FE are fixed effects for cells of layoff $\times$ age band $\times$ seniority band $\times$ job category. $R^2$ is that of the full regression, including the cell fixed effects. Standard errors clustered by firm are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Across the four splits, the reduction in purchases is largest among high-exposure renters for whom waiting costs little and a purchase commits the most future income: households without children, stayers under 40 and stayers in tech hubs. The estimated reduction in borrowing is of similar size in every subgroup, between 0.21 and 0.43 quarters per 100 owners, although it is not statistically significant in the splits by children and by sex.

## 5.2 Channels

**Stayers who keep their job (Panel A).** If high-exposure stayers lose their jobs soon after the layoff, or leave because they expect to, the reductions could reflect lower income rather than what stayers learn from the layoff. Panel A of Table 7 keeps the stayers who still hold a position at the layoff firm or its parent two and four quarters after the layoff. Most stayers remain: 96 percent of the renters and 97 percent of the owners after two quarters, and 91 and 93 percent after four. Among stayers still at the firm after four quarters, high-exposure renters record 0.44 fewer quarters with a purchase per 100 renters (s.e. 0.12), and high-exposure owners 0.25 fewer quarters with new home equity borrowing per 100 owners (s.e. 0.05), against $-0.44$ and $-0.27$ in the full samples. After two quarters, the estimates are $-0.52$ (s.e. 0.14) and $-0.26$ (s.e. 0.05). The reductions come from stayers who keep their jobs, so they do not reflect realized job loss.

**Dispersion of salary losses (Panel B).** Stayers learn about the value of their own human capital from what happens to the workers cut from their role. When those workers have similar outcomes after the layoff, the outcomes are more informative about every worker in the role, including those who stay, and when the outcomes are dispersed, they are less informative. Panel B measures this with the standard deviation of the change in log salary from the old to the new job among the workers cut from the stayer's own role who find a new job within 12 months, computed where at least five do, and splits stayers at its median. The point estimates are larger where the losses are less dispersed, which is where the outcomes of the workers cut are more informative: $-0.65$ (s.e. 0.09) for purchases and $-0.47$ (s.e. 0.16) for borrowing, against $-0.38$ (s.e. 0.10) and $-0.25$ (s.e. 0.13) where the losses are dispersed. This pattern is consistent with learning: a worker who learns from the outcomes of others puts more weight on them when they are more precise.

**Profile updates after the layoff (Panel C).** High-exposure stayers who update their Revelio profile after the layoff, a sign of job search, have larger point estimates for purchases and borrowing than those who do not. Panel C splits stayers by whether their profile records a change in the 12 months after the layoff. The estimates are $-0.64$ (s.e. 0.17) for purchases and $-0.38$ (s.e. 0.09) for borrowing, against $-0.29$ (s.e. 0.11) and $-0.20$ (s.e. 0.07) among stayers who do not update. Stayers who search are considering a move to another

## Table 7. Channels of the Housing Response

| | First-home purchases, renters | | | Home equity borrowing, CLTV $< 0.6$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A. Stayers who keep their job* | | | | | | |
| | *All stayers* | *After 2 quarters* | *After 4 quarters* | *All stayers* | *After 2 quarters* | *After 4 quarters* |
| High exposure | $-0.44^{***}$ | $-0.52^{***}$ | $-0.44^{***}$ | $-0.27^{***}$ | $-0.26^{***}$ | $-0.25^{***}$ |
| | (0.08) | (0.14) | (0.12) | (0.04) | (0.05) | (0.05) |
| Stayers | 29,411 | 28,343 | 26,857 | 23,538 | 22,808 | 21,824 |
| Layoffs | 30 | 30 | 30 | 27 | 27 | 27 |
| $R^2$ | 0.032 | 0.033 | 0.034 | 0.027 | 0.028 | 0.029 |
| Low-exposure mean | 2.68 | 2.68 | 2.69 | 1.39 | 1.39 | 1.41 |
| *Panel B. Dispersion of salary losses* | | | | | | |
| | *More dispersed* | *Less dispersed* | | *More dispersed* | *Less dispersed* | |
| High exposure | $-0.38^{***}$ | $-0.65^{***}$ | | $-0.25^{*}$ | $-0.47^{***}$ | |
| | (0.10) | (0.09) | | (0.13) | (0.16) | |
| Stayers | 13,424 | 14,295 | | 11,106 | 11,628 | |
| Layoffs | 21 | 25 | | 18 | 21 | |
| $R^2$ | 0.043 | 0.038 | | 0.045 | 0.035 | |
| Low-exposure mean | 2.17 | 3.31 | | 1.37 | 1.43 | |
| *Panel C. Profile updates after the layoff* | | | | | | |
| | *Updated* | *Not updated* | | *Updated* | *Not updated* | |
| High exposure | $-0.64^{***}$ | $-0.29^{***}$ | | $-0.38^{***}$ | $-0.20^{***}$ | |
| | (0.17) | (0.11) | | (0.09) | (0.07) | |
| Stayers | 12,465 | 16,431 | | 9,385 | 13,790 | |
| Layoffs | 29 | 28 | | 26 | 26 | |
| $R^2$ | 0.058 | 0.042 | | 0.055 | 0.041 | |
| Low-exposure mean | 2.52 | 2.79 | | 1.48 | 1.34 | |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Cell FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table estimates the AI results of Table 4 at 12 months within subsamples. Each column reports $\beta$, estimated within the subsample in its header, from

$$Y_i = \beta \, \text{HighExp}_i + X_i'\gamma + \alpha_{c(i)} + \varepsilon_i,$$

with the outcome and sample of Table 4. Panel A keeps stayers who still hold a position at the layoff firm or its parent 2 or 4 quarters after the layoff. Panel B splits stayers at the median of $\sigma$, the standard deviation of the change in log salary from the old to the new job among the workers cut from the stayer's own role (50 Revelio roles) who find a new job within 12 months, where at least five do. Panel C splits stayers by whether their Revelio profile records a change in the 12 months after the layoff, a proxy for job search. *Low-exposure mean* is the number of quarters with the event in the 12 months after the layoff per 100 low-exposure stayers in the subsample. Controls are log salary, seniority and a female indicator. Cell FE are fixed effects for cells of layoff $\times$ age band $\times$ seniority band $\times$ job category. $R^2$ is that of the full regression, including the cell fixed effects. Standard errors clustered by firm are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

employer, and possibly another city, and for them a home in the current location, or a larger loan against it, is the commitment most costly to undo. Stayers who do not update their profiles also reduce both, by about half as much.

### 5.3 Interpretation

The evidence in this section and in Section 4 is consistent with a single explanation. Workers cut in AI layoffs fare worse in the labor market than comparable workers cut in firm contractions, so stayers can learn from the layoff that the market value of this work has fallen. High-exposure stayers start more training programs and postpone first-home purchases and new home equity borrowing. The reductions appear among stayers still at the firm a year later, so they do not come from lost income. They appear among owners with a CLTV below 0.6, who could borrow against their homes if they were short of liquid funds, and these owners borrow less. Their point estimates are larger where the salary losses of the workers cut from the stayer's role are less dispersed and among stayers who look for other jobs, and the reduction in purchases is concentrated among renters for whom waiting is cheap and a purchase commits the most future income. Information that all employees of the firm share, such as information about the firm's prospects, is the same for high- and low-exposure stayers and is removed by the comparison within the layoff. The gap is also not statistically significant after industry downturns, firm contractions, layoffs due to other technologies and layoffs that mention AI without citing it as a reason (Tables 4 and 5).

These are the responses one would expect from a household that learns its human capital may be worth less. A home commits future income to a fixed level of housing in one place (Chetty and Szeidl, 2007), and because a purchase is costly to reverse, a household that has become less sure of its future earnings gains from waiting (Dixit and Pindyck, 1994). New home equity borrowing adds payments that must come out of the same income. Stayers who train respond to the same risk in a different way: training lowers the chance that the new technology can replace their own work. Section 6 builds a model of these choices, in which households learn from layoffs at their employer whether a new technology can replace their work, can retrain so that it can no longer be replaced, and decide whether to buy a home and borrow against it.

## 6 A Quantitative Model

The previous sections show that stayers whose roles an AI layoff over-cut buy fewer homes, borrow less against their homes and start more short training programs after AI layoffs, and that they keep their jobs. I build a life-cycle model of housing and mortgage choices

in which workers learn whether a new technology can replace their work from layoffs at their employer. The model serves three purposes:

- It shows how a layoff triggered by a new technology serves as a local signal: a stayer sees how heavily the layoff over-cut its role and uses this to update its belief about whether the technology can replace its own work.
- It compares economies with and without the new technology to measure the new technology's effects on homeownership and welfare and to show which households bear them.
- It allows counterfactuals, in which I change one feature of the economy at a time and trace how the purchase gap, retraining and welfare respond: households cannot learn their type from layoffs, so a layoff does not change their beliefs; households cannot retrain; workers are insured against the loss from a cut, retraining is subsidized, or owners who are cut receive mortgage relief, each paid for within the economy; and firms make technology layoffs more or less often.

The model describes any new technology that firms use to replace part of their workforce; Section 6.5 calibrates it to AI. Prices are exogenous to workers, so the model is a partial-equilibrium model.

### 6.1 Environment

**Demographics.** Time is discrete and a period is a year. Each year a cohort of households of measure one enters at age $j = 1$, which corresponds to age 25, and leaves after age $J = 40$, which corresponds to age 64, at the end of working life. Every cohort enters with the same size, so the age distribution is stationary.

**Preferences.** A household maximizes

$$\mathbf{E}_1\left[\sum_{j=1}^{J}\beta^{j-1}u(c_j,h_j)+\beta^J V_{J+1}(n_{J+1})\right], \qquad u(c,h)=\frac{\left(c^{1-\alpha}h^{\alpha}\right)^{1-\gamma}}{1-\gamma}, \tag{6}$$

where $c_j$ is nondurable consumption, $\beta$ is the discount factor and $\gamma$ is the coefficient of relative risk aversion. With Cobb–Douglas preferences, households spend a constant share of their expenditure on housing, as they do in the data (Davis and Ortalo-Magné, 2011).

**Housing.** Households obtain housing services by renting or owning a home, as in Kaplan et al. (2020). A renter chooses a quantity of housing $\tilde{h}_j$ each year, pays a rent of $q$ per unit and gets services $h_j = \tilde{h}_j$. Owned homes come in one size, normalized to one unit of housing. A buyer pays the price $P$ and gets services $h_j = \omega$, where $\omega \geq 1$ captures

the additional utility from owning; it pays a fraction $\delta$ of the home's value each year for maintenance and property taxes and keeps the home until it sells, at a cost of a fraction $\kappa_s$ of the value. Because the size of an owned home is fixed, an owner's state needs no house size. Buying a home therefore commits future income to a fixed level of housing, a consumption commitment in the sense of Chetty and Szeidl (2007), so a change in expected future earnings matters more for the decision to buy than for how much to rent. Each year an owner must move with probability $\pi_m$, for reasons outside the model such as a family event, and then sells and rents for the rest of the year (Cocco, 2005).

**Saving and mortgages.**

- *Liquid saving.* Households save in a liquid asset that earns the real rate $r$ and cannot borrow without collateral, $a_{j+1} \geq 0$.
- *Buying.* A buyer pays for the house with its liquid assets and a mortgage. Mortgages are thirty-year fixed-rate loans at the real rate $r_m > r$.
- *Repayment schedule.* An owner who keeps its house repays on a schedule that lowers the balance to $(1-\theta_m)m_j$ each year, so $m_{j+1} \geq (1-\theta_m)m_j$. $\theta_m$ is the share of principal that makes the payment equal to that of a thirty-year mortgage (Garriga et al., 2017).
- *Home equity borrowing.* An owner can borrow against its home, raising the balance above the schedule, $m_{j+1} > (1-\theta_m)m_j$, but pays a fixed fee $\kappa_e$ to do so.
- *Loan-to-value limit.* At purchase and later, the balance cannot exceed a fraction $\ell$ of the value of the home, $m_{j+1} \leq \ell P$.

**Initial conditions.** Households enter as renters with no mortgage. Their liquid assets $a_1$ are drawn from a lognormal distribution fitted to college-educated households aged 25–27, and their initial income shock $z_1$ is drawn from $N(0, \sigma_{z_1}^2)$.[2]

**End of working life.** The value of net worth at the end of working life summarizes what the household's wealth is worth in retirement. The house is valued net of the cost of selling it (Cocco, 2005):

$$V_{J+1}(n_{J+1}) = \vartheta \frac{\left(n_{J+1} + \underline{n}\right)^{(1-\alpha)(1-\gamma)}}{1-\gamma}, \qquad (7)$$
$$n_{J+1} = (1+r)\, a_{J+1} + o_J\left[(1-\kappa_s)P - (1+r_m)\, m_{J+1}\right].$$

[2]Financial assets of households with a college degree aged 25–27 in the 2022 Survey of Consumer Finances have a median of \$23,100 and a mean of \$122,600, or 0.22 and 1.16 in model units of the stayers' mean annual after-tax earnings (\$105,200). The lognormal has this mean, and the standard deviation of $\log a_1$, 1.83, matches the ratio of the mean to the median, $\sqrt{2\ln(122{,}600/23{,}100)}$. The standard deviation of the initial income shock, $\sigma_{z_1} = 0.42$, follows Kaplan et al. (2020).

Here $o_J$ indicates ownership at the end of working life, $\vartheta$ governs how much the household values resources after working life, and $\underline{n} > 0$ is the present value of Social Security benefits, which keeps the value finite at zero net worth.

### 6.2 Income, Human Capital and Beliefs

**Firms.** Households work at a continuum of identical firms, so a representative firm describes how earnings are set: all workers have the same earnings function and differ only in age, in their history of income shocks, and in whether their work can be replaced by the new technology. Firms differ only in when they make technology layoffs, which happen at each firm independently. Each household works at one firm and learns about its own type only from the layoffs at that firm, as stayers do in the data.

**Earnings.** A household of age $j$ earns, after taxes,

$$y_j = \left(1 - d\, x_j\right) f(j)\, e^{z_j}, \qquad z_j = \rho z_{j-1} + \eta_j, \quad \eta_j \sim N(0, \sigma_\eta^2), \tag{8}$$

where $x_j \in \{0, 1\}$ indicates that the household has been cut in a technology layoff and $d$ is the share of earnings it loses. The deterministic function of age $f(j)$ captures the hump-shaped profile of earnings, which rise steeply early in a career and flatten later as workers accumulate human capital on the job (Ben-Porath, 1967; Huggett et al., 2011). The profile matters for the housing choice: young households expect their earnings to grow, so many wait to buy until their income is high enough to afford a home. The persistent shock $z_j$ gives households a precautionary motive to save (Carroll and Samwick, 1997; Gourinchas and Parker, 2002), makes them differ in when they can afford to buy, and gives owners a reason to borrow against their homes.

A household cut in a technology layoff earns the fraction $1 - d$ of what it earned before for the rest of its working life, whatever its age or income shock. In the Revelio records, most workers cut in AI layoffs find new jobs at lower pay (Section 4.1), and some have no new position two years later. The model combines the two into a single lasting loss and abstracts from the timing of the unemployment spell.

**Replaceable work.** Households are of two types: replaceable ($R$), whose work the new technology can replace, and not replaceable ($N$). The type $\tau_j \in \{R, N\}$ is drawn at entry, replaceable with probability $\mu_0$, and changes only through retraining, described below. A household knows $\mu_0$ but not its own type. Consider a data analyst in 2023. AI could already write some of the analyst's queries, but the analyst could not tell whether AI could do enough of the work for the firm to cut the analyst in an AI layoff.

**Technology layoffs.** Each year, with probability $\psi$, the household's firm makes a technology layoff, in which it replaces part of its workforce with the new technology. In

a layoff, the firm cuts a replaceable household with probability $\kappa_R$ and a household that is not replaceable with a smaller probability $\kappa_N$, because a layoff also cuts some workers whose tasks the technology does not perform. A household that is cut loses the same share of its earnings whatever its type, and stays cut, $x_{j+1} = 1$ if $x_j = 1$:

$$\Pr\left(x_{j+1} = 1 \,\middle|\, x_j = 0,\ R\right) = \psi\,\kappa_R, \qquad \Pr\left(x_{j+1} = 1 \,\middle|\, x_j = 0,\ N\right) = \psi\,\kappa_N, \qquad \kappa_R > \kappa_N. \quad (9)$$

**What a stayer observes.** A household kept in a technology layoff sees which roles the firm over-cut. Its exposure to the layoff is high ($H$) if the layoff over-cut its role by more than the role of its median coworker, and low ($L$) otherwise, and high exposure is more likely for a replaceable household:

$$\Pr(H \mid R) = \pi_R \ > \ \Pr(H \mid N) = \pi_N. \quad (10)$$

**Beliefs.** The household learns about its type only from technology layoffs at its firm; in a year without one, its belief does not change. Let $\mu_j$ denote the probability the household assigns to being replaceable. By Bayes' rule, a household that is kept in a layoff with high exposure updates its belief to

$$\mu_{j+1} = \frac{\mu_j\,(1-\kappa_R)\,\pi_R}{\mu_j\,(1-\kappa_R)\,\pi_R + (1-\mu_j)\,(1-\kappa_N)\,\pi_N}, \quad (11)$$

and one that is kept with low exposure updates in the same way, with $1-\pi_R$ and $1-\pi_N$ in place of $\pi_R$ and $\pi_N$. Being kept in a layoff by itself lowers the belief, from 0.19 to 0.11 at the calibrated values, since replaceable households are cut more often. High exposure raises the belief and low exposure lowers it, and how much a single layoff changes the belief depends on $\pi_R/\pi_N$ together with $\kappa_R$ and $\kappa_N$. In a year, a household that has not been cut is cut with probability $\psi\,[\kappa_R\mu_j + \kappa_N(1-\mu_j)]$, is kept with high exposure with probability $\psi\,[\mu_j(1-\kappa_R)\pi_R + (1-\mu_j)(1-\kappa_N)\pi_N]$ and is kept with low exposure with probability $\psi\,[\mu_j(1-\kappa_R)(1-\pi_R) + (1-\mu_j)(1-\kappa_N)(1-\pi_N)]$. Because households update from the correct prior, these probabilities are also the frequencies of the events in the population.

**The response to a first technology layoff.** The data measure the response of stayers to the first AI layoff at their firm, so the model counterpart is a household that holds its prior, $\mu_j = \mu_0$, when the layoff comes. After the layoff, the stayers' beliefs depend on their exposure to it. A high-exposure stayer raises its belief to $\mu_H$, given by equation (11) at $\mu_j = \mu_0$, and so its chance of being cut in the firm's next technology layoff to $\kappa_N + (\kappa_R - \kappa_N)\mu_H$; a low-exposure stayer lowers its belief to $\mu_L$ and its chance of being cut to $\kappa_N + (\kappa_R - \kappa_N)\mu_L$. Two stayers in the same layoff face the same firm, the same prices and the same housing

market, and differ only in their exposure to the layoff, and so in their beliefs about their own work. The estimates in Section 4 make the same comparison in the data.

How much the two stayers' housing choices differ depends on three things: how likely the firm is to make another technology layoff, $\psi$; how much more likely a replaceable household is to be cut, $\kappa_R - \kappa_N$, and how much a household loses if it is cut, $d$; and how much one layoff changes beliefs, which depends on $\pi_R/\pi_N$, $\kappa_R$ and $\kappa_N$. The chance of another layoff in any year is small, but a household that buys a house keeps it for many years, and over the life of a mortgage a stayer that comes to believe its work can be replaced by the new technology faces a sizable chance of a permanent loss.

**Retraining.** A household that has not been cut can retrain, for example by completing a program that teaches skills the new technology complements. Retraining costs $\kappa_T$ in the year it is undertaken, and it turns a replaceable household into one whose work the new technology cannot replace with probability $\lambda_T$:

$$\Pr\left(\tau_{j+1} = R \,\middle|\, \tau_j = R,\ \text{retrain}_j\right) = 1 - \lambda_T. \tag{12}$$

The household does not observe whether retraining has worked, so its belief falls to $(1-\lambda_T)\mu_j$ and it keeps learning from later layoffs. Households in the same state differ in whether they retrain, because each year a household draws independent extreme-value shocks, with scale $\sigma_T$, to the values of retraining and of not retraining (Rust, 1987; Iskhakov et al., 2017). A household that has not been cut therefore retrains with probability

$$\Pr(\text{retrain}_j) = \frac{1}{1 + \exp\left[-\left(W_j^1 - W_j^0\right)/\sigma_T\right]}, \tag{13}$$

where $W_j^1$ and $W_j^0$ are its values with and without retraining before the shocks. The gain from retraining rises with the belief: a household that assigns a high probability to being replaceable expects to lose more if it does not retrain. A high-exposure stayer therefore retrains more often and postpones a purchase. Because a household pays for retraining and for a down payment out of the same liquid assets, a young renter whose belief rises must choose between paying for retraining and saving for a home, and a household that has retrained faces less risk when it buys.

**Timing.** A year has three stages:

1. *Start of the year.* The household enters with its liquid assets $a_j$, its mortgage balance $m_j$ if it owns, its income shock $z_j$, whether it has been cut $x_j$, and its belief $\mu_j$. It earns $y_j$, and an owner learns whether it must move.

2. *Choices.* The household chooses whether to rent, buy, keep or sell its home, how

much housing to rent if it rents, how much to borrow, how much to consume and save, and, if it has not been cut, whether to retrain.

3. *End of the year.* The firm makes a technology layoff with probability $\psi$. A household that has not been cut is cut or kept; if kept, it sees whether its exposure to the layoff is high or low and updates its belief to $\mu_{j+1}$. The next income shock $z_{j+1}$ is then drawn.

### 6.3 The Household Problem

The household's state at age $j$ is its liquid assets $a_j$, its income shock $z_j$, whether it has been cut $x_j$, its belief $\mu_j$, and, for owners, its mortgage balance $m_j$. Its type is not a state, because the household does not observe it; it enters only through the belief. In each problem below, a household that has not been cut can also retrain, with the probability in equation (13); retraining lowers its cash on hand by $\kappa_T$ and its belief to $(1-\lambda_T)\mu_j$. Let $w_j \equiv (1+r)a_j + y_j$ denote cash on hand. As in Kaplan et al. (2020), renters and owners solve separate problems.

**Renters.** A renter chooses whether to keep renting or to buy:

$$V_j^{\text{rent}}(a,z,x,\mu) = \max\Big\{\, \mathcal{R}_j(a,z,x,\mu),\ \max_{m'} B_j(a,m',z,x,\mu) \Big\}. \tag{14}$$

- *Renting.* The value of renting is

$$\mathcal{R}_j = \max_{c,\tilde{h}_j,a'} u(c,\tilde{h}_j) + \beta\, \mathbf{E}_j V_{j+1}^{\text{rent}}(a',z',x',\mu') \quad \text{s.t.} \quad c + q\tilde{h}_j + a' = w_j.$$

  Because utility is Cobb–Douglas, a renter spends a share $\alpha$ of its expenditure on rent. A renter who cannot cover a minimum expenditure receives a transfer that guarantees it (Hubbard et al., 1995).

- *Buying.* The value of buying with mortgage $m'$ is

$$\begin{aligned} B_j = \max_{c,a'}\ & u(c,\omega) + \beta\, \mathbf{E}_j V_{j+1}^{\text{own}}(a',m',z',x',\mu') \\ \text{s.t.}\quad & c + a' = w_j - (1+\delta)P + m', \qquad m' \le \ell P. \end{aligned}$$

**Owners.** An owner chooses whether to keep its house, adjusting its mortgage, or to sell it, unless it must move:

$$V_j^{\text{own}}(a,m,z,x,\mu) = (1-\pi_m)\max\{K_j, S_j\} + \pi_m S_j. \tag{15}$$

- *Keeping the house.* The value of keeping is

$$\begin{aligned} K_j = \max_{c,a',m'} \; & u(c,\omega) + \beta\, \mathbf{E}_j V_{j+1}^{\text{own}}(a', m', z', x', \mu') \\ \text{s.t.} \quad & c + a' = w_j - \delta P - (1 + r_m)m + m' - \kappa_e \mathbf{1}\{m' > (1-\theta_m)m\}, \\ & (1-\theta_m)m \le m' \le \ell P. \end{aligned}$$

- *Selling.* A seller sells its home, repays its mortgage from the proceeds and rents for the year:

$$\begin{aligned} S_j = \max_{c,\tilde{h}_j,a'} \; & u(c,\tilde{h}_j) + \beta\, \mathbf{E}_j V_{j+1}^{\text{rent}}(a', z', x', \mu') \\ \text{s.t.} \quad & c + q\tilde{h}_j + a' = w_j + (1-\kappa_s)P - (1+r_m)m. \end{aligned}$$

In every problem $a' \geq 0$. The expectation is over the income shock and, under the household's belief, over technology layoffs and the household's exposure to them, following the timing above. At the end of working life, $V_{J+1}^{\text{rent}}$ and $V_{J+1}^{\text{own}}$ are given by $V_{J+1}$.

### 6.4 Equilibrium

Prices $(P, q, r, r_m)$ are exogenous and constant. Let $\Phi_j$ denote the distribution of households of age $j$ over tenure, liquid assets, mortgage balances, income shocks, whether they have been cut, beliefs $\mu_j$ and types. Types are unobserved by households, but they govern how often households are cut and how exposed they are to the layoffs they survive.

A stationary equilibrium consists of three objects:

1. the value functions $V_j^{\text{rent}}$ and $V_j^{\text{own}}$;
2. the policy functions for retraining, tenure, consumption, rental housing, liquid assets and mortgage balances;
3. the distributions $\{\Phi_j\}_{j=1}^{J}$.

These satisfy three conditions:

1. the policy functions solve the renter and owner problems;
2. $\Phi_1$ is given by the initial conditions;
3. $\Phi_{j+1}$ is generated from $\Phi_j$ by the policy functions and the transitions of income shocks, technology layoffs, retraining and beliefs.

Aggregate quantities, such as the homeownership rate, the purchase rate or new home equity borrowing, are averages of household outcomes over these distributions.

### 6.5 Calibration

I measure all quantities in units of the stayers' mean annual after-tax earnings, $105,200, as Kaplan et al. (2020) do with median earnings. Most parameters are set outside the model, from the literature or from the data on the stayers and their layoffs (Table 8). Eight are chosen so that the model matches eight moments of wealth, housing, borrowing, retraining and the purchases of high- and low-exposure stayers after AI layoffs (Table 9). Table 10 compares the model with moments it does not target.

**Households and housing.** Risk aversion, the income process, the length of retirement, Social Security, the cost of maintenance and property taxes, $\delta = 0.025$, and the cost of selling, $\kappa_s = 0.07$, follow Kaplan et al. (2020), and the housing share $\alpha = 0.16$ is their target for the share of expenditure on housing. The maximum loan-to-value ratio, $\ell = 0.85$, and the interest rates follow Cocco (2005): a real riskless rate of 2 percent and a mortgage rate of 4 percent. Mortgages amortize over thirty years. The minimum expenditure is the consumption floor of Hubbard et al. (1995). Three parameters come from the data on the stayers. The age profile $f(j)$ is fitted to their mean after-tax salary by age. The price of the owned home, $P$, is the median value of the stayers' homes in the year before the layoff, $582,000, or 5.5 years of earnings. The rent of one unit of housing is 3.7 percent of this price, $q = 0.037P$, the ratio of rents to home values in the stayers' counties.

**The new technology.** The parameters of the technology are set so that the model's technology layoffs are the AI layoffs that the stayers saw. I measure whether AI can replace a household's work with the exposure of tasks to large language models. The share of households whose work AI can replace, $\mu_0 = 0.19$, rounds the 18.5 percent of U.S. workers who have more than half of their tasks exposed to large language models when complementary software is partly adopted (Eloundou et al., 2024). A task is exposed if a large language model, or software built on one, can cut the time needed to complete it by at least half without lowering quality. The probability that a firm makes an AI layoff in a year, $\psi = 0.035$, is the rate at which firms in the layoff catalog follow one AI layoff with another: of the 47 firms that made an AI layoff in 2023–25, 2 made another in the 60 firm-years observed after the first. This rate is imprecise, with a 95 percent interval from 0.004 to 0.12, and Section 6.8 reports how the results change with it. The probabilities of being cut satisfy $\kappa_R\mu_0 + \kappa_N(1 - \mu_0) = 0.154$, so that the share of the workforce cut is the 15.4 percent of the average AI layoff in layoffs.fyi; their ratio is chosen jointly with the other internal parameters below. The earnings loss $d = 0.275$ is the fall in annual earnings of the workers cut in AI layoffs, relative to the stayers of the same layoffs, from the quarter before the layoff to the second year after it, as a share of their earnings before the layoff, computed from the Revelio position histories of both groups. It counts workers not yet employed again as earning nothing, so it combines

the lower pay of those who find new jobs, 16.5 log points, with the jobs that others have not regained. The probability of high exposure for a household that is not replaceable, $\pi_N$, is set so that half of the stayers at a first AI layoff have high exposure; given $\pi_R$, this requires $\mu_0(1-\kappa_R)\pi_R + (1-\mu_0)(1-\kappa_N)\pi_N = \frac{1}{2}\left[1-\kappa_R\mu_0-\kappa_N(1-\mu_0)\right]$. Retraining costs $\kappa_T =$ \$13,500, the tuition of a typical coding bootcamp, one of the short programs of Table 3. The scale of the extreme-value shocks to retraining is $\sigma_T = 0.01$.

**Eight parameters chosen to match moments.** The remaining eight parameters are chosen by the simulated method of moments. The first seven are chosen jointly to minimize the sum of squared percent deviations of seven model moments from the data; $\lambda_T$ is then set to match the rate of retraining, because retraining barely moves the other moments (Table 9). Every parameter moves every moment, but each has one it moves most: the discount factor $\beta$ moves median net worth relative to earnings; the owning premium $\omega$, homeownership at 25–64; the weight on final net worth $\vartheta$, homeownership at 55–64; the probability of a forced move $\pi_m$, the owners' sale rate; the cost of home equity borrowing $\kappa_e$, home equity borrowing; the probability of high exposure for a replaceable household $\pi_R$, the purchases of low-exposure stayers after AI layoffs; the ratio of the probabilities of being cut $\kappa_R/\kappa_N$, the purchase gap after AI layoffs; and the probability that retraining works $\lambda_T$, the rate of retraining. Wealth comes from the Survey of Consumer Finances for college-educated households; the other moments come from the stayers before their layoff. Home equity borrowing is the annual rate among owners with a CLTV below 0.6, the sample of Table 4. The purchases of low-exposure stayers are their 12-month purchase rate after AI layoffs over their own rate before the layoff, relative to the same ratio for the stayers of industry downturns and firm contractions of 2022 or later: low-exposure renters at AI layoffs buy 13.5 percent more. Retraining is the rate at which low-exposure stayers under 40 at AI layoffs start a short program in the year before the layoff (Table 3, last row).

The ratio $\kappa_R/\kappa_N$ determines how much more a replaceable household expects to lose than one that is not replaceable, and so how much a stayer's housing choice depends on its exposure to the layoff; it is chosen to match the purchase gap after AI layoffs. Over the 12 months after the layoff, low-exposure renters buy 2.77 homes per 100 and high-exposure renters in the same cell 0.37 fewer, a gap of 13.3 percent of the low-exposure rate. The model counterpart compares two groups of households after the same layoff that share the same history before it. I take every household that is at its first AI layoff and is kept, and follow it twice, once with high and once with low exposure and the same shocks otherwise. Each copy is weighted by the probability, given the household's type, of that exposure. The calibrated ratio is 6.95, so that a replaceable household is cut with probability $\kappa_R = 0.50$ and one that is not replaceable with $\kappa_N = 0.07$. Among the workers of the same AI layoff, the share cut is 1.57 times as high for the 19 percent of workers whose occupations are

**Table 8. Parameters Set outside the Model**

| Parameter | Description | Value | Source |
|---|---|---|---|
| *Panel A. Demographics, preferences and earnings* | | | |
| $J$ | Years of working life | 40 | Ages 25–64 |
| $T_R$ | Years of retirement | 16 | Kaplan et al. (2020) |
| $\gamma$ | Relative risk aversion | 2 | Kaplan et al. (2020) |
| $\alpha$ | Housing share in utility | 0.16 | Kaplan et al. (2020) (housing expenditure share) |
| $f(j)$ | Age profile of earnings | Quadratic | Stayers' mean after-tax salary by age |
| $\rho$ | Persistence of income shock | 0.97 | Kaplan et al. (2020) |
| $\sigma_\eta$ | S.D. of income shock | 0.20 | Kaplan et al. (2020) |
| $\sigma_{z_1}$ | S.D. of income shock at entry | 0.42 | Kaplan et al. (2020) |
| $\varsigma$ | Social Security replacement rate | 0.40 | Kaplan et al. (2020) |
| $\sigma_{a_1}$ | S.D. of log initial liquid assets | 1.83 | SCF 2022, college, ages 25–27 |
| *Panel B. Housing and mortgages* | | | |
| $P$ | House price | 5.53 | Stayers' median home value ($582,000) |
| $q/P$ | Rent per unit of housing services (one house), relative to $P$ | 0.037 | ACS 2019–23, stayers' counties |
| $\delta$ | Maintenance and property tax (share of $P$) | 0.025 | Kaplan et al. (2020) |
| $\kappa_s$ | Cost of selling (share of $P$) | 0.07 | Kaplan et al. (2020) |
| $\ell$ | Maximum loan-to-value ratio | 0.85 | Cocco (2005) |
| $r$ | Real return on liquid assets | 0.02 | Cocco (2005) |
| $r_m$ | Real mortgage rate | 0.04 | Cocco (2005) |
| $\theta_m$ | Scheduled principal repayment | 0.018 | 30-year amortization, Garriga et al. (2017) |
| $\underline{c}$ | Minimum renter spending, net of the rent of one house | 0.19 | Hubbard et al. (1995) |
| *Panel C. Technology and retraining* | | | |
| $\mu_0$ | Share of households whose work AI can replace | 0.19 | Eloundou et al. (2024) |
| $\psi$ | Probability of an AI layoff in a year | 0.035 | Layoff catalog, 2023–25 |
| $\kappa_R, \kappa_N$ | Share of the workforce cut in an AI layoff, $\kappa_R\mu_0 + \kappa_N(1-\mu_0)$ | 0.154 | layoffs.fyi |
| $d$ | Share of earnings lost if cut | 0.275 | Workers cut in AI layoffs |
| $\pi_N$ | High exposure if not replaceable | 0.443 | Half of stayers have high exposure |
| $\kappa_T$ | Cost of retraining | $13,500 | Coding bootcamp tuition |
| $\sigma_T$ | Scale of the taste shocks to retraining | 0.01 | |

*Notes:* A period is a year. The unit of account is the stayers' mean annual after-tax earnings, $105,200. The age profile of earnings is $\log f(j) = \log f(1) + g_1(j-1) + g_2(j-1)^2$, fitted to the log of the mean after-tax Revelio salary of the stayers at each age ($f(1) = 0.84$, $g_1 = 0.0233$, $g_2 = -0.00045$); after-tax salary is $0.75\,\bar{y}\,(y/\bar{y})^{1-0.151}$, the tax function of Heathcote et al. (2017) with the parameters of Kaplan et al. (2020). Initial liquid assets are lognormal, with the mean and the ratio of the mean to the median of the 2022 Survey of Consumer Finances (Section 6.1). The rent-to-price ratio is twelve times the median gross rent over the median home value (ACS 5-year, B25064 and B25077) in the stayers' counties, weighted by stayers. Interest rates are real and follow Cocco (2005): the riskless rate and a mortgage premium of 2 percent. $\theta_m$ makes interest and scheduled principal equal to the payment of a 30-year loan at $r_m$. A household that rents, including one that sells, and cannot afford spending (consumption and rent) of $\underline{c} + q$ receives a transfer that raises its spending to $\underline{c} + q$: the consumption floor of Hubbard et al. (1995), $7,000 in 1984 dollars or $20,500 in 2023 dollars, plus the rent of one house. Section 6.5 describes the sources of the parameters in Panel C; $\pi_N$ is set so that half of the stayers at a first AI layoff have high exposure, given the calibrated $\pi_R$ and $\kappa_R/\kappa_N$ (Table 9).

**Table 9. Parameters Chosen Jointly and Targeted Moments**

| Parameter | Description | Value | Targeted moment | Data | Model |
|---|---|---|---|---|---|
| $\beta$ | Discount factor | 0.991 | Net worth / earnings | 4.19 | 4.24 |
| $\omega$ | Owning premium | 7.51 | Homeownership, ages 25–64 | 55.8% | 54.5% |
| $\vartheta$ | Weight on final net worth | 199 | Homeownership, ages 55–64 | 67.6% | 70.4% |
| $\pi_m$ | Forced-move probability | 0.027 | Owners' annual sale rate | 3.5% | 3.5% |
| $\kappa_e$ | Cost of home equity borrowing | 0.023 | Home equity borrowing, per 100 | 1.09 | 1.11 |
| $\pi_R$ | High exposure if replaceable | 0.956 | Low-exposure purchases vs. no layoff | 13.5% | 13.2% |
| $\kappa_R/\kappa_N$ | Cut probability, R/N | 6.95 | Purchase gap, high vs. low | −13.3% | −12.8% |
| $\lambda_T$ | Retraining succeeds | 0.17 | Short programs, per 100 | 0.36 | 0.35 |

*Notes:* The first seven parameters are chosen jointly to minimize the sum of squared percent deviations of the model moments from their data counterparts, and $\lambda_T$ is then set to match the rate of retraining; each row pairs a parameter with the moment it moves most. The probability of high exposure for a household that is not replaceable, $\pi_N = 0.443$, is set so that half of the stayers at a first AI layoff have high exposure, and $\kappa_R = 0.503$ and $\kappa_N = 0.072$ follow from the ratio and the 15.4 percent of the workforce cut in an AI layoff. Net worth is the median for college-educated households in the 2022 Survey of Consumer Finances. Homeownership, the sale rate and home equity borrowing (owners with a CLTV below 0.6) describe the stayers before the layoff. The purchase gap is the 12-month purchase rate of high-exposure renters at AI layoffs relative to that of their low-exposure coworkers in the same cell, minus one. The low-exposure purchase moment is the 12-month purchase rate of low-exposure renters at AI layoffs over their pre-layoff rate, relative to the same ratio for stayers at industry downturns and firm contractions of 2022 or later, minus one. Short programs are those started by low-exposure stayers under 40 at AI layoffs in the year before the layoff (Table 3, Panel C).

most exposed to AI (Felten et al., 2021) as for the others, against 1.03 to 1.09 in the other types of layoff. Occupation measures AI exposure with error, which biases this ratio toward one, so $\kappa_R/\kappa_N$ is likely above 1.57. The probability $\pi_R = 0.96$ governs how much a low-exposure stayer learns that its work is safe, and so how much more it buys than a household that saw no layoff. The probability $\lambda_T = 0.17$ governs how much retraining is worth, and so how many households retrain.

**Fit.** Table 9 reports the calibrated values. The largest deviation from a target is in homeownership at 55–64, 70.4 percent in the model against 67.6 percent in the data.

**Moments not targeted.** Table 10 reports moments the calibration does not target. The model has a single measure of the purchase gap, the one the calibration targets: the two copies of a household share their history before the layoff, so netting out the pre-layoff purchase rate, as the regression in Table 4 does, leaves the model's gap at 12.8 percent, against a regression estimate of 16 percent in the data. Two untargeted moments concern the response to a layoff. First, high-exposure stayers under 40 start 0.25 more short programs per 100 in the year of the layoff than their low-exposure coworkers (Table 3); in the model they retrain 0.32 more per 100, because high exposure raises the belief that their work can be replaced and low exposure lowers it. Second, high-exposure renters buy about as often as households that saw no layoff, in the data (0.1 percent more) and in the model (1.3 percent less), so the purchase gap comes mostly from low-exposure stayers

**Table 10. Moments Not Targeted**

| | Data | Model |
|---|---|---|
| *Panel A. Homeownership over the life cycle* | | |
| Ages 25–29 | 42.3% | 14.3% |
| Ages 30–34 | 49.4% | 34.3% |
| *Panel B. Leverage* | | |
| Loan-to-value ratio at first purchase | 0.80 | 0.39 |
| Median CLTV of owners | 0.68 | 0.31 |
| *Panel C. Response to a first AI layoff, high- vs. low-exposure stayers* | | |
| Home equity borrowing (12 months) | −19.0% | 0.1% |
| Short programs, per 100 stayers under 40 | 0.25 | 0.32 |
| Purchases of high-exposure stayers vs. no layoff | 0.1% | −1.3% |

*Notes:* Panel A: share of stayers whose household owns a home in the year before the layoff, by age. Panel B: the first mortgage at origination over the price for the stayers' first purchases, and the combined loan-to-value ratio of owners in the year before the layoff (Table 1). Panel C: the regression estimates of Table 4 and Table 3 relative to the low-exposure rate, and the 12-month purchases of high-exposure renters at AI layoffs over their pre-layoff rate relative to the same ratio for stayers at industry downturns and firm contractions, minus one. Model moments are computed in the same way on 400,000 simulated households.

who buy more. The model misses two features of the life cycle. Households in the model buy their first home later than the stayers do: homeownership is 14 percent at 25–29 in the model and 42 percent in the data. With no prepayment and a mortgage rate above the return on the liquid asset, borrowing costs more than saving earns, so a household builds a large down payment before it buys and borrows less at purchase; the loan-to-value ratio of first purchases is 0.39, against 0.80 in the data.

**The borrowing gap.** The model does not generate the gap in home equity borrowing. In the data, high-exposure owners with ample equity borrow 19 percent less than their low-exposure coworkers after AI layoffs. In the model, owners with ample equity also hold liquid savings, so a change in expected earnings changes how fast they spend those savings rather than whether they borrow against their homes; the model's borrowing gap is 0.1 percent. A response like the one in the data needs owners who are short of liquid assets but rich in home equity, or large and lumpy uses of home equity, such as a renovation, that become worthwhile when a household expects higher earnings (Zhou, 2022).

## 6.6 What the Model Explains

After a first AI layoff, high- and low-exposure stayers hold different beliefs. A high-exposure stayer raises the probability that its work can be replaced from $\mu_0 = 0.19$ to $\mu_H = 0.21$, and a low-exposure stayer lowers it to $\mu_L = 0.01$. Their chance of being cut in

the firm's next AI layoff, 15 percent at the prior, rises to 16 percent for the high-exposure stayer and falls to 8 percent for the low-exposure stayer. Because a cut is permanent, at these beliefs a high-exposure stayer with 30 working years left expects to lose 2.3 percent of its remaining earnings, against 1.1 percent for its low-exposure coworker.

The two stayers respond on two margins. The high-exposure stayer is 3.2 times as likely to retrain as its low-exposure coworker (0.47 against 0.15 per 100), and it postpones buying a home. The gap in purchases is concentrated in the year of the layoff: it is 12.8 percent in the first year and 1.8 percent in the second, as beliefs keep changing with later layoffs and some households retrain.

Almost all of the gap comes from learning. Panel A of Table 12 shows that if households could not learn their type from layoffs, the two copies of a household would make the same choices and there would be no gap. The size of the gap depends on how much a stayer expects to lose, $\psi(\kappa_R - \kappa_N)d$, and on how much one layoff changes beliefs, which depends on $\pi_R$, $\pi_N$, $\kappa_R$ and $\kappa_N$.

### 6.7 Aggregate Effects

Table 11 compares the calibrated economy with the same economy without the new technology ($\psi = 0$); house prices, rents, preferences and every other parameter are the same. The technology in the model only lowers the earnings of the workers it cuts, so the comparison measures the cost of this risk to human capital, not the gains AI brings elsewhere.

**Housing.** AI layoffs lower homeownership by 1.3 percentage points, by 2.1 percentage points at 25–34 and 1.2 percentage points at 55–64. Households buy 6.7 percent fewer homes, and the share that has never owned a home by age 64 rises from 19.7 to 21.0 percent. The share of households that retrain at least once over their working lives rises from 12.3 to 12.8 percent; most retraining in the model reflects the idiosyncratic value of a program, which is why it occurs without the technology as well.

**Welfare.** Panel B of Table 11 reports the welfare effect as the consumption-equivalent variation relative to the economy without the new technology. AI layoffs cost households 2.75 percent of consumption. The cost is concentrated on the households whose work AI can replace: replaceable households lose 8.0 percent, households that are not replaceable 1.4 percent. Households in the top third of initial earnings, who lose more earnings if they are cut, lose 3.3 percent, against 2.6 percent in the bottom third.

**Table 11. Aggregate Effects of AI Layoffs**

| | Without AI | With AI | Difference |
|---|---|---|---|
| *Panel A. Housing and retraining* | | | |
| Homeownership, ages 25–64 | 55.8% | 54.5% | −1.3 |
| Homeownership, ages 25–34 | 26.4% | 24.3% | −2.1 |
| Homeownership, ages 55–64 | 71.6% | 70.4% | −1.2 |
| Never owned by age 64 | 19.7% | 21.0% | 1.4 |
| Purchases per 100 renters per year | 8.5 | 8.0 | −0.6 |
| Ever retrained | 12.3% | 12.8% | 0.6 |
| *Panel B. Welfare cost of AI (percent of consumption)* | | | |
| All households | | | −2.75 |
| Replaceable | | | −8.00 |
| Not replaceable | | | −1.43 |
| Top third of initial earnings | | | −3.26 |
| Bottom third of initial earnings | | | −2.59 |

*Notes:* The table compares the calibrated economy (With AI) with the same economy without technology layoffs ($\psi = 0$, Without AI); house prices, rents and all other parameters are the same. Panel A: differences in percentage points, except purchases per 100 renters. Panel B: consumption-equivalent variation of the economy with AI relative to the economy without it, from the household's remaining-life utility at age 25, including the utility of the taste shocks to retraining; negative values are losses. Replaceable households are those whose work AI can replace at entry. 400,000 simulated households.

## 6.8 Counterfactuals

The welfare cost of the new technology is mostly the expected loss of earnings, so it is a poor guide to what learning and retraining are worth. The counterfactuals in Table 12 ask three questions. Each changes one feature of the economy, and policies are financed within it, so that a policy raises welfare only if it allocates risk or resources better. In Panels A and C the welfare column is the cost of the technology in each economy; in Panel B it is the change relative to the calibrated economy.

**What learning and retraining are worth.** Panel A decomposes the cost of the technology. If households could not learn their type from layoffs, and so kept their prior until they were cut, the purchase gap would vanish (0.2 percent), and the cost would be 2.753 percent of consumption instead of 2.752. Learning is worth little, less than 0.01 percent of consumption, with or without the option to retrain: a high-exposure stayer that postpones a purchase or retrains gives up or gains little relative to the expected loss of earnings, which learning does not change. Without the option to retrain, the cost would be 2.758 percent. When selling a home costs nothing, a household that buys can sell at no loss if its expected earnings fall: the purchase gap falls to 8.0 percent, and the cost of the technology is 2.80 percent.

**Policies.** Panel B compares three policies. Wage insurance replaces half of the earnings loss of a worker who is cut, like the wage insurance of the Trade Adjustment Assistance

**Table 12. Counterfactuals**

| | Purchase gap (12 months) | Welfare (% of consumption) | Retraining (% change) |
|---|---|---|---|
| *Panel A. Cost of AI under alternative assumptions* | | | |
| Calibrated economy | −12.8% | −2.752 | |
| Households cannot learn from layoffs | −0.2% | −2.753 | |
| No retraining | −12.7% | −2.758 | |
| No learning and no retraining | 0.1% | −2.758 | |
| Selling a home is costless | −8.0% | −2.798 | |
| *Panel B. Policies financed within the economy (welfare relative to the calibrated economy)* | | | |
| Wage insurance, half of the loss | −5.3% | −0.07 | −16% |
| Training subsidy, half of the cost | −12.4% | −0.22 | 212% |
| Mortgage relief when cut | 2.3% | 0.02 | −1% |
| *Panel C. The technology (cost of AI relative to no AI)* | | | |
| Rate of AI layoffs $\psi = 0.01$ | −6.5% | −0.88 | |
| Rate of AI layoffs $\psi = 0.12$ | −25.4% | −7.10 | |
| Earnings loss $d = 0.165$ | −11.7% | −1.55 | |

*Notes:* The purchase gap is the 12-month purchase rate of high-exposure renters relative to low-exposure renters after the same first AI layoff, minus one (Table 9). Panels A and C report the welfare cost of AI, the consumption-equivalent variation of the economy with AI layoffs relative to the same economy without them; Panel B reports the welfare effect of each policy relative to the calibrated economy, and the change in the number of retraining spells. Households that cannot learn act on the prior until they are cut. The economy without retraining sets the cost of retraining prohibitively high. Wage insurance replaces half of the earnings loss of a worker who is cut and the training subsidy pays half of $\kappa_T$, both financed by a payroll premium that balances the program; mortgage relief lowers the balance of an owner who is cut by two years of payments, financed by a higher mortgage rate. 400,000 simulated households.

program, which pays up to half of the gap between a reemployed worker's old and new wages (Hyman et al., 2021). A training subsidy pays half of the cost of retraining; the same program pays for the retraining of displaced workers (Hyman, 2018). Both are financed by a payroll premium paid by all workers. Mortgage relief reduces the mortgage balance of an owner who is cut by about two years of payments, and owners pay for it through a higher mortgage rate. Wage insurance lowers what a household loses if it is cut, so its belief about its type matters less for a purchase: the purchase gap narrows to 5.3 percent, and retraining falls by 16 percent, because a smaller loss makes it less worth lowering the risk. The training subsidy instead makes it cheaper to lower the risk itself: retraining rises by 212 percent, and the purchase gap is 12.4 percent. Mortgage relief protects the households whose commitment is largest, and it reverses the purchase gap, to 2.3 percent, because the owners most likely to be cut are the ones it pays. The three policies change welfare by $-0.07$, $-0.22$ and 0.02 percent of consumption. Wage insurance raises the welfare of replaceable households by 3.0 percent and lowers that of households that are not replaceable, who pay most of the premium, by 0.8 percent. Most of the extra retraining under the subsidy is done by households that are unlikely to be replaceable, so the subsidy pays for retraining that does little to lower risk. Of the three policies, only mortgage relief, which pays out only when a household is cut, raises welfare.

**The technology.** Panel C changes the technology. At the bottom of the interval for the rate of AI layoffs ($\psi = 0.01$), the purchase gap after the same first layoff is 6.5 percent; at the top ($\psi = 0.12$), it is 25.4 percent. A stayer whose belief that AI can do its work rises responds more the more likely the firm is to make another AI layoff soon. If a worker who is cut lost only the lower pay of those who find new jobs ($d = 0.165$), the gap would be 11.7 percent. The gap and the welfare cost rise with how much a household loses if it is cut. Appendix A discusses these and the other features of a technology that could explain why the responses of stayers after layoffs due to other technologies are not statistically significant.

## 7 Conclusion

Workers fear that AI will replace them. This paper asks how individual workers assess the risk to their human capital while the technology is still spreading, and whether this assessment changes their training and housing decisions. I code the reasons for each of 4,987 layoffs from the firm's statements and press coverage, link the workers to their households and to the deeds and mortgages that name them, and compare stayers in the same layoff by how heavily the layoff over-cut their roles.

AI layoffs are informative about the value of human capital in the roles they cut.

Workers cut in AI layoffs take longer to find new jobs than comparable workers cut in firm contractions, earn less in those jobs, and more often take a lower-seniority position or change job title. Stayers respond before their own earnings change. Over the 12 months after an AI layoff, high-exposure renters reduce first-home purchases by 16 percent relative to their low-exposure coworkers, and high-exposure owners with ample equity reduce new home equity borrowing by 19 percent. The same stayers start more short training programs in the year of the layoff, mostly in technology fields, and more degree programs in the year after. After industry downturns, firm contractions and layoffs due to other technologies, the differences between high- and low-exposure stayers in purchases, home equity borrowing and short programs are not statistically significant. The reductions in purchases and home equity borrowing hold among stayers who are still at the firm a year later, and they are larger when the salary changes of the workers cut from the stayer's role are less dispersed.

A life-cycle model quantifies what this learning implies for homeownership and welfare. In the model, households are uncertain whether the new technology can replace their work, learn about it from layoffs at their employer, and can retrain so that their work can no longer be replaced. Calibrated to the stayers and to AI, the model accounts for about four fifths of the regression estimate of the purchase gap after AI layoffs, and almost all of the model's gap comes from changed beliefs. In the model, AI layoffs lower homeownership by 1.3 percentage points and cost households 2.75 percent of consumption. The workers whose work AI can replace lose 8.0 percent and the others 1.4 percent, and most of the cost comes from the expected loss of earnings. Learning from layoffs changes what households do but is worth less than 0.01 percent of consumption, because it does not change the expected loss of earnings. Among policies financed within the economy, wage insurance changes welfare by $-0.07$ percent of consumption, a training subsidy by $-0.22$ percent, and mortgage relief for owners who are cut by 0.02 percent.

Workers learn what a new technology means for their human capital by observing which coworkers their firm lets go, and they reduce their largest financial commitments in response. Households respond to technological change before it reaches their own jobs.

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# Appendix

## A The Model and Other Technologies

The model in Section 6 describes any technology that firms use to replace part of their workforce, and I calibrate it to AI. After layoffs due to other technologies, the differences between high- and low-exposure stayers in purchases and home equity borrowing are not statistically significant (Table 4). This appendix uses the model to discuss which features of a technology account for the difference.

In the model, after a first layoff a high-exposure stayer updates its belief from $\mu_0$ to $\mu_H$ and a low-exposure coworker updates its belief to $\mu_L$, both given by equation (11). The housing gap is the difference between the housing choices the two households make with these beliefs. Three features of a technology determine the size of this gap.

**Prior uncertainty.** The gap $\mu_H - \mu_L$ vanishes as $\mu_0$ approaches zero or one: a household that already knows whether the technology can replace its work learns nothing from which workers the firm cuts. Workers have known for decades which tasks industrial automation and enterprise software can perform (Autor et al., 2003), so whether these technologies can replace their work is close to known. In contrast, AI performs well on some tasks and poorly on others, and it is hard to predict which tasks these are (Dell'Acqua et al., 2026; Eloundou et al., 2024).

**Informativeness of a layoff.** The gap also shrinks as $\pi_R$ approaches $\pi_N$. A high-exposure signal is informative about whether a stayer's own work can be replaced when the firm cuts the workers whose tasks the technology performs. When a firm adopts a technology but cuts workers for other reasons, stayers learn little about their own work from which roles the layoff over-cut.

**Stakes.** Housing decisions respond to a given change in beliefs in proportion to how much more a replaceable household expects to lose, $\psi(\kappa_R - \kappa_N)d$. The three terms are how often the firm uses the technology to cut workers ($\psi$), how much more likely a replaceable worker is to be cut ($\kappa_R - \kappa_N$), and how much a worker who is cut loses ($d$). Workers cut in layoffs due to other technologies take about as long to find a new job as workers cut in firm contractions who held the same role, seniority and pay, and none of the differences in their outcomes is statistically significant (Table 2). In the model's terms, the loss from being cut in these layoffs is no larger than the loss from any layoff, so stayers who learn from a layoff that their work can be replaced expect to lose little beyond that. Panel C of Table 12 shows how the purchase gap after a first AI layoff changes with $\psi$ and $d$.

# Appendix Figures

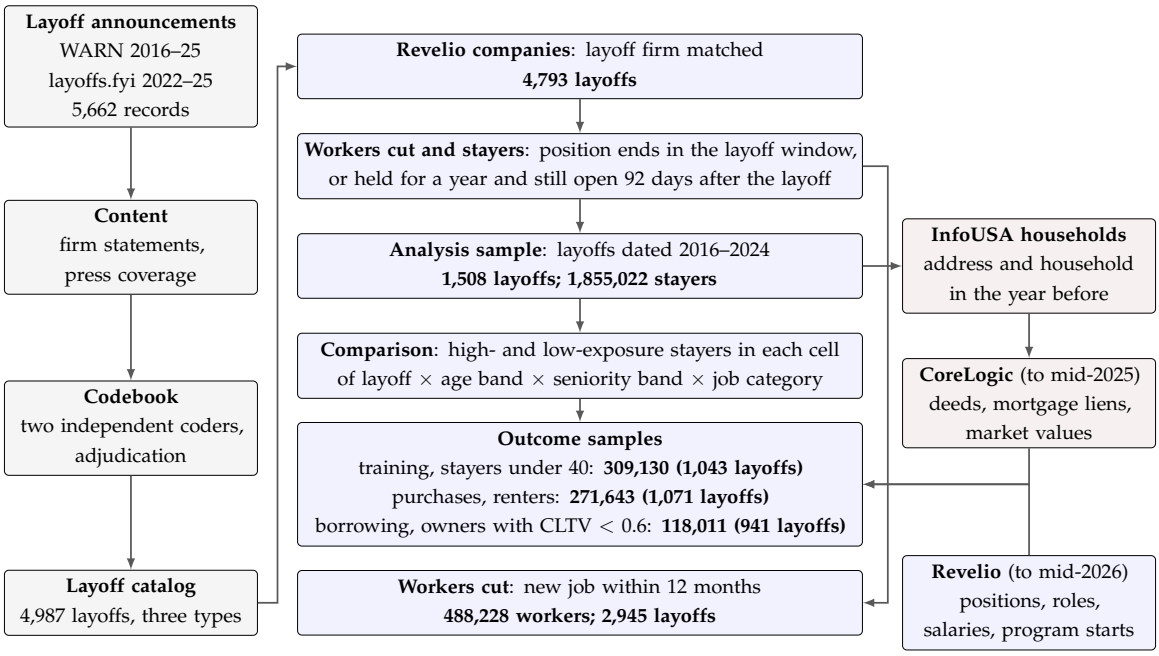



**Figure A1. Data Construction**

*Notes:* This figure summarizes the construction of the data. Grey boxes describe the layoff catalog, blue boxes the worker data (Revelio) and red boxes the household and property data. WARN notices cover a balanced panel of 11 states before 2022 and all states thereafter, and the catalog leaves out 2020. Each layoff is coded by two independent coders with a written codebook, and disagreements are adjudicated under written rules (Section 2.2); repeated announcements are collapsed and site-level WARN filings are merged into the announced layoff. Stayers exclude workers who move to another position at the firm within 92 days, and each stayer's window ends before the firm's next layoff of at least 50 workers (Section 2.4). The analysis sample uses layoffs dated 2016–2024; industry downturns and firm contractions enter from 2022, the first year of AI layoffs. Each outcome sample keeps the stayers for whom the decision is relevant and who are observed for the whole window (Section 2.7). CoreLogic deeds and mortgages are complete through mid-2025, and Revelio positions and education records through mid-2026.

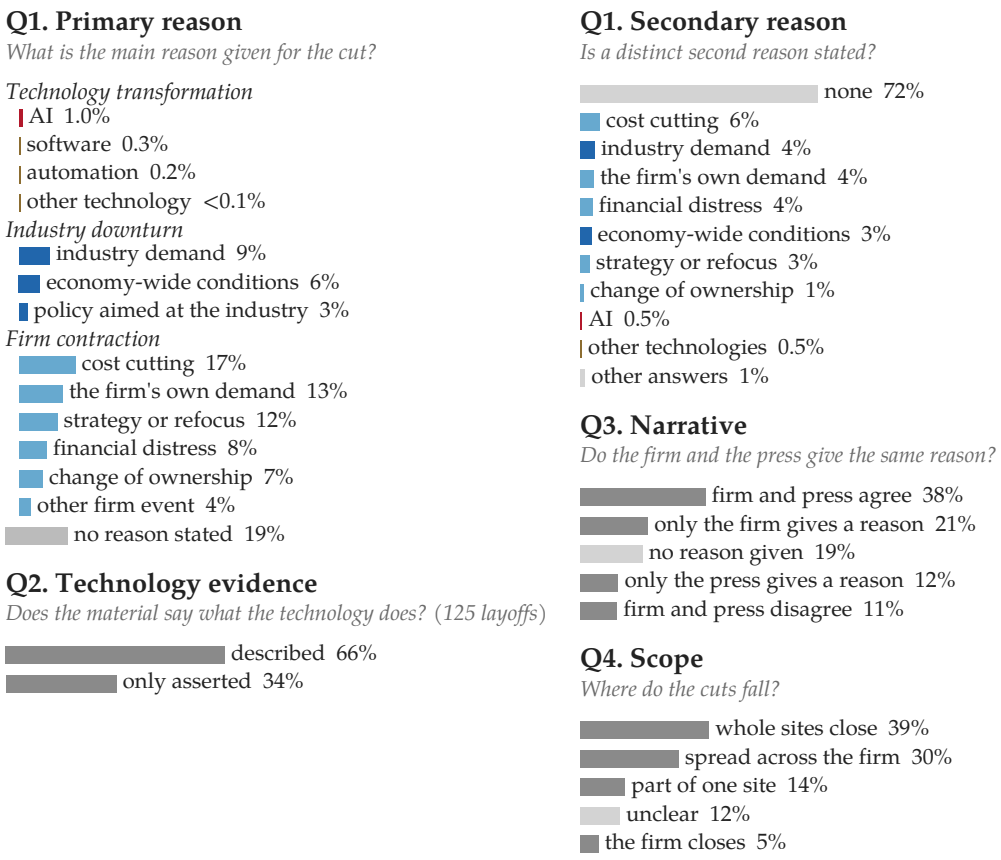



**Figure A2. The Layoff Codebook**

*Notes:* This figure shows the four questions of the codebook and the share of the 4,987 layoffs in the catalog giving each answer (final codes). The primary reason is assigned by ordered steps that make the labels mutually exclusive: no stated reason; a technology named as the reason for this cut (it does work the cut workers did, or the firm moves resources from the activities cut toward it); a pressure common to the industry or the economy; otherwise a reason specific to the firm. Bar colors give the type each reason implies (Figure 1); a technology named as the primary or a secondary reason makes the layoff a Technology transformation (125 layoffs). Technology evidence is coded for these layoffs only. Answers given in fewer than 1 percent of layoffs are grouped as other answers, except technologies. Each layoff is coded independently by two coders, both Claude Opus (`claude-opus-5-5`), reading the collected firm statements and press coverage; disagreements are adjudicated under written rules. The two coders agree on the primary reason for 91 percent of layoffs, on the type for 94 percent, on the narrative for 91 percent and on the scope for 90 percent (Appendix Table A2).

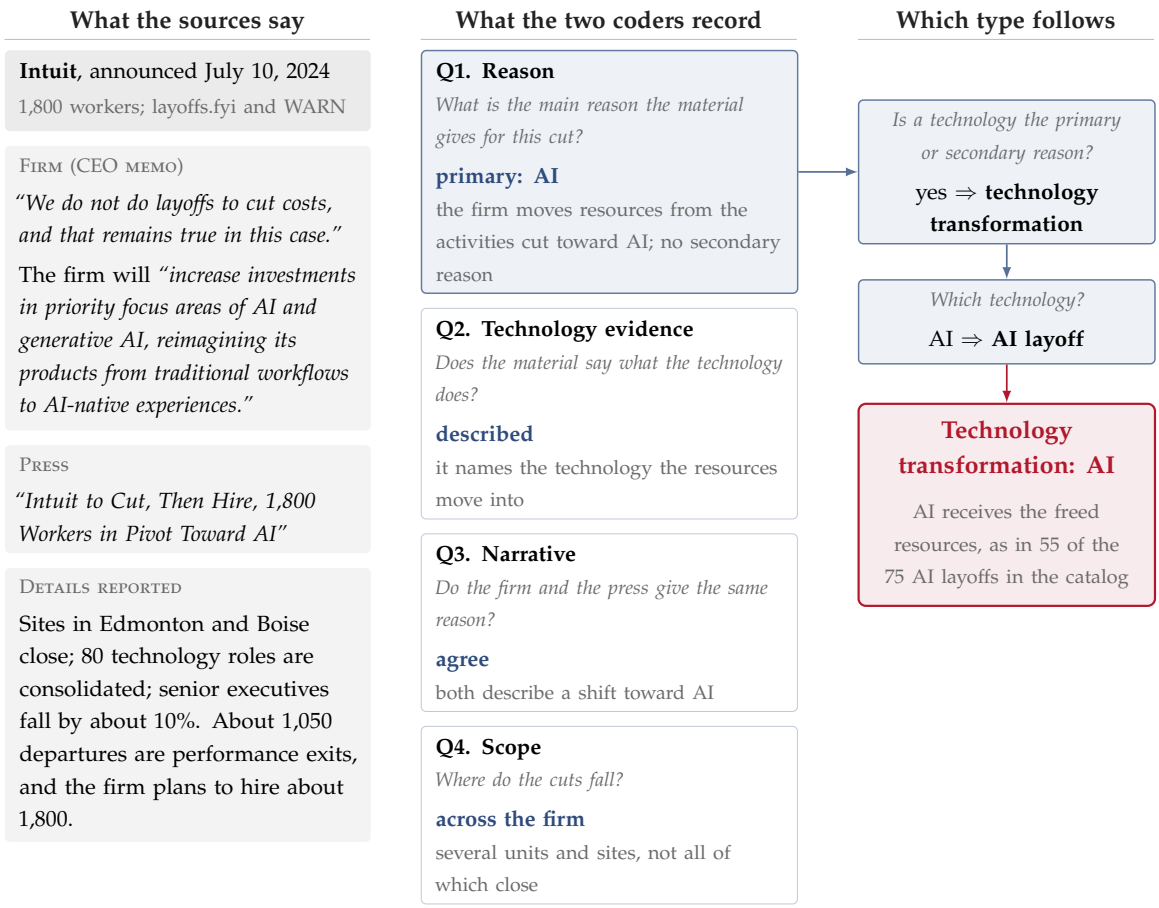



**Figure A3. Coding One Layoff: Intuit, July 2024**

*Notes:* This figure traces one layoff through the codebook of Appendix Figure A2. The left column shows excerpts of the material the coders read: the firm's statement, a press headline and the details reported about which sites and roles were cut. The middle column shows the four questions of the codebook and the answers; both coders gave the same answers. The right column shows how the reasons set the type (Figure 1): a technology is the primary reason and the technology is AI, so the layoff is a Technology transformation: AI. The type follows where the freed resources go, so the firm's statement that the layoff is not about costs leaves it unchanged. Of the 75 AI layoffs in the catalog, AI receives the freed resources in 55 and takes over the work of the workers cut in 11.

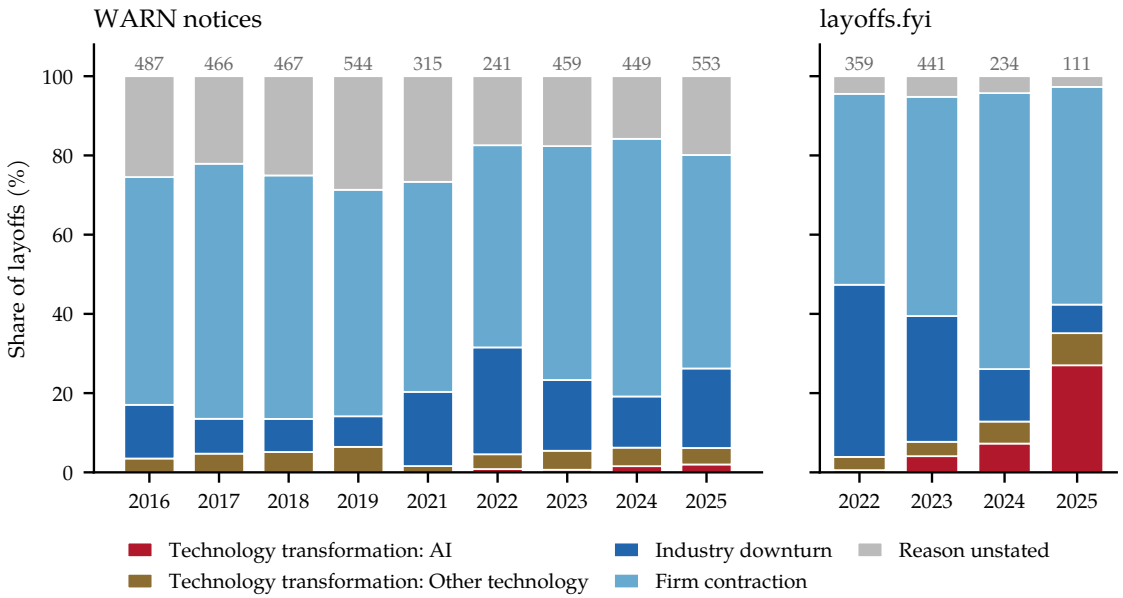



**Figure A4. Layoffs by Type and Year**

*Notes:* This figure shows the composition of the 4,987 layoffs in the cleaned catalog (2016–2025) by type and year, separately for WARN notices (3,981 layoffs) and layoffs.fyi (1,145 layoffs, from 2022); the 139 layoffs reported by both sources appear in both panels. The catalog leaves out 2020. A layoff is a Technology transformation: AI if AI is the primary or a secondary stated reason, and a Technology transformation: Other technology if another technology is the primary or a secondary reason or automation or software is mentioned among the stated reasons. Other layoffs are an Industry downturn or a Firm contraction by their primary reason (Figure 1); grey marks layoffs with no stated reason. In the whole catalog there are 75 AI layoffs, 217 Other technology layoffs, 860 Industry downturns, 2,895 Firm contractions and 940 layoffs with no stated reason. Numbers above the bars are layoff counts.

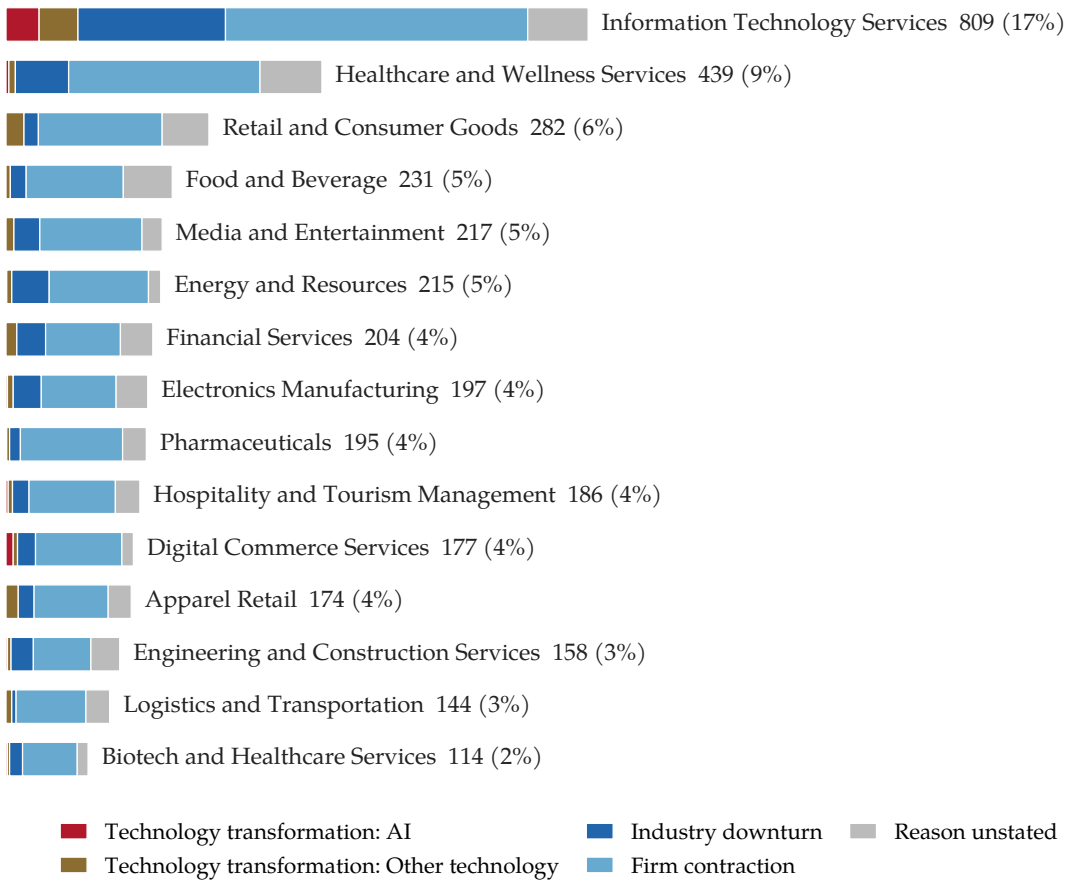



**Figure A5. Layoffs by Industry**

*Notes:* This figure shows the number of layoffs by industry for the 4,772 catalog layoffs whose firm is matched to a Revelio company with an industry code (Revelio industry classification, 50 industries), split by type of layoff. The 15 industries shown account for 78 percent of these layoffs; none of the other industries accounts for more than 2 percent. Of the 75 AI layoffs, 46 are in information technology services, and 10 in digital commerce services. Types follow Figure A4.

# Appendix Tables

**Table A1. Balance between High- and Low-Exposure Stayers**

| | Mean | | |
|---|---|---|---|
| | Low exposure | High exposure | Stayers |
| | (1) | (2) | (3) |
| *Panel A. All stayers* | | | |
| Age (years) | 34.88 | 35.58 | 1,844,381 |
| Female | 0.37 | 0.37 | 1,855,022 |
| Salary ($000) | 145.0 | 150.6 | 1,855,022 |
| Seniority (1–7) | 3.07 | 3.37 | 1,855,022 |
| Years in the position | 4.70 | 4.63 | 1,855,022 |
| Married | 0.64 | 0.65 | 1,855,022 |
| Household income ($000) | 129.0 | 134.1 | 1,855,022 |
| Homeowner | 0.52 | 0.55 | 1,855,022 |
| *Panel B. Owners in the year before the layoff* | | | |
| Home value ($000) | 741.3 | 730.0 | 965,754 |
| CLTV | 0.72 | 0.72 | 965,754 |
| *Panel C. Outcomes before the layoff (per 100 stayers per year)* | | | |
| Short programs, under 40 | 0.71 | 0.62 | 1,273,888 |
| Home purchases, renters | 1.01 | 1.11 | 276,779 |
| Equity borrowing, owners | 1.07 | 1.14 | 124,682 |

*Notes:* Columns (1) and (2) report the means of the row variable among low- and high-exposure stayers, where high-exposure stayers are those whose role the layoff over-cut by more than the role of the median stayer in their cell (layoff $\times$ age band $\times$ seniority band $\times$ job category; equation (2)). Column (3) gives the number of stayers. The sample is the stayers of Table 1. Panels A and B are measured in the year before the layoff; Panel C uses the stayers of Table 1 under 40, renters and owners with a CLTV below 0.6, over the years or months before the layoff.

## Table A2. Reliability of the Codebook

| | Agreement (%) | Cohen's $\kappa$ | Layoffs |
|---|---|---|---|
| *Panel A. Nodes of the typology* | | | |
| Reason stated (vs. unstated) | 97.2 | 0.90 | 4,987 |
| Technology a primary or secondary reason | 99.7 | 0.95 | 4,059 |
| AI vs. other technology reason | 100.0 | 1.00 | 123 |
| Industry downturn vs. firm contraction | 97.0 | 0.92 | 3,924 |
| Automation or software mentioned | 98.7 | 0.82 | 3,924 |
| AI layoff (vs. all other layoffs) | 99.9 | 0.96 | 4,987 |
| Type of layoff (four types and unstated) | 93.9 | 0.90 | 4,987 |
| *Panel B. Items of the codebook* | | | |
| Primary reason (15 labels) | 90.8 | 0.90 | 4,987 |
| Secondary reason (incl. none) | 88.6 | 0.78 | 4,987 |
| Basis of the primary reason | 87.3 | 0.73 | 4,987 |
| Technology evidence (described vs. asserted) | 92.7 | 0.83 | 123 |
| Firm vs. press account (5 classes) | 91.3 | 0.88 | 4,987 |
| Scope (5 classes) | 90.5 | 0.87 | 4,987 |

*Notes:* This table reports the agreement (percent of layoffs with the same answer) and Cohen's $\kappa$ between two independent Claude Opus coders who code each of the 4,987 layoffs of the catalog with the codebook of Appendix Figure A2, before adjudication; the 1,075 layoffs on which they differ on the primary reason, on whether the firm and the press give the same reason, or on the scope of the cuts are adjudicated under written rules. Panel A computes each node of the types of Figure 1 on the layoffs where both coders reach it: technology among layoffs with a stated reason; AI versus other technology among layoffs with a technology reason; downturn versus contraction, and the mention of automation or software, among layoffs with a stated reason that is not a technology. A layoff is an AI layoff if AI is the primary or a secondary reason, and an Other technology layoff if another technology is, or if automation or software is mentioned among the stated reasons; the mention is recorded by a separate pair of Opus coders, and each coder's type combines the two codings. Panel B reports the items of the codebook. *Layoffs* is the number of layoffs on which each row is computed.

## Table A3. Revelio Job Categories and Roles

| Role | Stayers (%) | Category (%) | Role | Stayers (%) | Category (%) |
|---|---|---|---|---|---|
| *Engineer* | *42.8* | | *Operations* | *9.3* | |
| Software Developer | 11.6 | 97 | Delivery Driver | 5.3 | 66 |
| Product Manager | 7.5 | 51 | Procurement Specialist | 2.8 | 63 |
| Systems Engineer | 5.8 | 93 | | | |
| Engineer | 5.6 | 92 | *Marketing* | *8.8* | |
| Data Professional | 3.4 | 78 | Marketing Professional | 2.1 | 69 |
| IT Support | 3.0 | 82 | Design | 2.0 | 89 |
| Business Consultant | 2.4 | 61 | Content | 1.4 | 85 |
| Security Specialist | 2.0 | 76 | Communications | 1.1 | 69 |
| Project Manager | 1.6 | 66 | Creative Arts | 0.4 | 53 |
| Maintenance Technician | 1.4 | 88 | | | |
| Quality Assurance | 1.4 | 88 | *Admin* | *7.9* | |
| Analyst | 1.2 | 36 | Recruiter | 3.2 | 75 |
| Production Operator | 1.1 | 53 | Legal Services | 1.5 | 58 |
| Construction Engineer | 0.9 | 92 | Administrative Assistant | 1.1 | 60 |
| Equipment Operator | 0.7 | 57 | Education Professionals | 0.6 | 50 |
| Environmental Scientist | 0.2 | 60 | Educator | 0.2 | 66 |
| | | | Teacher | 0.1 | 72 |
| *Sales* | *20.4* | | Business Professional | 0.1 | 40 |
| Sales Representative | 4.5 | 75 | | | |
| Manager | 2.8 | 39 | *Finance* | *6.3* | |
| Retail Sales Associate | 2.0 | 84 | Financial Services Representative | 2.6 | 45 |
| Healthcare Administration | 1.9 | 42 | Financial Professionals | 2.3 | 45 |
| Corporate Development | 1.5 | 52 | Accounting | 1.9 | 80 |
| Customer Service Representative | 1.3 | 71 | Real Estate Agent | 1.1 | 73 |
| Sales Manager | 1.1 | 77 | Executive Leadership | 0.3 | 20 |
| Food Service Worker | 0.6 | 84 | | | |
| Hospitality Worker | 0.6 | 76 | *Scientist* | *4.4* | |
| Security Officer | 0.4 | 73 | Healthcare | 1.4 | 86 |
| Receptionist | 0.3 | 46 | Research Associate | 1.0 | 65 |
| Service Worker | 0.2 | 47 | Therapist | 0.6 | 56 |

*Notes:* This table lists the 7 job categories and the 50 roles of Revelio Labs that define the cells and the layoff exposure of stayers (Section 2.5). Roles do not nest in job categories, so each role is listed under the job category most common among its stayers; *Category* is the share of the role's stayers in that job category, and *Stayers* the role's share of all stayers. Rows in italics give each job category's share of all stayers. A further 0.05 percent of stayers have no role or a miscellaneous one. The sample is the stayers of Table 1.