# 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 before its effects reach an individual's own career. How do workers assess their own human-capital risk while the transformation is still unfolding? I study this using AI-related layoffs at technology firms, which turn a diffuse shift into a local signal—retained workers observe which coworkers and skill bundles the firm separates from. Linking layoff announcements to worker skill histories, household records, and property transactions, I ask whether workers act on this displaced-coworker signal in a costly, illiquid housing commitment. Comparing high- and lower-similarity stayers within the same event, benchmarked against ordinary layoffs with event-year fixed effects, I find that high-similarity stayers reduce their home-purchase probability by 32% after AI-related layoffs, near zero after ordinary ones. Because stayers keep their jobs, the response reveals perceived human-capital risk before any job loss is realized.

**JEL Codes:** O33, J24, D84

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## 1 Introduction

Technological change repeatedly reshapes how firms organize tasks, allocate workers, and value skills (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022), and artificial intelligence is its latest and most visible form. This transformation is not a uniform labor-market shock: evidence from generative-AI adoption and experiments points to both substitutive and complementary effects (Brynjolfsson et al., 2025; Noy and Zhang, 2023; Dell'Acqua et al., 2023), and existing exposure measures document variation across tasks, occupations, and workplaces (Webb, 2019; Felten et al., 2021; Acemoglu et al., 2022; Hampole et al., 2025). Yet how individual workers interpret this transformation is not yet well understood. The question is therefore how workers infer human-capital risk while these changes are still unfolding.

I study this question in AI-related layoff events. These events turn an otherwise diffuse AI transformation into a firm-level labor-market signal that retained workers can observe. The empirical strategy compares retained workers whose skills are close to the displaced coworkers in the same event with retained workers whose skills are more distant, and benchmarks that comparison against ordinary technology layoffs. The main result is that the probability of a home purchase falls for high-similarity stayers after AI-related layoffs, while the same displaced-skill proximity margin is close to zero after ordinary layoffs.

The focus on retained workers anchors the design. Actual job loss combines information with immediate income, employment, and liquidity shocks, making it difficult to separate anticipatory updating from mechanical adjustment (Jacobson et al., 1993; Ganong and Noel, 2019). Stayers have not yet experienced their own separation. Their response is therefore an anticipatory margin: they react to information contained in coworker displacement while their current job continues. This logic connects to evidence on experience-based belief formation, in which personal experience shapes financial beliefs and decisions (Malmendier and Nagel, 2011; Koudijs and Voth, 2016; Kuchler and Zafar, 2019; D'Acunto et al., 2021), but the experience here is indirect and labor-market specific: workers observe the displacement of coworkers whose skills may resemble their own. Stayer behavior is therefore informative about perceived human-capital risk rather than realized job loss.

The home-purchase decision is useful because it is large, financed, forward-looking, and ge-

ographically sticky (Ferreira et al., 2010; Molloy et al., 2011). A purchase ties the household to a location and a mortgage contract, entails transaction costs, and reduces the option value of waiting (Dixit and Pindyck, 1994; Chetty and Szeidl, 2007). If a worker perceives higher human-capital risk, postponing a purchase preserves liquidity, mobility, and the option to adjust before undertaking a costly commitment (Carroll and Samwick, 1997; Dixit and Pindyck, 1994; Chetty and Szeidl, 2007; Sinai and Souleles, 2005). The purchase decision therefore provides a revealed-response margin for perceived human-capital risk.

I link technology-firm layoff announcements to Revelio worker histories and skills, InfoUSA household records, and CoreLogic property transactions. For each event, I construct the displaced-worker skill bundle from external leavers, who form the displaced side of the event in the analysis, and compute each retained worker's similarity to that bundle. The main comparison is between high-similarity and lower-similarity stayers, estimated separately for AI-related and ordinary layoffs. Worker-household fixed effects absorb permanent differences in purchase propensities, while event-year fixed effects absorb shocks common to workers exposed to the same event environment.

I first show that AI-related layoff events contain human-capital repricing rather than simple bad firm news. External leavers from AI-related events experience a median Revelio-imputed salary decline of $-26.7$ thousand, compared with $-8.2$ thousand for external leavers from ordinary layoffs, a decline more than three times as large. By contrast, internal movers in AI-related events experience a positive median salary change of $+10.1$ thousand. The contrast between external losses and internal gains indicates heterogeneous human-capital repricing: AI-related layoffs appear to replace or devalue some skill bundles while preserving or redeploying others, consistent with evidence that AI changes labor demand unevenly across tasks and skill groups (Acemoglu et al., 2022; Agrawal et al., 2024; Autor, 2024).

The main housing result shows that retained workers respond to this AI-specific human-capital signal. The probability of a home purchase falls for high-similarity stayers after AI-related layoffs. The differential AI-related minus ordinary-layoff estimate implies a 32 percent decline relative to the pre-period purchase mean. The same displaced-skill proximity margin is close to zero after ordinary layoffs. This pattern suggests that the purchase decline is not a generic response to technology-

sector layoffs, but a revealed-response margin for perceived human-capital risk tied to similarity with displaced coworkers in AI-related reorganizations.

Heterogeneity patterns support this interpretation. The response becomes more negative at higher skill-overlap quartiles, consistent with workers responding more when the coworker signal is stronger. The response is also larger among high-seniority stayers, who are more likely to understand the firm's task structure and interpret what coworker displacement implies for future skill demand. These patterns are consistent with a perceived-human-capital-risk channel in which the signal is both stronger and more interpretable.

The analysis addresses several endogeneity concerns. The design uses worker-household fixed effects to absorb permanent differences in purchase propensities and event-year comparisons to absorb shocks common to workers in the same event environment. It also uses the ordinary-layoff benchmark to compare the AI-related displaced-skill proximity margin with the same margin in non-AI technology layoffs, isolating the AI-specific component from the response to displaced-coworker proximity in general. Event-study estimates show that the purchase response emerges after the layoff event rather than from a visible pre-trend. Wild bootstrap inference addresses the small number of event clusters. Pre-period balance tests show that high- and lower-similarity stayers are similar on observed household, job, and housing characteristics before the event.

I then examine alternative explanations. The main concern is that high-similarity status could proxy for another post-event channel rather than perceived human-capital risk. High-similarity status does not predict near-term realized separations from the event firm, so the purchase decline is not simply a response to workers actually losing their jobs. Internal movers do not exhibit the same AI-related purchase decline, which argues against generic disruption from being close to the layoff event. The result is also present across remote-work suitability groups, reducing the concern that the response reflects location flexibility rather than perceived human-capital risk (Howard et al., 2023). Among observed buyers, mortgage leverage does not show clear evidence of a credit-tightening channel (Demyanyk et al., 2017; DeFusco and Mondragon, 2020). Finally, AI-related events do not display stock-price declines that would explain the housing response through a direct wealth effect from employer equity exposure. These tests point to perceived human-capital risk rather than

realized separations or generic layoff effects.

The paper makes three contributions. First, it contributes to the literature on how broad technological change reprices skills and human capital. Existing work measures exposure to AI and automation, documents technology-driven shifts in labor demand, and estimates productivity effects of generative AI (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022; Webb, 2019; Felten et al., 2021; Acemoglu et al., 2022; Brynjolfsson et al., 2025; Noy and Zhang, 2023). This paper shifts the object from exposure measurement to worker interpretation. It shows that AI-related reorganizations can operate as information events: retained workers appear to use coworker displacement to infer the future value of their own human capital.

Second, the paper contributes to the literature on experience-based belief formation and financial decisions. Prior work shows that personal experiences shape risk taking, inflation expectations, beliefs about aggregate outcomes, and housing-market behavior (Malmendier and Nagel, 2011, 2016; Koudijs and Voth, 2016; Bailey et al., 2018; Kuchler and Zafar, 2019; D'Acunto et al., 2021). This paper studies experience-based updating about human-capital risk: retained workers appear to learn from the displacement of coworkers whose skills resemble their own. Using the home-purchase decision as a revealed-response margin, the analysis shows that beliefs shift—and move a large household financial commitment—before any job loss is realized.

Third, the paper contributes empirically by linking labor-market events to household balance-sheet decisions. Studies of displaced workers and worker histories document large earnings losses, mobility, and career adjustment after job displacement (Jacobson et al., 1993; Kambourov and Manovskii, 2009). This paper connects that worker-history perspective to household records and property transactions. By linking layoff announcements, worker histories, skills, household records, and housing transactions, the analysis shows how information generated inside labor markets is reflected in household investment decisions.

The rest of the paper proceeds as follows. Section 2 describes the setting, data, and measurement. Section 3 presents the framework and empirical design. Section 4 reports the labor-market signal and housing results, organized around main effects, identification checks, signal intensity, information quality, and alternative explanations. The paper concludes by summarizing the interpre-

tation and limits.

## 2 Information Events, Linked Data, and Measurement

### 2.1 AI-related layoffs as information events

The empirical setting is a set of technology-firm layoff announcements in the early generative-AI period. I construct a curated event catalog from company announcements, public filings, press releases, major news coverage, and layoff trackers. The catalog records the announcement date, firm, event description, and whether the event is coded as AI-related. The broader catalog covers announcements from June 2022 through April 2026, while the main analysis uses 2023–2024 events to focus on the post-ChatGPT period and to avoid right-censoring in worker and housing outcomes.

AI-related layoffs are useful because they turn a diffuse technological transformation into an observable firm-level signal. Workers may know that AI is changing tasks, production, and labor demand, but a general technology trend does not reveal how a particular firm values a particular set of skills. A layoff announcement is more concrete. It identifies a firm, a date, a public narrative, and a set of workers whose employment histories reveal whether they leave, move internally, or remain. The event is therefore not only a labor-market shock. It is also an information event through which retained workers can observe how the firm is reallocating workers and tasks.

The main sample contains 21 technology-firm layoff events, including 6 events coded as broad AI-related reorganizations. The coding captures announcements that explicitly connect workforce reductions to AI, automation, or AI-centered reallocation, as well as high-salience AI-adjacent reorganizations during the early generative-AI period. The design uses public AI-related reorganization narratives as information events rather than requiring that AI mechanically caused every separation in the event. It asks whether those narratives reveal information that retained workers treat as relevant for the value of their own human capital. Figure 1 maps the event locations, distinguishing AI-related events from ordinary technology layoffs. Appendix Table A2 reports the event catalog.

Ordinary technology layoffs provide the benchmark. They are not no-shock events: workers still face high-skill job risk, firm restructuring, public layoff news, and technology-sector uncertainty.

Their role is to measure the housing response to displaced-skill proximity in comparable layoff environments that are not framed around AI-related reallocation. The paper's identifying comparison is therefore not between AI layoffs and calm labor markets. It is between the displaced-skill proximity margin after AI-related layoffs and the same margin after ordinary technology layoffs.

This event definition shapes the interpretation of the results. The analysis does not estimate the aggregate effect of AI on housing demand, nor does it classify every affected worker as replaced by an AI system. The empirical object is narrower: when a firm announces an AI-related reorganization, retained workers observe which coworkers are displaced, and the paper asks whether workers whose own skills resemble those displaced coworkers reduce new housing commitments. The event design is useful precisely because it makes an otherwise broad technological transformation local, dated, and observable.

## 2.2 Worker groups and the labor-market signal

For each event, I use Revelio employment histories to identify workers employed at the event firm before the announcement. I classify workers into three groups based on their event-window employment transitions. External leavers, who form the displaced side of the event in the analysis, are workers whose event-firm position ends within 0–92 days after the announcement and who do not remain at the same firm. Internal movers are workers whose event-firm position ends within the same window but who later appear in another position at the same firm. Stayers are workers with no observed event-firm position ending within 92 days.

The 0–92 day window is chosen to capture separations and internal moves plausibly linked to the announced reorganization while avoiding later career changes that may be unrelated to the event. The window also gives the worker groups clear economic roles. External leavers define the displaced side of the event in the analysis. Internal movers capture redeployment within the same firm. Stayers are the retained workers whose current jobs continue through the event window. They are the main group for measuring anticipatory household responses because they can react to coworker displacement without mechanically experiencing their own contemporaneous separation.

This classification also motivates the paper's first empirical step. Section 4 shows that AI-

related events contain heterogeneous human-capital repricing. External leavers from AI-related events experience substantially larger Revelio-imputed salary declines than external leavers from ordinary technology layoffs, while internal movers in AI-related events experience positive median salary changes. This pattern matters for interpretation. If AI-related layoffs were only bad firm news, one would expect a more uniformly negative signal across worker groups. Instead, the worker histories show both displacement and redeployment, consistent with reallocation across skill bundles.

The stayer sample matters because realized job loss would confound the perceived-risk margin. A worker who loses a job faces an immediate income shock, employment shock, and liquidity shock. A retained worker has not yet experienced those mechanical effects. If the retained worker changes a major household commitment after observing coworker displacement, the response is more naturally interpreted as anticipatory updating about perceived human-capital risk. The empirical design therefore studies stayers not because they are unaffected, but because their own labor-market outcome has not yet been realized in the event window.

### 2.3 Linking labor-market events to household decisions

The empirical contribution requires linking information in the labor market to decisions in the housing market. I combine four data sources. The layoff catalog provides firm-event dates and AI-related coding. Revelio provides worker employment histories, job transitions, imputed salary measures, seniority, location, and skills. InfoUSA links workers to household records and household locations. CoreLogic provides property transactions, owner-occupancy measures, and mortgage information. Together, these data create a worker-household-event panel that connects observed firm reallocation to subsequent home-purchase outcomes.

The unit of analysis in the housing regressions is a linked worker-household observed around a layoff event. A worker can be attached to an event through the event firm, classified as a stayer, external leaver, or internal mover using Revelio histories, linked to a household through InfoUSA, and matched to housing transactions in CoreLogic. Table 2 reports linkage rates by worker group. Table 3 reports summary statistics for the linked worker-household sample used in the stayer and internal-mover housing regressions.

This linkage is important because the paper studies a response that occurs outside the firm. The labor-market event is observed at the firm-worker level, but the outcome is a household investment decision. By connecting worker histories to household and property records, the data make it possible to ask whether information revealed in one market is reflected in decisions in another. This is also why the analysis focuses on within-worker and within-event-year variation rather than cross-sectional differences between workers who can and cannot be linked to housing records.

The linked sample should be interpreted accordingly. It does not observe every worker in the technology sector, every rental move, or every household adjustment after a layoff announcement. It observes a discrete and economically meaningful decision among workers who can be linked to household and property records. The empirical question is whether the probability of a home purchase changes when a retained worker's skills resemble the skills of coworkers displaced in an AI-related event.

### 2.4 Measuring displaced-skill proximity

The relevant worker-level measure is displaced-skill proximity. For each layoff event, I construct a displaced-worker skill bundle from the Revelio skills of external leavers. Let $S_i$ denote stayer $i$'s Revelio skill set and let $L_e$ denote the union of Revelio skills among external leavers in event $e$. I measure displaced-skill proximity using the Jaccard overlap

$$J_{ie} = \frac{|S_i \cap L_e|}{|S_i \cup L_e|}.$$

The baseline high-similarity measure is defined within event $\times$ state $\times$ sex $\times$ salary-band $\times$ seniority-band cells. A high-similarity stayer is at or above the cell median of $J_{ie}$, with at least one overlapping skill and at least eight stayers in the cell.

This construction is deliberately local. A high-similarity stayer is not simply a software worker, a high-paid worker, or a worker in an AI-exposed occupation. The worker is someone whose observed skill set is close to the skill set of external leavers from the same firm-event environment, relative to otherwise comparable stayers in the same event cell. The measure therefore captures proximity to what the firm actually separated from in that event, rather than exposure to AI measured at a broad

occupation or industry level.

The local nature of the measure matters for the perceived-risk interpretation. Existing AI exposure indices are useful for describing where AI may matter in the economy, but they need not tell a worker how their own firm is reallocating tasks. The displaced-skill measure uses the event itself to reveal the relevant skill bundle. If a retained worker observes that displaced coworkers have skills similar to their own, the event may provide a more personally relevant signal about future human-capital risk than a general AI-exposure score.

The high-similarity measure also supports the ordinary-layoff benchmark. I construct the same displaced-skill proximity margin for both AI-related and ordinary layoff events. The design can therefore ask whether proximity to displaced coworkers matters differently when the event is framed around AI-related reallocation. This keeps the empirical object tied to coworker displacement while allowing the AI-related component to be isolated through comparison with ordinary technology layoffs.

### 2.5 Home-purchase decision as a revealed-response margin

The main household outcome is whether the linked worker-household undertakes a new home purchase after the event. Purchase equals a buyer-name matched CoreLogic purchase record with positive mortgage amount in the worker-household-year. The measure is extensive-margin and mortgage-financed by construction. It is designed to capture a new housing commitment rather than every change in housing demand or residential location.

The home-purchase decision is useful for this paper because it is large, financed, forward-looking, and geographically sticky. A purchase ties the household to a location, a mortgage contract, transaction costs, and future moving costs. If a retained worker perceives higher human-capital risk after observing coworker displacement, delaying a purchase preserves liquidity, mobility, and the option to adjust. The outcome is therefore a revealed margin of willingness to undertake a costly housing commitment while labor-market risk is being reassessed.

This interpretation is narrower than a full model of housing demand. The data do not observe every rental move, every desired change in housing consumption, or every reason a household buys.

The purchase decision may also reflect family structure, local housing markets, credit access, wealth, and expectations about future mobility. The empirical design addresses these concerns with worker-household fixed effects, event-by-year fixed effects, the ordinary-layoff benchmark, and additional tests. The purpose of the outcome is not to capture all household adjustment, but to identify whether retained workers delay a major forward-looking commitment when the event reveals a personally relevant displaced-skill signal.

The resulting measurement structure is summarized by a single chain. AI-related layoff events reveal a labor-market signal. The relevant worker-level measure is displaced-skill proximity. High values define high-similarity stayers. The outcome is the home-purchase decision. The interpretation is a revealed-response margin for perceived human-capital risk. The next section formalizes this logic and presents the empirical design.

## 3 Framework, Empirical Design, and Identification

### 3.1 Conceptual Framework

The framework treats an AI-related layoff as an information event about human-capital repricing. The event reveals a set of workers and skills that the firm separates from, and retained workers can compare that displaced-skill bundle with their own skills. The relevant belief is therefore not whether AI is good or bad in the aggregate. It is whether the worker's own human capital is exposed to the particular reallocation revealed by the firm.

This is why the paper studies stayers rather than only displaced workers. A displaced worker faces contemporaneous income, employment, and liquidity shocks, making it difficult to separate belief updating from mechanical adjustment. A stayer has not experienced a separation in the event window. If that worker changes a major household decision after observing coworker displacement, the response is closer to an anticipatory reaction to perceived human-capital risk. The signal is especially relevant for stayers whose skills resemble the displaced skill bundle.

The home-purchase decision is the paper's revealed-response margin for perceived human-capital risk. A purchase is large, financed, forward-looking, and geographically sticky. It exposes

the household to mortgage obligations, transaction costs, and future moving costs, while reducing the flexibility to adjust location if labor-market conditions change (Carroll and Samwick, 1997; Dixit and Pindyck, 1994; Chetty and Szeidl, 2007; Sinai and Souleles, 2005). If a retained worker infers higher human-capital risk from the displaced-skill signal, postponing a purchase preserves liquidity, mobility, and the option to adjust. The prediction is therefore about new purchases, where the household decides whether to undertake a costly new commitment.

### 3.2 Empirical design

The empirical object is the purchase response to displaced-skill proximity among stayers. For each event, I construct the displaced-skill bundle from external leavers and measure each stayer's similarity to that bundle using Revelio skills. High-similarity stayers are retained workers whose skills are closer to the skills the firm separated from in the same event. The comparison is therefore not between displaced and retained workers; it is between retained workers with different proximity to displaced coworkers.

Ordinary layoffs provide the benchmark. Similarity to displaced coworkers can matter in any layoff if workers infer future risk from coworker outcomes. The paper's main claim is that the displaced-skill proximity margin is more negative when the event is AI-related. Comparing AI-related and ordinary technology layoffs separates an AI-specific human-capital signal from generic layoff exposure.

Let $HighSim_{ie}$ indicate that stayer $i$ is at or above the cell median of Jaccard skill overlap with external leavers in event $e$. The high-similarity indicator is defined within event $\times$ state $\times$ sex $\times$ salary-band $\times$ seniority-band cells, with at least one overlapping skill and at least eight stayers in the cell. I estimate the following equation separately for AI-related and ordinary layoff events:

$$Y_{iey} = \beta_f(HighSim_{ie} \times Post_{ey}) + \alpha_i + \lambda_{e\times y} + \varepsilon_{iey}, \qquad f \in \{A, O\}. \tag{1}$$

$Y_{iey}$ is a purchase indicator for worker-household $i$, event $e$, and year $y$. $\alpha_i$ are worker-household fixed effects, and $\lambda_{e\times y}$ are event-by-year fixed effects. The post period excludes the

announcement year, so the comparison does not assign partial-year purchase exposure mechanically to either the pre- or post-period. The coefficient $\beta_f$ measures whether the purchase probability changes for high-similarity stayers after the event relative to lower-similarity stayers in the same layoff family.

I estimate Equation 1 separately for AI-related events, denoted by $A$, and ordinary technology layoffs, denoted by $O$. The headline comparison is $\beta_A - \beta_O$. This difference compares the same displaced-skill proximity margin across two layoff families: one in which the announcement carries AI-related reallocation content and one in which it does not. The estimand is not the aggregate effect of AI on housing demand. It is the differential purchase response of retained workers whose skills resemble displaced coworkers after AI-related layoffs, relative to the same proximity margin after ordinary layoffs.

The fixed effects define the level at which the comparison is made. Worker-household fixed effects absorb permanent differences in homeownership preferences, family structure, local attachment, baseline wealth, and purchase propensity. Event-by-year fixed effects absorb shocks common to all workers attached to the same event in the same year, including local housing conditions, mortgage-rate changes, firm-year news, and technology-sector conditions. The remaining variation asks whether the high-similarity margin opens after AI-related events more than it opens after ordinary events.

### 3.3 Identification and inference

The fixed-effect structure in Equation 1 defines the main comparison. I then use three checks to assess the comparison: pre-period balance, event-study timing, and event-level inference.

The balance exercise asks whether the high-similarity contrast is already separating different types of households before the event. For each pre-period characteristic $X_i$, I estimate

$$X_{ie}^{pre} = \delta_f HighSim_{ie} + \eta_{c(i,e)} + \nu_{ie}, \qquad f \in \{A, O\}, \tag{2}$$

where $\eta_{c(i,e)}$ denotes the event $\times$ state $\times$ sex $\times$ salary-band $\times$ seniority-band cell used to define

high-similarity status. Appendix Table A4 reports $\delta_f$ for pre-event worker, household, and housing variables. This exercise addresses whether the high-similarity contrast is proxying for observable differences that predate the layoff event.

The event-study specification asks whether the purchase response appears only after the event. Let $r = y - y_e$ denote event time relative to event year $y_e$. I estimate

$$Y_{iey} = \sum_{r \in \mathcal{R},\, r \neq -1,0} \beta_{f,r} \left( HighSim_{ie} \times \mathbf{1}\{y - y_e = r\} \right) + \alpha_i + \lambda_{e \times y} + \varepsilon_{iey}, \qquad f \in \{A, O\}. \tag{3}$$

Event time $-1$ is the omitted reference period. Event time $0$, the announcement year, is excluded because annual purchase outcomes combine months before and after the layoff announcement. Figure 4 plots $\beta_{f,r}$ separately for AI-related and ordinary events. The pre-event coefficients examine whether high- and lower-similarity stayers were already on different purchase paths, while the post-event coefficients describe the timing of the response after the information event.

The linked worker-household sample is large, but the main variation comes from a small number of layoff events. Appendix Table A5 therefore reports event-level wild cluster bootstrap tests for the main AI-related estimate and for the AI-related minus ordinary comparison,

$$H_0 : \theta = 0, \qquad \theta \in \{\beta_A,\ \beta_A - \beta_O\}.$$

For each parameter $\theta$, the reported bootstrap $p$-value is based on the studentized statistic

$$T(\theta) = \frac{\widehat{\theta}}{\widehat{\mathrm{se}}(\widehat{\theta})}.$$

The bootstrap check is important because conventional worker-level precision can understate uncertainty when treatment variation is concentrated across events. Together, the balance regression, event-study specification, and wild bootstrap address three distinct concerns: observable pre-event selection, differential pre-trends and timing, and inference with a limited number of layoff events.

## 4 Labor-Market Signals and Housing Commitment Responses

This section presents the main evidence in two steps. I first show that AI-related layoffs contain a sharper labor-market signal than ordinary technology layoffs. External leavers, who form the displaced side of the event in the analysis, experience larger earnings losses and greater occupational reallocation after AI-related events, while internal movers do not show the same negative pattern. I then ask whether retained workers whose skills resemble the displaced workers respond on a large household commitment margin: the home-purchase decision.

The section is organized around a single empirical chain. AI-related events first have to contain economically meaningful information about labor-market repricing. The displaced-skill signal then has to matter for retained workers, rather than only for workers who actually leave the firm. Finally, the housing response has to survive alternative interpretations based on ordinary layoff news, pre-existing differences across workers, credit conditions, remote work, or firm-value shocks. The evidence below follows that order.

### 4.1 AI-related layoffs as human-capital repricing signals

The housing analysis relies on the premise that AI-related layoff events reveal information about human-capital repricing, not only information about aggregate firm distress. Table 1 reports the worker groups in the main 2023–2024 sample. AI-related events contain 12,763 external leavers, 5,241 internal movers, and 204,339 stayers. Ordinary layoff events contain 6,726 external leavers, 2,907 internal movers, and 119,850 stayers. These counts establish that the events are large enough in Revelio to observe displaced workers, internally redeployed workers, and retained workers around the same firm-event environment.

The three groups play different roles in the interpretation. External leavers form the displaced side of the event in the analysis: their post-event outcomes reveal how workers whose event-firm positions end fare outside the firm. Internal movers are the redeployed side: their old positions end, but they later appear in another position at the same firm. Stayers are the anticipatory group: their event-firm positions do not end in the short event window, so their household behavior is not mechanically driven by contemporaneous separation. The first empirical task is therefore to show

that the event contains a labor-market signal strong enough for stayers to update on.

Figure 2 shows the labor-market content of these events. AI-related external leavers experience substantially larger declines in Revelio-imputed salary than external leavers in ordinary layoff events: their median salary change is $-26.7$ thousand, compared with $-8.2$ thousand for ordinary-layoff external leavers. The same figure also shows greater occupation switching among AI-related external leavers. This second margin is important because it points beyond a standard earnings loss. When displaced workers are more likely to move across broad occupational categories, the event appears to reveal a mismatch between the worker's previous skill bundle and the post-event labor market.

The occupation-switching result sharpens the interpretation of the salary result. A worker can lose salary after an ordinary layoff because search takes time, bargaining power falls, or the next job is at a lower-paying firm. A move across broad occupations points to a deeper adjustment margin. It suggests that the worker is not simply moving to a similar job at a worse wage, but is changing the task bundle attached to the next job. That is precisely the type of adjustment one would expect if the event reveals that some skills have been repriced relative to others.

The pattern is not uniformly negative within AI-related events. Internal movers in AI-related events have a positive median salary change of $+10.1$ thousand. The same class of events therefore contains both a negative external-displacement margin and a positive internal-redeployment margin. This contrast is the key labor-market fact. AI-related layoffs do not look like a simple firm-wide bad-news shock in which all worker groups receive the same signal. They look more like heterogeneous repricing: some workers and skills are pushed into weaker outside outcomes, while other workers are redeployed inside the firm.

This distinction matters for the household analysis. If AI-related layoffs were only broad firm distress, the natural prediction would be a common negative signal for all workers attached to the firm. The worker histories instead show that the event contains information about which workers and skills are separated from the firm and which workers are retained or moved internally. The housing analysis uses this local displaced-worker signal, rather than treating all employees at the event firm as equally exposed.

This labor-market evidence motivates the housing tests. Stayers observe the displaced side of the event while their own event-firm positions continue in the short window. The empirical question is whether stayers whose own skills are close to the displaced-worker skill bundle act as if the event contains information about their future human capital. Housing is useful for this purpose because a home purchase is large, financed, forward-looking, and geographically sticky. A change in the home-purchase decision therefore provides a revealed-response margin for perceived human-capital risk.

The claim is deliberately narrower than saying that every AI-related layoff is caused by automation or that every external leaver is replaced by AI. The evidence shows that events publicly described as AI-related contain stronger external losses and more occupational reallocation than ordinary technology layoffs. That is enough for the paper's purpose: the events reveal a displaced-skill signal that retained workers may use when assessing perceived human-capital risk.

### 4.2 Main housing commitment response

Table 4 reports the main housing result. The table estimates the purchase response of high-similarity stayers after AI-related layoff events and compares it with the same high-similarity margin after ordinary technology layoffs. The omitted group is lower-similarity stayers in the same layoff family. Because high-similarity status is defined within event $\times$ state $\times$ sex $\times$ salary-band $\times$ seniority-band cells, the comparison is between retained workers attached to similar event environments whose skills differ in displaced-skill proximity.

The estimates deliver three comparisons. The AI-related column measures whether the purchase probability falls for high-similarity stayers after AI-related events relative to lower-similarity stayers in the same layoff family. The ordinary-layoff column estimates the same margin when the event does not carry the AI-related reallocation narrative. The difference column subtracts the ordinary-layoff coefficient from the AI-related coefficient. That last comparison is the headline object because it measures whether the same displaced-skill proximity margin becomes more negative specifically in AI-related environments.

The probability of a home purchase falls for high-similarity stayers after AI-related events. The

AI-related coefficient is $-0.3$ percentage points, while the corresponding ordinary-layoff coefficient is close to zero. The AI-related minus ordinary difference is $-0.4$ percentage points, a 32 percent decline relative to the pre-period purchase mean of lower-similarity stayers in AI-related events. The magnitude is economically meaningful because home purchases are rare in worker-household panels. A coefficient of a few tenths of a percentage point represents a substantial proportional change in the probability that a household undertakes a new housing commitment.

The outcome is an extensive-margin commitment. The estimate does not measure the price of the home that would have been purchased, nor the welfare cost of delay. It measures whether the household crosses the purchase threshold at all. That threshold is economically meaningful because buying a home combines a down payment, mortgage underwriting, transaction costs, and location commitment. A lower purchase probability therefore captures a consequential change in household behavior, not a small adjustment in a continuous consumption category.

The sign of the estimate is informative. If high-similarity stayers interpreted the event primarily as a reason to buy before income documentation or credit access deteriorated, the purchase response would be positive. The estimate instead points to delay. High-similarity stayers behave as if similarity to displaced coworkers raises the option value of waiting: postponing a purchase preserves liquidity, mobility, and flexibility while the worker learns whether the displaced-skill signal is relevant for their own labor-market path.

This does not require households to forecast layoffs perfectly. The decision margin is forward-looking under uncertainty. A retained worker who sees similar coworkers displaced after an AI-related reorganization may not know whether her own job will end, whether future wage growth will slow, or whether relocation will become more valuable. Waiting is valuable in each case. The housing response is therefore best interpreted as a revealed-response margin for perceived human-capital risk, not as evidence that the worker already knows the realized labor-market outcome.

The ordinary-layoff benchmark anchors the interpretation. The result is not that technology-sector layoffs in general reduce purchases among workers with skills close to displaced coworkers. The same proximity margin is near zero after ordinary layoffs. The differential response appears when the layoff event carries AI-related reallocation content. This is the sense in which the pur-

chase response is tied to perceived human-capital risk rather than to generic layoff news or broad technology-sector uncertainty.

The pooled purchase outcome also keeps the empirical object aligned with the economic question. The paper is not primarily about whether renters become owners or whether existing homeowners sell. It is about whether a household undertakes a new illiquid housing commitment after observing a labor-market signal. Pooling tenure groups avoids making the main estimate depend on one baseline tenure state and focuses on the decision to enter a new purchase transaction.

### 4.3 Identification checks

The main specification already compares high- and lower-similarity stayers within worker-households and event-year environments, with the ordinary-layoff estimate providing the benchmark for generic layoff exposure. I summarize three checks for reading the purchase estimate. Appendix Table A4 compares pre-period worker, household, and housing characteristics between high- and lower-similarity stayers. Observable differences are modest within layoff family. AI-related high-similarity stayers have a slightly higher pre-period purchase rate, which is why the design relies on within-household changes and event-year fixed effects rather than cross-sectional levels.

The balance table assesses whether the high-sim contrast is visibly sorting workers on pre-event observables. The relevant concern is that skill similarity might proxy for salary, seniority, household composition, or baseline housing demand. The balance evidence helps address that concern, while the main regression removes time-invariant household differences and event-year shocks before estimating the post-event high-sim margin.

Figure 4 reports the timing of the purchase response. The event-study specification normalizes event time $-1$ to zero and excludes event time $0$, the announcement year, because annual purchase outcomes combine months before and after the announcement. The event study examines whether the high-sim minus lower-sim purchase gap is already moving before the event, and whether the response opens after the information event. The AI-related profile is close to flat before the announcement and turns negative afterward; the ordinary-layoff profile remains close to flat. This timing is difficult to reconcile with a stable pre-existing difference between high- and lower-similarity stayers.

The exclusion of the announcement year is especially important for this outcome. A layoff announcement in March and a layoff announcement in November generate very different within-year exposure windows, but the CoreLogic purchase outcome is annual. Excluding event time $0$ avoids assigning a mixed year mechanically to either the pre-period or the post-period. The event-study plot therefore focuses on years that can be interpreted more cleanly relative to the event.

Appendix Table A5 reports event-level wild cluster bootstrap inference. This check matters because the worker-household panel is large, but the economically relevant variation comes from a limited number of layoff events. The wild bootstrap leaves the main AI-related estimate and the AI-related minus ordinary comparison statistically distinguishable from zero.[1] The balance, event-study, and bootstrap exercises do not make the design experimental. They show that the result is not driven by obvious pre-period imbalance, visible pre-trends, or worker-level precision that ignores event-level concentration.

Taken together, these checks set a demanding comparison. An alternative explanation has to generate a purchase decline among high-similarity stayers after AI-related events, not after ordinary layoff events, without showing up as a comparable pre-event divergence and while allowing for event-level inference. This is why the coefficient is best read as event-based evidence on a specific behavioral margin rather than as an aggregate elasticity of housing demand with respect to AI exposure.

### 4.4 Signal intensity and information quality

Table 5 studies signal intensity by replacing the binary high-sim indicator with skill-overlap quartiles. If the relevant information were only that the firm announced layoffs, the purchase response need not vary systematically with proximity to the displaced-worker skill set. If the relevant information is displaced-skill exposure, the response should be stronger for workers with higher overlap.

This exercise also clarifies the role of the high-sim indicator. The median split is not intended to define a structural cutoff at which workers suddenly become exposed. It is a transparent way to

[1] Unreported leave-one-event-out exercises give a similar message for most omitted AI-related events, but they also show that the estimate is not perfectly diffuse across events. I therefore treat the leave-one-out evidence as a concentration caveat rather than as the main inference result.

summarize a continuous signal. The quartile specification checks whether that summary masks a monotone relationship between skill proximity and housing behavior.

The estimates follow that pattern. Relative to Q1 stayers, the purchase response in AI-related events is $-0.2$ percentage points in Q2, $-0.4$ percentage points in Q3, and $-0.5$ percentage points in Q4. Ordinary layoffs do not show the same negative gradient. The quartile pattern clarifies the binary high-sim result: the median split is a parsimonious summary of a more continuous relationship between proximity to displaced-worker skills and the decision to delay a purchase.

The dose-response pattern is useful because public layoff news is common to all retained workers attached to the same event. Event-by-year fixed effects absorb event-year shocks common to those workers. What remains is whether the response varies with the worker's own proximity to the displaced skill bundle. The negative gradient in AI-related events is therefore closely aligned with the displaced-skill interpretation.

Table 6 studies information quality. Senior workers may better understand the firm's production process, internal reallocation, and the meaning of a layoff announcement. The table therefore augments the main specification with seniority interactions. The relevant coefficient is not the average response of senior workers. It is the additional response of workers who are both high-sim and senior.

The seniority result is not meant to say that senior workers are mechanically more pessimistic. The mechanism predicts a sharper response when two conditions hold at the same time: the worker is personally close to the displaced skill set, and the worker can better interpret what the reorganization means. Seniority is an imperfect proxy for the second condition, but it is a natural one in worker-history data because senior employees are more likely to understand internal production, task allocation, and the difference between routine cost cutting and reallocation of skill demand.

The high-sim senior interaction is negative in AI-related events and negative in the AI-related minus ordinary comparison. This pattern is consistent with stronger responses when the coworker signal is both more intense and more interpretable. It also helps separate the displaced-skill interpretation from a broad public-news channel. Public layoff news is common to all stayers attached

to the same event, but the response is concentrated along the two dimensions emphasized by the mechanism: similarity to displaced skills and the ability to interpret the event.

These heterogeneity results are not a replacement for the main design. They instead examine whether the estimate varies along the dimensions implied by the displaced-skill interpretation. The main estimate establishes that the high-sim purchase margin is more negative after AI-related events than after ordinary layoff events. The quartile and seniority results show that the response is stronger when the signal is more intense and when the worker is better positioned to understand it.

### 4.5 Alternative explanations

Table 7 evaluates leading alternative explanations for the purchase response. The main concern is that high-similarity status could proxy for another post-event channel rather than perceived human-capital risk. The table therefore asks whether the main coefficient is accounted for by realized job loss, generic layoff disruption, credit conditions among observed buyers, remote-work suitability, or firm-value shocks.

A purchase decline can arise from many forces: a worker may anticipate future earnings risk, face current credit constraints, change location plans, receive negative firm-value news, or simply become more cautious after a public layoff announcement. The table separates these channels as much as the linked data allow.

Panel A separates perceived human-capital risk from realized near-term job loss. Among AI-related event stayers, high-sim status does not predict a higher probability of event-firm position ending within the observed 3–24 month follow-up window. Replacing the binary split with skill-overlap quartiles gives the same message. The purchase response should therefore not be described as a mechanical consequence of observed near-term separation. It is a response that appears before the corresponding labor-market outcome is realized in the stayer's own employment record.

This result is important for the paper's interpretation. The outcome is not the response of a worker who has already lost her job. It is the response of a worker who remains employed at the event firm but observes what happened to similar coworkers. That distinction is what makes the housing response informative about perceived human-capital risk rather than only about realized

income, employment, or liquidity shocks.

Panel B asks whether the result is a generic event-firm disruption effect. Internal movers experience an event-firm position ending and are therefore informative about whether any transition around the layoff event produces a similar purchase response. Their AI-related minus ordinary purchase response is small and positive, 0.2 percentage points, with a standard error of 0.4 percentage points. This does not reproduce the high-sim stayer decline.

Internal movers are not a perfect control group, because their own positions change around the event. They are nevertheless informative about generic disruption. If any event-firm transition mechanically reduced housing commitments, internal movers should display a similar decline. The fact that they do not points back to the specific displaced-skill signal among retained workers.

Panel C examines credit access among observed buyers. A credit-timing force would predict either front-loaded purchasing while workers can still qualify for credit, or worse mortgage-burden proxies among households that still buy (Demyanyk et al., 2017; DeFusco and Mondragon, 2020). The main purchase result has the opposite sign from front-loading. Among observed buyers, loan-to-income and loan-to-price ratios do not show statistically clear increases in AI-related events. These measures are imperfect proxies rather than true debt-to-income ratios, but they provide no evidence that the purchase decline is driven by deteriorating mortgage access among buyers.

The credit evidence is necessarily conditional on observing a purchase, so it cannot rule out every credit channel. It does rule out the most direct version in the observed-buyer sample: high-sim buyers after AI-related events do not appear to take on systematically worse mortgage-burden proxies. Combined with the negative extensive-margin response, the evidence is more consistent with delayed commitment than with a rush to buy before credit access disappears.

Panel D addresses remote work. Remote work can change location choice and housing demand, so it is a natural concern in the post-pandemic technology sector (Howard et al., 2023). I split workers by Revelio remote-work suitability and estimate the main purchase specification separately for below- and above-median groups. The purchase gap remains negative in both groups, and the high-remote minus low-remote difference is statistically imprecise. The result therefore does not

appear to be primarily a remote-work or location-flexibility effect.

This matters because many technology workers faced changing work-location arrangements during the same period. If the result were primarily a remote-work story, one would expect the purchase response to be concentrated among workers whose jobs are more suitable for remote work. The split by remote-work suitability does not show that pattern.

Panel E addresses firm-value shocks. Technology workers may hold equity-linked compensation, so a fall in firm value could reduce housing demand through a wealth channel. I measure annual stock returns from one trading day before the layoff announcement to 252 trading days after the announcement, net of QQQ. AI-related events do not show statistically significant annual underperformance relative to ordinary layoff events. The AI-related minus ordinary difference is $-9.3$ percentage points with a standard error of $22.4$ percentage points. The purchase decline is therefore not simply a response to AI-related layoff events producing persistent firm-value losses.

This check is distinct from the firm-distress interpretation in the labor analysis. The labor evidence asks whether worker outcomes look like heterogeneous repricing rather than uniform decline. The stock-return exercise asks whether high-similarity stayers might reduce purchases because equity-linked compensation or wealth falls after AI-related announcements. The market-adjusted return evidence does not support that explanation.

These tests narrow the set of explanations consistent with the main coefficient. The result is not explained by observed near-term separations, general layoff disruption, worse mortgage-burden proxies among observed buyers, remote-work suitability, or annual firm-value declines. The evidence does not observe beliefs directly and does not rule out every unobserved channel. It supports the narrower interpretation that high-similarity stayers act on AI-related displaced-skill information before their own realized job loss.

Because the paper observes actions rather than beliefs, the strongest statement is that the leading observable alternatives do not account for the timing, sign, and cross-worker pattern of the purchase response. That leaves a revealed-response interpretation: retained workers whose skills resemble displaced coworkers delay large housing commitments after AI-related events.

## 4.6 Interpretation

The evidence in this section links labor-market repricing to household commitments. AI-related layoffs reveal heterogeneous human-capital repricing: external leavers experience larger earnings losses and greater occupational switching, while internal movers do not show the same negative pattern. For retained workers whose skills resemble the displaced side of this repricing, the probability of a home purchase falls after AI-related events, while the same displaced-skill proximity margin is close to zero after ordinary layoffs.

The economic object is not a generic decline in housing demand. It is a change in the willingness to undertake a new housing commitment when a worker observes a personally relevant labor-market signal. That distinction is why the paper focuses on retained workers and on skill proximity to displaced coworkers. The response occurs before the worker's own job loss is observed, and it is concentrated among workers closest to the displaced-skill bundle.

The result is best read as a revealed-response margin for perceived human-capital risk. It is not a claim that AI lowers the value of all workers, nor that stayers necessarily overreact. Such claims would require longer-run evidence on the same stayers' realized labor-market outcomes. The current evidence shows that households respond before their own separation is observed. Housing matters here because the home-purchase decision is large, financed, forward-looking, and difficult to reverse. When high-similarity stayers delay that decision after AI-related events, they reveal reluctance to take on a new illiquid commitment while the value of their own skill bundle is being reassessed.

The result also helps interpret the labor evidence. External leavers reveal the displaced side of AI-related repricing; internal movers reveal that the same events can include redeployment; stayers reveal how workers act on this information before their own realized labor-market outcome changes. The housing response therefore connects two markets. Information generated inside the firm appears in household investment behavior outside the firm.

Several limits remain. The number of AI-related events is small, linkage to InfoUSA and CoreLogic is incomplete, and Revelio skills may measure reported or inferred skills imperfectly. The strongest evidence is also tied to technology firms and a displaced-coworker signal, so it should

not be extrapolated mechanically to all sectors. Within those limits, the evidence shows that AI-related labor-market information affects household investment before workers experience job loss themselves.

## 5 Conclusion

AI is changing how firms organize work and value skills, but workers do not observe this transformation directly. They observe local signals: layoffs, redeployments, and the labor-market outcomes of coworkers. This paper studies AI-related layoff events as such information events. The question is how retained workers use coworker displacement to assess their own human-capital risk before that risk is realized in their own employment histories.

The labor-market evidence shows that AI-related layoffs contain heterogeneous human-capital repricing. External leavers, who form the displaced side of the event in the analysis, experience larger Revelio-imputed salary losses and greater occupational switching after AI-related events than after ordinary technology layoffs. Internal movers do not show the same negative pattern. This contrast is inconsistent with a simple uniform firm-distress interpretation and instead points to reallocation across workers and skill bundles.

The housing evidence shows that this labor-market signal is reflected in household choices. For retained workers whose skills resemble displaced coworkers, the probability of a home purchase falls after AI-related events, while the same displaced-skill proximity margin is close to zero after ordinary layoffs. The response is economically meaningful, about 32 percent relative to the pre-period purchase mean, and is stronger at higher skill-overlap levels and among high-seniority high-similarity workers. Because the home-purchase decision is large, financed, and forward-looking, this response provides a revealed-response margin for perceived human-capital risk before realized job loss.

The interpretation is supported by a set of checks. The results are not explained by large observable pre-period imbalance, visible pre-trends, event-level inference concerns, near-term realized job loss, generic layoff disruption, credit conditions among observed buyers, remote-work suitability, or firm-value declines. These checks do not make the setting experimental. They narrow the set of

explanations consistent with the timing, sign, and cross-worker pattern of the purchase response.

The broader implication is that AI affects households before workers lose jobs. Firm labor-market reallocation signals travel into household investment decisions, linking internal labor markets to household finance through expectations about human capital. Housing commitments are useful in this setting because they are costly to reverse; they reveal how workers act when technological change creates uncertainty about the future value of their own skills.

Several limits remain. The evidence is event-based, concentrated in technology firms, and tied to linked worker-household records. The paper does not estimate the aggregate housing-market effect of AI, nor does it show whether retained workers overreact relative to their eventual labor-market outcomes. Within those limits, housing commitments provide a window into how workers internalize technological change while the labor-market consequences are still unfolding.

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## Figures

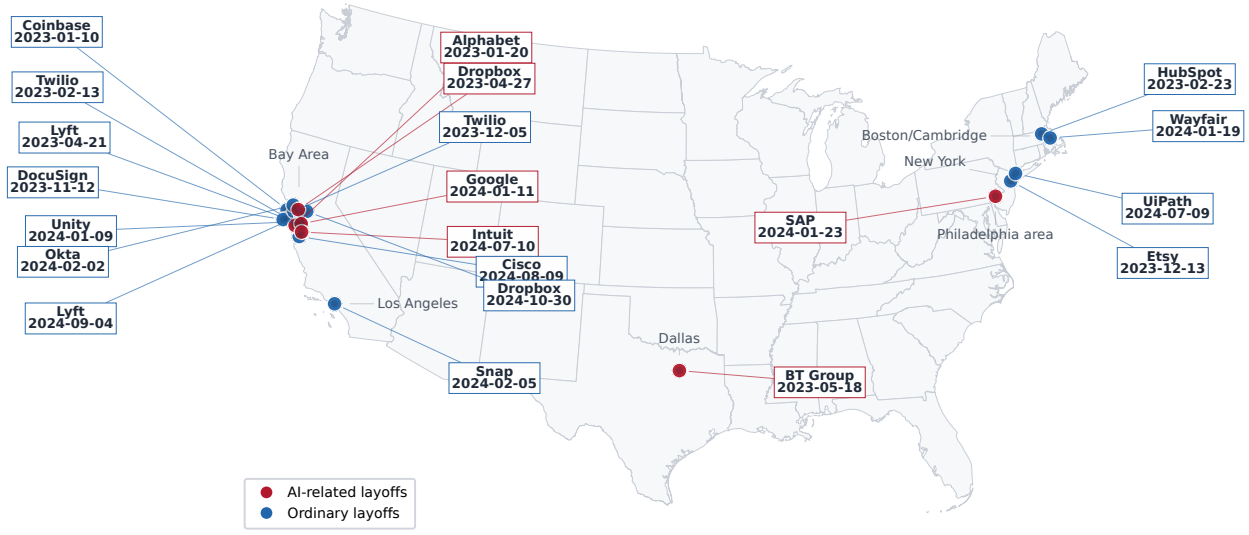



**Figure 1. Technology layoff events in the main sample, 2023–2024**

*Notes:* The figure shows the geographic distribution of technology-firm layoff events in the main 2023–2024 sample. Red pins mark AI-related layoffs and blue pins mark ordinary layoff events. Callouts report the firm and announcement date. Locations are assigned to the firm headquarters or primary U.S. operating location associated with the event; overlapping events are slightly displaced for readability.

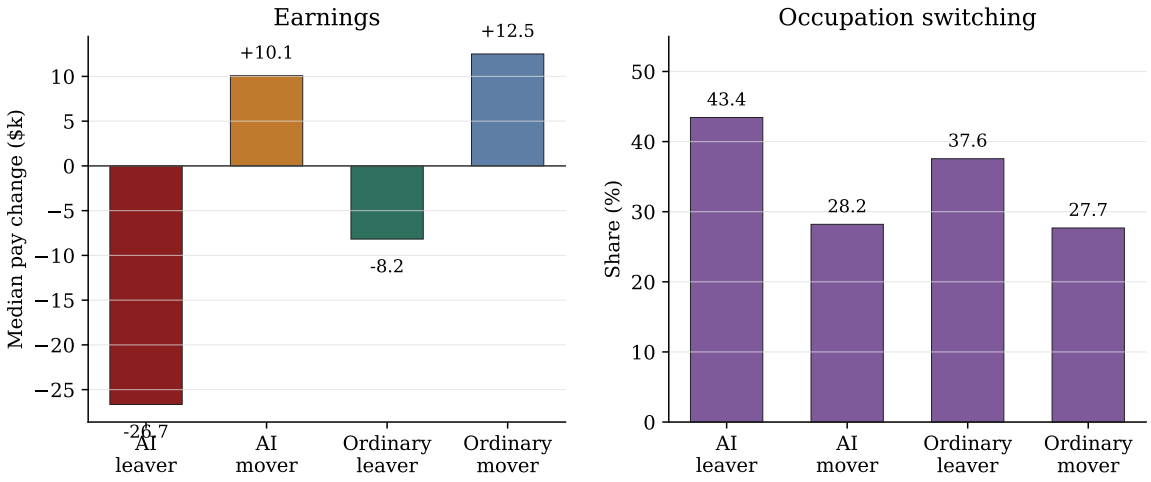



**Figure 2. External-leaver and internal-mover labor-market changes**

*Notes:* The figure compares external leavers and internal movers in the main 2023–2024 layoff-event sample. External leavers, who form the displaced side of the event in the analysis, leave the event firm after their event-firm position ends; internal movers later appear in another position at the same firm. Stayers are omitted because they have no event-firm position ending within 92 days; their event-window salary change is zero in this transition-based measure. Pay change is measured in thousands of dollars. Occupation switching is measured using broad title-based occupation groups. For example, software engineers and data scientists are classified as engineering/data; product and program managers as product/program; account executives and sales managers as sales/business development.

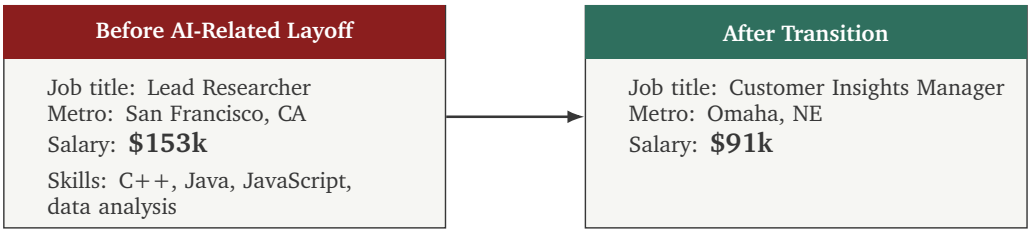



**Figure 3. Anonymized example of an AI-related external-leaver transition**

*Notes:* The figure illustrates one matched external leaver from an AI-related layoff event. The transition combines a change in job title, location, and Revelio-imputed salary. Listed skills come from the worker's Revelio skill profile and illustrate the type of skill bundle used to construct displaced-skill proximity.

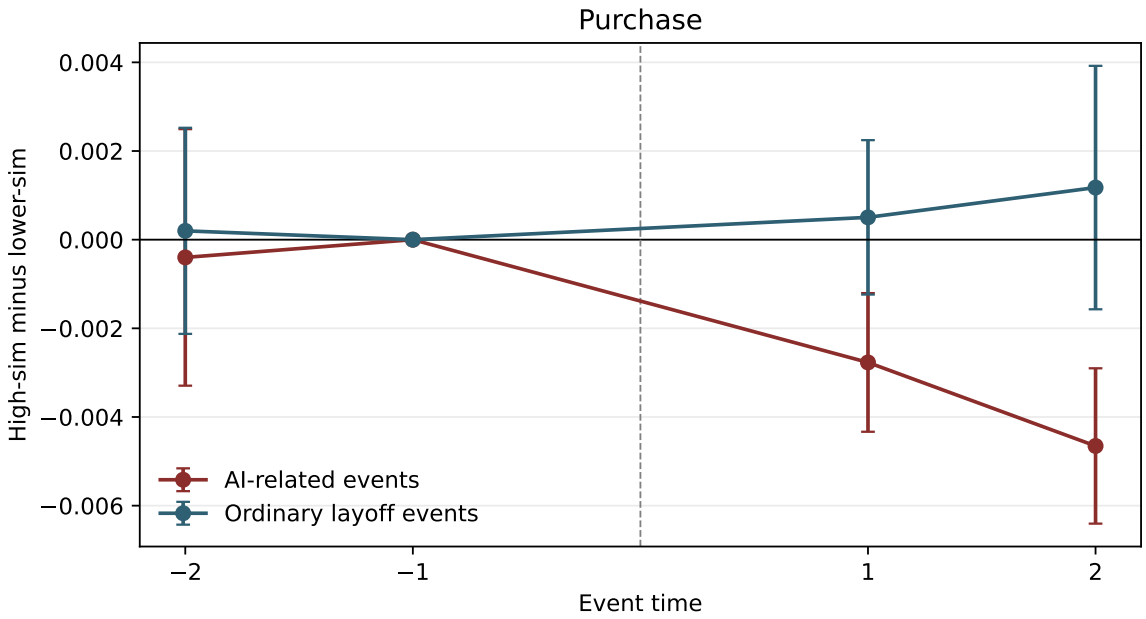



**Figure 4. High-similarity stayer event-study coefficients**

*Notes:* The figure reports event-time coefficients for high-similarity stayers relative to lower-similarity stayers within AI-related and ordinary layoff-event families. The sample is restricted to eligible stayers in event × state × sex × salary-band × seniority-band cells with at least eight stayers. Event time −1 is the omitted reference period, and the announcement year is excluded. Regressions include worker-household and event-by-year fixed effects. Bars report 95 percent confidence intervals using HC1 standard errors after fixed-effect residualization.

## Tables

**Table 1. Layoff events and worker-level separation margins, U.S. sample**

| *Panel A. Layoff events by announcement year* | | |
|---|---|---|
| Year | AI-related events | Ordinary layoff events |
| 2023 | 3 | 7 |
| 2024 | 3 | 8 |
| Total | 6 | 15 |
| *Panel B. Worker-level separation margins* | | |
| Group | AI-related workers | Ordinary-layoff workers |
| External leavers | 12,763 | 6,726 |
| Internal movers | 5,241 | 2,907 |
| Stayers | 204,339 | 119,850 |

*Notes:* Data are Revelio worker histories linked to the curated 2023–2024 technology layoff-event catalog. Panel A counts unique layoff events in the main estimation sample; Appendix Table A2 reports the event-level catalog. Panel B counts unique U.S.-linked workers in the main event sample. External leavers have an event-firm position ending within 0–92 days and do not remain at the same firm; internal movers end the event-firm position within 0–92 days and later appear at the same firm; stayers have no observed event-firm position end within 92 days. AI-related status is event-level broad AI coding.

## Table 2. Revelio–InfoUSA–CoreLogic linkage rates by worker group

| Sample | Revelio | InfoUSA | CoreLogic | InfoUSA rate | CL rate |
|---|---|---|---|---|---|
| AI-related external leavers | 12,782 | 6,864 | 5,571 | 53.7% | 43.6% |
| AI-related internal movers | 5,241 | 3,017 | 2,361 | 57.6% | 45.0% |
| AI-related stayers | 206,047 | 116,704 | 92,168 | 56.6% | 44.7% |
| Ordinary-layoff external leavers | 6,730 | 3,686 | 2,988 | 54.8% | 44.4% |
| Ordinary-layoff internal movers | 2,907 | 1,606 | 1,249 | 55.2% | 43.0% |
| Ordinary-layoff stayers | 120,678 | 68,784 | 54,688 | 57.0% | 45.3% |

*Notes:* Rows report the worker-level denominators used in the 2023–2024 Revelio–InfoUSA–CoreLogic linkage pipeline. These denominators differ slightly from the separation-margin counts in Table 1, which are event-position counts after applying the worker-group classification. Revelio users are linked to InfoUSA households by tiered person matching on normalized first name, last name, city, and state: exact first-name matches, nickname-canonicalized first-name matches, and fuzzy first-name matches within first-initial $\times$ last-name $\times$ city $\times$ state blocks. Coarse ethnicity agreement is used as a soft score adjustment, and only unique top-scoring household locations are retained. CoreLogic links use the matched InfoUSA address to recover an InfoUSA address ID and then a CoreLogic address ID, `cl_addid`, through the InfoUSA–CoreLogic address crosswalk. InfoUSA and CoreLogic rates use the Revelio worker denominator shown in the table. Stayers combine high-sim and lower-sim stayers.

## Table 3. Summary statistics for linked worker-household sample

| Group | Workers | Female | Median salary | Median seniority | Homeowner | Renter |
|---|---|---|---|---|---|---|
| AI-related external leavers | 5,027 | 33.7% | $177k | 4 | 77.0% | 23.0% |
| AI-related internal movers | 2,153 | 37.1% | $180k | 4 | 74.0% | 26.0% |
| AI-related high-sim stayers | 42,118 | 30.6% | $189k | 3 | 78.4% | 21.6% |
| AI-related lower-sim stayers | 33,991 | 31.6% | $185k | 3 | 77.3% | 22.7% |
| Ordinary-layoff external leavers | 2,718 | 37.0% | $146k | 4 | 79.2% | 20.8% |
| Ordinary-layoff internal movers | 1,139 | 41.3% | $142k | 4 | 78.5% | 21.5% |
| Ordinary-layoff high-sim stayers | 22,074 | 32.3% | $138k | 3 | 81.0% | 19.0% |
| Ordinary-layoff lower-sim stayers | 17,927 | 31.9% | $138k | 3 | 79.7% | 20.3% |

Notes: Data are unique workers in the 2023–2024 linked worker-household sample with 2022 InfoUSA–CoreLogic address linkage. Homeowner and renter status are measured from CoreLogic 2022 owner-occupancy codes: owner-occupied properties are homeowners and absentee-owner properties are renters. External leavers have an event-firm position ending within 0–92 days after the announcement and do not remain at the same firm. Internal movers have an event-firm position ending within 0–92 days and later appear in another position at the same firm. Salary and seniority are from Revelio; seniority is Revelio's numeric career-level measure, with 1–2 junior, 3–4 mid, 5 director, and 6–7 high seniority. High-sim stayers are workers with no event-firm position ending within 92 days whose Revelio skills are close to the displaced-worker skills in the same event. Let $S_i$ denote stayer $i$'s Revelio skill set and let $L_e$ denote the union of Revelio skills among external leavers in event $e$. Skill overlap is $J_{ie} = |S_i \cap L_e|/|S_i \cup L_e|$. High-sim stayers are those with $J_{ie}$ at or above the median within event $\times$ state $\times$ sex $\times$ salary-band $\times$ seniority-band cells and with $|S_i \cap L_e| > 0$; cells require at least eight stayers. Lower-sim stayers are the remaining eligible stayers in the same cells.

## Table 4. Stayer Purchase Responses in AI-Related and Ordinary Layoff Events

| Outcome | High-sim stayer: AI-related events | High-sim stayer: ordinary layoff events | AI-related − ordinary |
|---|---|---|---|
| Purchase | -0.003*** | 0.001 | -0.004*** |
| | (0.001) | (0.001) | (0.001) |
| Benchmark group | Lower-sim stayers within the same layoff family | | |
| Worker-household FE | Yes | Yes | Yes |
| Event-by-year FE | Yes | Yes | Yes |
| Announcement year excluded | Yes | Yes | Yes |

*Notes:* Data are worker-household-year observations linking Revelio layoff-event workers to 2022 InfoUSA–CoreLogic address links and CoreLogic housing and mortgage records. The sample includes stayers and internal movers at 2023–2024 AI-related and ordinary layoff events. The table reports the coefficient on $HighSimStayer_i \times Post_{et}$ from family-specific regressions estimated separately for AI-related and ordinary layoff events; internal movers are included in the same regressions and used as a diagnostic comparison in Table 7. High-sim stayers are workers with Jaccard skill overlap with external leavers at or above the median within event × state × sex × salary-band × seniority-band cells, requiring at least one overlapping skill and a minimum cell size of eight stayers. The omitted group is lower-sim stayers in the same layoff family. Post excludes the announcement year. Purchase equals any buyer-name matched CoreLogic purchase record with a positive mortgage amount in the worker-household-year. The pre-period purchase mean among lower-sim stayers in AI-related events is 1.25 percent; relative to this mean, the AI-related minus ordinary coefficient implies a 32 percent decline. Standard errors are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table 5. Skill-Overlap Dose Response in Stayer Purchase Responses**

| Outcome | Skill-overlap quartile | AI-related events | Ordinary layoff events |
|---|---|---|---|
| Purchase | Q2 vs. Q1 | -0.002* (0.001) | 0.002* (0.001) |
| Purchase | Q3 vs. Q1 | -0.004*** (0.001) | 0.002 (0.001) |
| Purchase | Q4 vs. Q1 | -0.005*** (0.001) | 0.001 (0.001) |
| Benchmark group | Skill-overlap Q1 stayers within the same layoff family | | |
| Worker-household FE | | Yes | Yes |
| Event-by-year FE | | Yes | Yes |
| Announcement year excluded | | Yes | Yes |

*Notes:* The table replaces the binary high-sim indicator with quartiles of Jaccard skill overlap among eligible stayers within event × state × sex × salary-band × seniority-band cells. Q1 is the omitted group. Regressions include worker-household and event-by-year fixed effects and exclude the announcement year. Standard errors are HC1 after fixed-effect residualization. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

## Table 6. High-Seniority Interaction in High-Sim Stayer Purchase Responses

| Outcome | Coefficient | AI-related events | Ordinary layoff events | AI-related − ordinary |
|---|---|---|---|---|
| Purchase | High-sim stayer × post | -0.003*** (0.001) | 0.000 (0.001) | -0.003*** (0.001) |
| Purchase | Senior stayer × post | 0.006*** (0.002) | -0.002 (0.002) | 0.008*** (0.003) |
| Purchase | High-sim × senior stayer × post | -0.008*** (0.003) | 0.002 (0.003) | -0.009** (0.004) |
| Benchmark group | | Lower-sim non-senior stayers within the same layoff family | | |
| Worker-household FE | | Yes | Yes | Yes |
| Event-by-year FE | | Yes | Yes | Yes |
| Announcement year excluded | | Yes | Yes | Yes |

*Notes:* The table augments the main family-specific regression with a senior-stayer post interaction and an interaction between $HighSimStayer_i \times Post_{et}$ and an indicator for Revelio seniority bands 6–7. The omitted group is lower-sim non-senior stayers in the same layoff family; internal movers enter as a separate post interaction. Coefficients are estimated with worker-household and event-by-year fixed effects. Standard errors are HC1 after fixed-effect residualization. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

## Table 7. Alternative Explanations for the Purchase Response

| Check | Estimate | Std. error | Interpretation |
|---|---|---|---|
| *A. Perceived vs. real risk* | | | |
| High-sim stayer | -0.004 | 0.003 | Does not predict later position ending |
| Skill-overlap Q2 vs. Q1 | 0.001 | 0.004 | No realized-risk gradient |
| Skill-overlap Q3 vs. Q1 | -0.000 | 0.004 | No realized-risk gradient |
| Skill-overlap Q4 vs. Q1 | -0.001 | 0.004 | No realized-risk gradient |
| *B. General layoff shock* | | | |
| Internal-mover purchase gap | 0.002 | 0.004 | Internal movers do not reproduce the decline |
| *C. Credit access* | | | |
| Loan-to-income | 0.852 | 0.595 | No evidence of worse buyer leverage |
| Loan-to-price | 0.005 | 0.027 | No evidence of higher LTV proxy |
| *D. Remote work* | | | |
| Low remote suitability | -0.005*** | 0.001 | Purchase gap remains negative |
| High remote suitability | -0.003* | 0.002 | Purchase gap remains negative |
| Remote interaction | 0.003 | 0.002 | High-minus-low gap is imprecise |
| *E. Firm value* | | | |
| AI-related annual return | -1.8 | 13.0 | Event-firm return minus QQQ, pp |
| Ordinary-layoff annual return | 7.5 | 18.2 | Event-firm return minus QQQ, pp |
| AI-related minus ordinary | -9.3 | 22.4 | Difference is statistically imprecise |

*Notes:* All estimates are in probability units unless otherwise noted. Panel A uses AI-related event stayers and reports within-event regressions of future event-firm position endings on the baseline high-sim indicator or skill-overlap quartile indicators, controlling for log salary, seniority, and Revelio remote-work suitability. Skill-overlap quartiles are measured within the baseline event $\times$ state $\times$ sex $\times$ salary-band $\times$ seniority-band cells. Panel B reports the AI-related minus ordinary internal-mover purchase response from the family-specific worker-household-year regressions; the comparison tests whether the high-sim stayer result is a general layoff or firm-outlook effect. Panel C reports observed-buyer mortgage-burden proxies: loan-to-income divides mortgage amount by Revelio imputed salary, and loan-to-price divides mortgage amount by CoreLogic sale amount and is restricted to values between 0 and 1.2. These are not true debt-to-income ratios. Panel D estimates the main purchase regression separately for below- and above-median Revelio remote-work suitability. The remote interaction is the high-remote minus low-remote difference in the AI-related minus ordinary purchase gap. Panel E reports annual market-adjusted stock returns from one trading day before the layoff announcement to 252 trading days after the announcement, net of QQQ over the same window. Panel E estimates and standard errors are in percentage points; the AI-related minus ordinary row uses Welch standard errors. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# Appendix

## Appendix Tables

**Table A1. Variable definitions and sample rules**

| Concept | Definition |
|---|---|
| Event window | The full event catalog covers technology layoff announcements from June 2022 through April 2026. The main estimation window uses 2023–2024 announcements. Event time is measured relative to the announcement year, and the main post indicator excludes the announcement year. |
| External leaver | A worker whose event-firm position ends within 0–92 days after the announcement and who does not remain at the same firm. |
| Internal mover | A worker whose event-firm position ends within 0–92 days after the announcement but who later appears in another position at the same firm. |
| Stayer | A worker with no observed event-firm position ending within 92 days after the announcement. |
| High-sim stayer | A stayer whose Jaccard overlap with the event-specific displaced-worker skill set is at or above the median within event $\times$ state $\times$ sex $\times$ salary-band $\times$ seniority-band cells, requiring at least one overlapping skill and at least eight stayers in the cell. |
| Displaced-worker skill set | The union of Revelio skills among external leavers in the event. |
| Housing tenure | Baseline tenure is measured using CoreLogic 2022 owner-occupancy codes. The main housing regressions pool workers rather than estimating separate homeowner and renter effects. |
| Purchase | An indicator equal to one when the worker-household is linked to a buyer-name matched CoreLogic purchase record with a positive mortgage amount in the worker-household-year. |
| Inference | Main regressions include worker-household fixed effects and event-by-year fixed effects. Standard errors are reported in parentheses. |

*Notes:* The table summarizes the definitions used in the main text and tables. The high-sim definition is event-specific and uses only the displaced-worker skill set from external leavers in the same layoff event.

## Table A2. Main event catalog, 2023–2024

| Date | Firm | Coding | Announced scale | Matched scale | External leavers | Internal movers | Stayers |
|---|---|---|---|---|---|---|---|
| 2023-01-10 | Coinbase | Ordinary layoffs | 950 (20%) | 348 (8.8%) | 215 | 133 | 3,620 |
| 2023-01-20 | Alphabet | AI-related | 12,000 | 9,387 (5.9%) | 6,971 | 2,416 | 149,653 |
| 2023-02-13 | Twilio | Ordinary layoffs | 17% | 684 (14.6%) | 427 | 257 | 4,008 |
| 2023-02-23 | HubSpot | Ordinary layoffs | 500 (7%) | 625 (12.3%) | 237 | 388 | 4,457 |
| 2023-04-21 | Lyft | Ordinary layoffs | 1,072 (26%) | 855 (4.9%) | 721 | 134 | 16,716 |
| 2023-04-27 | Dropbox | AI-related | 500 (16%) | 272 (8.5%) | 222 | 50 | 2,946 |
| 2023-05-18 | BT Group | AI-related | | 34 (1.6%) | 29 | 5 | 2,042 |
| 2023-11-12 | DocuSign | Ordinary layoffs | 700 | 417 (7.9%) | 278 | 139 | 4,849 |
| 2023-12-05 | Twilio | Ordinary layoffs | 5% | 490 (11.8%) | 270 | 220 | 3,657 |
| 2023-12-13 | Etsy | Ordinary layoffs | 225 (11%) | 346 (4.9%) | 249 | 97 | 6,649 |
| 2024-01-09 | Unity | Ordinary layoffs | 1,800 (25%) | 302 (14.1%) | 269 | 33 | 1,836 |
| 2024-01-11 | Google | AI-related | | 5,778 (3.8%) | 3,818 | 1,960 | 148,110 |
| 2024-01-19 | Wayfair | Ordinary layoffs | 1,650 (13%) | 1,024 (12.6%) | 895 | 129 | 7,088 |
| 2024-01-23 | SAP | AI-related | 8,000 roles | 1,082 (4.9%) | 680 | 402 | 21,217 |
| 2024-02-02 | Okta | Ordinary layoffs | 400 (7%) | 552 (12.6%) | 316 | 236 | 3,846 |
| 2024-02-05 | Snap | Ordinary layoffs | 10% | 316 (7.0%) | 252 | 64 | 4,177 |
| 2024-07-09 | UiPath | Ordinary layoffs | 10% | 169 (9.6%) | 132 | 37 | 1,585 |
| 2024-07-10 | Intuit | AI-related | 1,800 | 1,563 (8.4%) | 1,062 | 501 | 17,116 |
| 2024-08-09 | Cisco | Ordinary layoffs | 7% | 3,105 (5.2%) | 2,068 | 1,037 | 56,852 |
| 2024-09-04 | Lyft | Ordinary layoffs | 1% | 218 (1.3%) | 205 | 13 | 16,379 |
| 2024-10-30 | Dropbox | Ordinary layoffs | 528 (20%) | 210 (7.1%) | 196 | 14 | 2,744 |

Notes: Data are curated technology layoff events matched to Revelio firm identifiers. The technology-firm focus is intentional: AI-related reallocation narratives are most visible in this sector, Revelio coverage is dense enough to observe leavers, internal movers, and stayers, and ordinary layoffs provide a within-sector benchmark. The table reports the 2023–2024 main estimation window. Coding uses the broad AI-related event classification. Announced scale reports public layoff counts or percentages when the announcement gives a clear scale; long-horizon plans or qualitative descriptions are left blank. Matched scale is the number of Revelio affected workers, defined as external leavers plus internal movers within 0–92 days after the announcement, with the matched affected share in parentheses. The denominator for the matched affected share is external leavers plus internal movers plus stayers. Counts are reported before restricting to the housing-linked regression sample. Overall, the matched scale is close to the announced scale for many events with clear near-term announcements, suggesting that the Revelio matching captures the relevant worker reallocation. Differences can arise because announcements often report global, firmwide, planned, or business-unit-specific reductions, while the matched scale is based on observed worker histories around the event and includes both external separations and internal moves.

## Table A3. Illustrative event examples

| Event | Coding | Public event narrative and role in design | External leavers | Internal movers | Stayers |
|---|---|---|---|---|---|
| Dropbox, Apr. 27, 2023 | AI-related | Company memo explicitly framed the reduction around the AI era, a changed skill mix, and investment in AI-centered product priorities. The event is treated as a clean AI reallocation signal. | 222 | 50 | 2,946 |
| Twilio, Feb. 13, 2023 | Ordinary layoff | Public reporting and the event audit describe the reduction as a profitability and reorganization layoff, without a documented AI channel. The event is used as an ordinary technology-layoff benchmark. | 427 | 257 | 4,008 |

Notes: The table gives two concrete examples from the event catalog. Counts are the same pre-housing-linkage Revelio worker-event counts reported in Appendix Table A2. External leavers and internal movers are affected workers whose event-firm position ends within 0–92 days after the announcement; internal movers later appear in another position at the same firm, while external leavers do not. Stayers have no observed event-firm position ending within 92 days. The examples are illustrative and do not define the estimation sample by themselves.

**Table A4. Pre-Event Balance for High-Sim and Lower-Sim Stayers**

| | AI-related events | | | Ordinary layoff events | | |
|---|---|---|---|---|---|---|
| Variable | Lower-sim | High-sim | Diff. | Lower-sim | High-sim | Diff. |
| Workers | 33,991 | 42,118 | 8,127 | 17,927 | 22,074 | 4,147 |
| Female | 31.6% | 30.6% | -1.0% | 31.9% | 32.3% | 0.5% |
| Median salary ($000s) | 185 | 189 | 4 | 138 | 138 | 0 |
| Median seniority | 3.000 | 3.000 | 0.000 | 3.000 | 3.000 | 0.000 |
| Homeowner in 2022 | 77.3% | 78.4% | 1.1% | 79.7% | 81.0% | 1.2% |
| Renter in 2022 | 22.7% | 21.6% | -1.1% | 20.3% | 19.0% | -1.2% |
| Pre purchase rate | 1.3% | 1.7% | 0.4% | 0.9% | 0.9% | -0.0% |
| Median skill Jaccard | 0.063 | 0.111 | 0.048 | 0.082 | 0.153 | 0.070 |
| Mean AIOE | 1.024 | 1.017 | -0.007 | 0.951 | 0.862 | -0.089 |

*Notes:* The table compares eligible stayers used in the high-sim design before estimating post-event housing responses. High-sim stayers have at-or-above-median Jaccard skill overlap with external leavers within event $\times$ state $\times$ sex $\times$ salary-band $\times$ seniority-band cells, requiring at least one overlapping skill and at least eight stayers in the cell. Pre purchase rates are worker-year means in years before the announcement year. Owner and renter status use CoreLogic 2022 tenure status.

**Table A5. Event-Level Wild Cluster Bootstrap Inference for Purchase Responses**

| Outcome | Coefficient | Estimate | HC1 SE | Wild $p$ | 95% bootstrap CI |
|---|---|---|---|---|---|
| Purchase | AI-related events | -0.003 | 0.001 | $< 0.001$ | [-0.006, -0.001] |
| Purchase | Ordinary layoff events | 0.001 | 0.001 | 0.536 | [-0.001, 0.002] |
| Purchase | AI-related − ordinary | -0.004 | 0.001 | $< 0.001$ | [-0.007, -0.001] |

*Notes:* The table reports event-level wild cluster bootstrap inference for the coefficient on $HighSimStayer_i \times Post_{et}$ in the main family-specific regressions. Bootstrap weights are drawn at the layoff-event level using Webb six-point weights with 9,999 repetitions. The AI-related minus ordinary row bootstraps the difference between the family-specific coefficients. HC1 standard errors are the baseline fixed-effect residualization standard errors. The bootstrap is intended as an event-level inference diagnostic.