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Abstract

Technological change alters both the usefulness of accumulated knowledge and the demands of applying it. We link Danish employer–employee records for 2010–2023 to vacancy-based measures of digital and general occupational skill churn, formal continuing education, prescription use, and firm innovation. Estimating outcome profiles jointly over actual employment experience and firm tenure, we find that digital churn is associated with steeper wage–tenure profiles and generally more negative associations with participation in continuing education at longer tenure, while general churn displays the opposite pattern. Baseline wage–experience interactions are less precisely estimated. Our framework allows changing requirements both to erode knowledge and to create new uses for incumbent expertise, while education and implementation can add strain. The joint tenure findings are consistent with incumbent knowledge helping workers meet changing digital requirements and formal learning partly offsetting erosion under general change. Prescription evidence is less decisive and varies across firm environments. In large innovating firms, favorable digital wage progression accompanies prescription estimates pointing toward greater strain. Around firm upgrading, high-ability workers with longer pre-event tenure exhibit relative wage preservation alongside higher unemployment associated with digital churn. These conditional associations do not isolate causal mechanisms, but highlight distinct roles for the productive usefulness of accumulated knowledge and the demands and employment risks of adaptation.

Keywords: Technological change; skill churn; tenure; experience; firm-specific human capital; worker well-being; mental health; mobility; continuing education.

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1 Introduction

Technological change reshapes both the value of workers’ knowledge and the demands they face in using it. New tools can make established skills less relevant, but their introduction into an existing firm may also require a detailed understanding of its systems, routines, and workflows. Employees who possess this knowledge may become more useful precisely because requirements are changing. Their contribution can nevertheless involve demanding work: configuring systems, revising established practices, troubleshooting, and helping colleagues adapt. The consequences for workers therefore depend on both the productive value of accumulated knowledge and the burdens accompanying its application.

Mental health is central to this process. Adapting to changing requirements can involve uncertainty about competence, additional learning, and responsibility for maintaining operations while established practices are revised. These pressures can arise within continuing employment relationships, including those in which earnings are preserved or increase. Conversely, familiarity with the workplace may make new requirements easier to meet and reduce the need for additional formal learning. Earnings alone cannot distinguish these possibilities. A favorable wage profile may reflect an employee’s continued usefulness while revealing little about the demands of remaining productive. Understanding adjustment requires examining how earnings, learning, and health outcomes develop together.

How firms obtain and use the knowledge needed to implement change is central to this question. Bijmans et al. (2026) show that firms acquire much of the specialized skill needed to integrate new machinery through external suppliers. Alongside this technical expertise, adaptation may draw on employees’ familiarity with the organization in which new tools must operate. Knowing how existing systems fit together, how work is coordinated, and where established practices can be modified may help incumbents turn new technologies into workable production arrangements. This raises a complementary question: how does the usefulness of this knowledge shape employees’ careers and the demands they face during adaptation?

Adjustment within firms can also involve retraining and movement into different jobs (Battisti et al., 2023). These responses bring workers’ accumulated knowledge into contact with new tasks and responsibilities. Employees may preserve their productive contribution by learning, changing roles, or applying existing expertise in new ways, each with different implications for the effort and strain involved. We examine these possibilities by following earnings, formal learning, prescription use, and employment outcomes for the same workers. This joint perspective allows us to assess whether favorable career progression accompanies fewer adjustment demands or whether the employees whose knowledge helps a firm adapt also bear substantial burdens in doing so.

Research on occupational skill change provides an important starting point. Deming and

Noray (2020) show that fast-changing occupations offer high initial earnings but flatter age-earnings profiles. Their framework interprets career progression as a race between learning and skill obsolescence: new requirements reduce the value of previously acquired skills and limit the gains from experience. An age profile, however, combines experience accumulated across employment with tenure at the current firm. These dimensions can have different economic content. Knowledge acquired over a career may lose relevance as tasks change, while familiarity with a particular firm’s operations may help employees incorporate new tools into established arrangements. Following the experience–tenure distinction in Topel (1991), we examine these dimensions jointly and ask how changing requirements are associated with progression across a career and within an employment relationship.

We use Danish matched employer–employee data linked to vacancy-based measures of occupational skill churn, prescription records, continuing-education registers, and firm innovation data. At the four-digit occupation level, we measure long-run changes in demanded skills from online job postings between 2010 and 2023. We distinguish digital skill churn, which captures changes in software, data analysis, IT, AI, and other digital requirements, from general skill churn, which captures changes in broader non-digital requirements such as communication, coordination, management, writing, and customer service. The measures remain fixed within occupations over the estimation period; workers’ assigned exposure can change when they move between occupations.

This distinction is central to the question of how changing requirements affect the usefulness of incumbent knowledge. Digital requirements often involve applying new tools within an existing production environment: local software systems, data infrastructures, digital production processes, and organization-specific workflows. Even when a technical skill is portable across employers, using it productively may require familiarity with the particular firm’s installed systems. Employees who understand those systems may therefore help connect new technical capabilities with established operations.

Changes in general requirements may involve reorganizing tasks, coordinating work differently, or assuming new managerial and customer-facing responsibilities. These changes can also draw on existing knowledge, but they may require employees to revise established practices or acquire capabilities that familiarity with the firm does not supply. Separating digital and general churn allows us to examine whether incumbent knowledge helps workers meet these different requirements, and whether adjustment is accompanied by additional formal learning or greater strain.¹

The private-sector estimation sample contains approximately 14.4 million worker-year observations over 2010–2023. Actual employment experience records accumulated time in

¹The digital–general distinction concerns the type of skill requirement. It is separate from the distinction between portable knowledge and knowledge specific to the current firm. Either family of requirements can draw on both forms of knowledge.

employment, while tenure measures continuous employment with the current firm. We estimate flexible profiles over both dimensions, allowing their associations with worker outcomes to vary with digital and general churn. Worker, firm, and year fixed effects absorb permanent worker differences, persistent firm premia, and common calendar shocks. Occupation-group-specific profiles account for broad differences in career progression. Comparisons across tenure categories therefore hold accumulated experience fixed, while comparisons across experience categories hold tenure fixed.

The central earnings finding is a sharp asymmetry over firm tenure. Conditional on accumulated experience, digital churn is associated with steeper wage–tenure profiles, while general churn is associated with flatter profiles. The differences from the first tenure year are statistically significant at long tenure. Formal education follows an opposing pattern: the association between digital churn and course participation generally becomes more negative with tenure, whereas the association with general churn becomes more positive at longer tenure. The baseline wage–experience patterns are less precisely estimated. The strongest evidence thus concerns the joint earnings and education patterns associated with time at the current employer.

These patterns suggest different roles for incumbent knowledge and formal learning. Under digital churn, stronger wage progression with less additional formal education supports an interpretation in which familiarity with the firm helps employees meet new requirements. Knowing how existing systems and workflows fit together can make accumulated expertise useful when those arrangements must be adapted. Under general churn, greater course participation accompanies weaker wage progression. This combination is consistent with education partly offsetting the declining relevance of existing knowledge. Its benefits may appear as losses avoided rather than higher observed earnings. The contrast also illustrates why greater participation in education need not identify a more favorable adjustment environment: it can reflect the effort required to preserve productive capacity.

We develop a framework that makes these relationships explicit. Workers accumulate portable knowledge through employment experience and familiarity with the firm’s systems and routines through tenure. Changing requirements can erode the usefulness of either stock, while incumbent knowledge can also help employees meet new requirements. Formal education improves the fit between workers’ knowledge and their tasks. The framework distinguishes this fit from the demands of adaptation. Education can itself be demanding, and implementation work can add strain even when employees’ knowledge makes them effective at meeting new requirements. Workers whose expertise remains useful can consequently experience favorable wage progression alongside substantial demands on their health and well-being.

This distinction gives the health evidence a central role in evaluating adaptation. We

use prescription records covering psychiatric medications and medication for stress-linked somatic conditions, examining both a broad indicator and separate clinical components. The records provide administrative measures of treatment that can be linked consistently to workers' employment histories. They also reflect morbidity, help-seeking, access to care, and prescribing decisions. Prescription use is therefore informative about recorded treatment, without directly measuring mental health or establishing that a condition was caused by workplace stress.

The prescription evidence is less decisive than the wage and education evidence. Average associations among workers observed at longer tenure link digital churn to lower prescription use and general churn to higher use, but the evidence is less conclusive about how these relationships change with tenure. Read alongside the earnings and education findings, these patterns are consistent with differences in the strain of adaptation, although they are not uniform across medication categories. Under general churn, greater formal learning may help employees maintain task fit while leaving part of the adjustment burden unresolved. The digital prescription evidence is less precise, however, and the firm comparisons reveal a further possibility. In large innovating firms, favorable wage progression under digital churn accompanies prescription estimates that point toward greater strain. Here, the same knowledge that helps employees remain productive may also bring demanding responsibilities for implementing change. Taken together, the findings are consistent with incumbent knowledge easing adaptation in some settings while its application creates additional demands in others. Preserving the value of what workers know need not eliminate the strain involved in putting it to use.

The ability profiles suggest that workers also draw on different resources in responding to change. Outside the high-ability group, defined using upper-secondary grades, the digital pattern is clearest over tenure: stronger wage progression accompanies a weaker formal-education response, with prescription differences comparatively close to zero. Among high-ability workers, the favorable digital wage pattern is more prominent over accumulated employment experience, alongside greater formal-education participation in the middle experience categories. This positive experience pattern extends beyond the benchmark's treatment of portable-knowledge erosion, pointing to possible productive uses of portable capabilities, learning complementarities, or selection across career paths. The profiles do not establish education's contribution to earnings or a uniform ranking of outcomes across ability groups. The framework fits the joint tenure patterns more closely than the experience profiles, which also reflect forces beyond its benchmark treatment of portable knowledge.

We complement the profile estimates with three additional pieces of evidence. First, sorting regressions describe which workers encounter different combinations of occupational skill change and firm environment. High-ability workers have greater digital churn and lower

general churn in their first and last observed occupations. Conditional on initial exposure, the association with final digital churn remains positive, while the corresponding general-churn estimate is negative but statistically insignificant. The firm-environment evidence is clearest for digital churn in large and old firms; the estimates for innovation-active firms are less decisive. These patterns show that measured adaptation capacity is related to the environments workers enter and remain in, making allocation and retention important to the interpretation of their subsequent outcomes.

Second, firm-upgrading event studies examine incumbent workers in large firms around their first observed innovation-expenditure episodes. We assign each worker the full-period churn measure of the occupation held before the event and fix ability and tenure groups at that point, following workers after they leave the baseline employer. Under digital churn, high-ability workers with longer pre-event tenure exhibit relative wage preservation, partly reflecting more adverse wage responses among their shorter-tenure counterparts. The formal-education comparisons also indicate a weaker response associated with the combination of high ability and long tenure, while the prescription evidence remains imprecise. Importantly, greater digital churn is associated with higher post-event unemployment within the high-ability, high-tenure group itself. These findings are consistent with useful incumbent knowledge supporting earnings, but also show that favorable wages among observed earners can coexist with employment losses.

Third, match fixed effects, occupation-stayer estimates, and occupational moves help assess the roles of match quality and reallocation. The broad digital-general patterns remain visible after accounting for stable worker-firm differences. This specification, however, does not separate tenure from experience accumulation. Among workers who remain in the same occupation throughout the observation window, the opposing wage-tenure patterns are weaker, although differences in formal education and prescription use remain more apparent. Occupational moves involving larger increases in digital churn are associated with more positive subsequent wage changes, with preparation and selection also visible before the move. Adaptation may therefore involve changes in roles and destinations alongside the use of knowledge accumulated within a firm.

Our estimates describe conditional outcome profiles rather than structural returns to knowledge. The additional exercises help assess whether the patterns are consistent with the proposed mechanisms, but selective retention, changing match value, and unobserved occupational developments remain possible contributors. Upgrading decisions are also selected, and some pre-event coefficients depart from zero. We therefore interpret the evidence jointly, recognizing that it cannot isolate the separate causal contributions of incumbent knowledge, learning, and implementation demands. Registered courses also capture only part of workers' learning, so a weaker formal-education response can coexist with substantial informal

learning or implementation work.

Our first contribution is to bring knowledge accumulated within the firm into the explanation of career progression under changing skill requirements. Building on Deming and Noray (2020), we distinguish progression over employment experience from progression over firm tenure. Digital churn is associated with stronger wage progression over tenure and generally less additional formal education, while general churn is associated with weaker wage progression and more formal education. These opposing patterns support different accounts of adjustment. Under digital change, employees’ familiarity with the firm can help them meet new requirements, giving accumulated knowledge new uses. Under general change, formal learning may partly compensate for the declining relevance of existing expertise. The findings therefore extend the learning–obsolescence account of careers by identifying a potential role for incumbent knowledge in implementing change.

Our second contribution is to develop and assess a framework that distinguishes the productive usefulness of incumbent knowledge from the demands involved in applying it. Research on displacement and technology adoption establishes that labor-market adjustment can have consequences for worker health (Kuhn et al., 2009; Humlum et al., 2024). We connect this health dimension to the changing value of accumulated knowledge by examining earnings, formal learning, prescriptions, and employment outcomes along the same employment histories. In large innovating firms, favorable digital wage progression accompanies prescription estimates pointing toward greater strain. Although the health estimates are less precise, this joint pattern is consistent with employees remaining productive while bearing demanding implementation responsibilities. Our framework explains how these outcomes can coexist: knowledge of the firm can improve employees’ ability to meet new requirements, while the work of adapting systems and practices imposes additional demands. This distinction helps explain why favorable earnings alone provide an incomplete assessment of workers’ adjustment.

Section 2 reviews the related literature. Section 3 presents the conceptual framework, Section 4 describes the empirical strategy, and Section 5 introduces the data and measures. Section 6 presents the results, Section 7 examines measurement and robustness, and Section 8 concludes.

2 Related Literature

This paper connects three strands of research: the measurement and organization of changing skill demand, the role of accumulated human capital in career progression, and the health consequences of labor-market change. We bring these strands together by linking vacancy-based measures of digital and general skill churn to separate outcome profiles over accu-

mulated employment experience and firm tenure. This allows us to examine how changing requirements are associated with wages, formal continuing education, mobility, and stress-related prescription use along different dimensions of workers' careers.

2.1 Technology, labor demand, and skill measurement

Research on technology and labor demand has developed from models of skill-biased technical change (Katz and Murphy, 1992; Berman et al., 1994) to task-based approaches emphasizing substitution and complementarity (Autor et al., 2003; Acemoglu and Autor, 2011), and models of automation, displacement, and new-task creation (Acemoglu and Restrepo, 2019, 2022). These approaches emphasize that technological change alters the value of workers' skills by changing the tasks required in production.

An important contribution to understanding how firms obtain the skills needed for technological change is Bijmens et al. (2026). Linking Belgian data on capital investment, buyer–supplier transactions, and workers' education, they show that the skill bias of machinery investment emerges through external suppliers. Following investment spikes, demand for workers with tertiary STEM education rises disproportionately through purchases from suppliers, while in-house employment expands relatively evenly across skill groups. Machine suppliers and integrators account for the initial increase, followed by sustained demand for complementary services such as software. Their framework explains these patterns through the fixed and adjustment costs of employing specialized skills internally: suppliers can spread fixed costs and smooth uneven demand across multiple clients. This evidence reconciles capital–skill complementarity with the limited changes in skill composition observed on adopting firms' own payrolls. More broadly, it establishes that the organization of adoption is central to understanding where technology creates demand for skills.

Vacancy data provide a complementary view of changing labor demand by revealing the skills employers request within occupations and across firms. Hershbein and Kahn (2018), Deming and Kahn (2018), and Atalay et al. (2020) demonstrate the value of job-posting text for measuring changes in job requirements and differences in skill demand. We build on this measurement approach by constructing separate occupation-level measures of long-run digital and general skill change. These measures allow us to examine whether changes in different types of requirements have distinct associations with workers' career profiles, including within continuing employment relationships.

2.2 Human capital, skill change, and career dynamics

The distinction between knowledge accumulated across a career and knowledge acquired within an employment relationship draws on the human-capital literature. Becker (1993)

distinguishes general from firm-specific human capital, while Topel (1991) develops an approach to separating wage growth associated with labor-market experience from that associated with firm tenure. Alternative estimates and subsequent reassessments highlight the difficulty of separating tenure returns from worker and match selection (Altonji and Shakotko, 1987; Abraham and Farber, 1987; Altonji and Williams, 2005; Heckman et al., 2006). Other contributions identify intermediate forms of specificity: Neal (1995) studies industry-specific capital, Gathmann and Schönberg (2010) emphasize task-specific human capital, and Lazear (2009) explains firm specificity through differences in the combinations of otherwise general skills used by employers. These perspectives inform our emphasis on employees’ knowledge of their firm’s systems, routines, and workflows.

Deming and Noray (2020) provide the closest starting point for our analysis of occupational skill churn and career profiles. They measure changes in the skill content of occupations using job postings and show that rapidly changing occupations, particularly technology-intensive STEM occupations, offer high initial earnings but flatter age-earnings profiles. Their framework interprets career wage growth as a balance between learning and skill obsolescence, building on models of technology-specific human capital such as Violante (2002). To our knowledge, this is the first study to use vacancy-based measures of occupational skill change to examine jointly how wage profiles over accumulated employment experience and firm tenure vary with changing skill requirements. An age-earnings profile combines these dimensions; estimating them jointly allows us to examine whether occupational skill change is associated with different patterns of progression across the career and within employment relationships. Separating digital from general skill churn further allows these associations to differ across types of changing requirements.

Related evidence shows how firms and workers adapt to changing tasks. Battisti et al. (2023) find that technological and organizational change in German firms reduces the employment share of routine jobs, but does not generally reduce employment or earnings growth among the workers initially holding those jobs. Retraining and movement into more abstract jobs facilitate adjustment, while older workers face greater risks of employment withdrawal and earnings losses. Braxton and Taska (2023) examine adjustment following job loss, showing that workers displaced from occupations with greater technological change suffer larger earnings losses. Their evidence connects changing skill requirements to the difficulty of returning to an occupation after displacement. Together, these studies establish the importance of learning, mobility, and the circumstances in which workers encounter changing requirements.

Our interpretation of firm tenure connects to the integration work emphasized by Bijmans et al. (2026). Their evidence shows that adopting new machinery creates demand for specialized skills to integrate it into production, often supplied by external providers. Our

framework highlights a complementary source of integration capacity: incumbent employees’ knowledge of the firm’s existing systems, routines, and workflows. Introducing new digital tools requires understanding how they can be incorporated into these established arrangements. Knowledge accumulated through tenure can therefore become more useful as digital requirements change, providing a mechanism for the more favorable wage–tenure profiles we observe in occupations with greater digital churn. External technical expertise and employees’ knowledge of the firm can contribute jointly to this process. This interpretation also connects to the authors’ observation that skills complementary to intangible capital may be difficult to outsource because they are tacit and firm-specific. We examine the implications of this integration role for workers’ career profiles, recognizing that using incumbent knowledge to implement change can involve additional responsibilities and strain. The productive value of that knowledge and the demands of putting it to use are therefore distinct aspects of adjustment.

2.3 Technology and worker well-being

Research on displacement shows that labor-market disruptions can have substantial health consequences, although findings differ across populations and outcomes. Sullivan and von Wachter (2009) document increased mortality following job displacement in the United States, while Browning and Heinesen (2012) find adverse mortality and hospitalization effects following plant closures in Denmark. Earlier Danish evidence from Browning et al. (2006), however, finds no increase in hospitalization for stress-related disease following displacement. Kuhn et al. (2009) find that plant-closure-induced job loss increases expenditure on antidepressants and related medications, and on mental-health hospitalization, among men in Austria. These studies provide a benchmark for understanding the health consequences of employment disruption.

A related literature examines the health consequences of exposure to particular technologies. Gihleb et al. (2022) find improvements in physical safety associated with industrial robots, alongside adverse mental-health-related outcomes in the United States but no significant mental-health effects in their German analysis. Using Danish administrative data, Humlum et al. (2024) show that robot adoption reduces workplace injuries while increasing stress-related diagnoses among employees. Abeliasky et al. (2024) find that greater robot intensity is associated with poorer mental health among German workers, while Lordan and Stringer (2022) document small adverse associations between working in an automatable job and mental health and life satisfaction in some Australian industries. These findings show why improvements in production or workplace safety need not be accompanied by improvements in every dimension of worker well-being.

Recent work also emphasizes the role of employers in workers’ mental health. Jensen

et al. (2026) link Danish matched employer–employee records to mental-health prescriptions and find that job loss increases medication use, while job finding reduces it. The benefits of employment vary with the workplace environment. This evidence reinforces the value of studying health outcomes jointly with employment histories and firm characteristics.

We contribute by examining long-run changes in the skills employers demand within occupations and distinguishing their associations with outcomes over employment experience and firm tenure. Our prescription records provide administrative measures of treatment for stress-related conditions that can be linked to the same workers and employment histories used to estimate wage and education profiles. These records avoid reliance on self-reported symptoms, although they also reflect help-seeking, access to care, and prescribing decisions, and therefore do not measure latent strain directly. Comparing prescription use with wages and formal continuing education allows us to assess whether more favorable earnings progression accompanies lower recorded morbidity, greater participation in formal learning, or additional health-related burdens as occupational requirements change.

3 Conceptual framework

Index workers by i , firms by f , and calendar years by t . Workers accumulate portable knowledge through actual employment experience, E_{it} , and knowledge of their current firm’s systems, routines, and workflows through tenure, T_{ift} . Following the experience–tenure distinction in Topel (1991), we use these employment clocks as local proxies for the two stocks. Changing requirements can erode accumulated knowledge, but incumbent knowledge can also help workers integrate new tools and practices into existing systems. Doing so may involve demanding implementation work. We therefore distinguish remaining skill mismatch, the demands of formal education, and the demands of implementation.²

Let o_{it} denote worker i ’s occupation in year t . For each occupation o , let Δ_o^s denote skill churn measured over the entire observation period, where $s \in \{D, G\}$ distinguishes digital skills, D , from general skills, G . The superscript identifies the skill family. This occupation-level measure is time invariant: each occupation receives the same churn value in every calendar year. Worker i is assigned $\Delta_{o_{it}}^s$, which can change only when the worker moves to an occupation with a different churn value. The framework therefore relates differences in full-period occupational skill churn to the profiles associated with accumulated experience and firm tenure.

²Online Appendix OA0.1 derives the training choice, boundary cases, comparative statics, and measurement qualifications.

The adjustment requirement before additional training is

$$M_{ift} = m_{0,ift} + \sum_{s \in \{D, G\}} \Delta_{oit}^s [d_s + \delta_s^E E_{it} + \kappa_{s,ift} T_{ift}], \quad \kappa_{s,ift} = \delta_s^T - b_s(a_i, f, t). \quad (1)$$

Here $m_{0,ift}$ is the baseline adjustment requirement, and d_s is the component of the response to churn that does not depend on experience or tenure. We work locally where $M_{ift} > 0$. The parameters $\delta_s^E, \delta_s^T \geq 0$ capture demands associated with erosion of portable and firm-specific knowledge; their superscripts identify the experience and tenure margins. The term $b_s(a_i, f, t) \geq 0$ captures how incumbent knowledge helps meet new requirements. It depends on worker adaptability, a_i , and firm characteristics, including size, innovation status, and existing technologies and workflows. Thus $\kappa_s < 0$ means that this benefit outweighs firm-specific erosion; $\kappa_s > 0$ means that erosion dominates. Omitted worker, firm, and time indices below refer to a fixed worker–firm state.

Implementation can require configuring systems, revising workflows, troubleshooting, and helping colleagues use new tools. Represent these demands, in strain units, by

$$L_{ift} = L_{ift}^0 + \sum_{s \in \{D, G\}} \Delta_{oit}^s \ell_s(a_i, f, t) T_{ift}, \quad L_{ift} \geq 0, \quad \ell_s(a_i, f, t) \geq 0. \quad (2)$$

Here L_{ift}^0 denotes baseline implementation demands, and ℓ_s describes how implementation demands associated with churn increase with tenure. Workers whose knowledge is especially useful may also receive greater implementation responsibilities, so b_s and ℓ_s can rise together. Their relationship is not imposed. Implementation demands are assigned by the production environment and held fixed in the training decision; this benchmark does not model their allocation or a separate implementation–effort choice. Conditional on worker and firm state, the local comparisons below hold baseline demands fixed as the occupational churn value and the employment clocks vary. The term L has no churn–experience interaction.

For formal training effort $\tau_{ift} \in [0, M_{ift}]$, define remaining mismatch, R_{ift} , and latent strain, S_{ift} , by

$$R_{ift} = M_{ift} - \tau_{ift}, \quad S_{ift} = R_{ift} + \eta_{ift} \tau_{ift} + L_{ift}, \quad \eta_{ift} \geq 0. \quad (3)$$

Training is measured so that one unit removes one unit of mismatch. The parameter η_{ift} measures the strain generated directly by each unit of education. Education improves task fit but can itself be demanding. Its net effect on strain at fixed M, L is $\eta - 1$: education relieves strain when $\eta < 1$, leaves it unchanged when $\eta = 1$, and adds net strain when $\eta > 1$.

Wages, w_{ift} , depend on remaining mismatch:

$$\ln w_{ift} = y_{ift}^0 - \lambda R_{ift}, \quad \lambda > 0. \quad (4)$$

The parameter λ measures the log-wage penalty associated with remaining mismatch. The baseline y^0 includes ordinary experience and tenure profiles and other wage determinants, without further churn–profile interactions at fixed state. There is no separate wage return to education beyond restoring task fit, or direct wage premium for implementation demands.

Suppressing subscripts, the worker chooses training to maximize

$$\tau^* \in \arg \max_{0 \leq \tau \leq M} \left\{ y^0 - \lambda(M - \tau) - \frac{\chi}{2} [M + L + (\eta - 1)\tau]^2 - \frac{c}{2} \tau^2 \right\}, \quad \chi, c > 0. \quad (5)$$

Here χ is the weight on strain disutility, and c measures the curvature of other training costs. The cost $c\tau^2/2$ excludes burdens already counted in strain. Both c and η may vary with worker and firm circumstances. An asterisk denotes the optimal training choice or an outcome evaluated at that choice. Registered courses capture formal education; informal learning and implementation work need not generate a course record.

For an interior solution, $0 < \tau^* < M$, write $H = M + L$ for combined mismatch and implementation demands before training. Define $\tau_H^* = \partial \tau^* / \partial H$ and $S_H^* = \partial S^* / \partial H$, holding the state parameters fixed. The subscript H denotes differentiation with respect to these combined demands. The optimized responses satisfy $S_H^* > 0$ and $\text{sgn}(\tau_H^*) = \text{sgn}(1 - \eta)$. Greater demands therefore raise resulting strain; they increase education when education relieves net strain and reduce education when it adds net strain.

We call the difference in an outcome’s churn gradient across levels of an employment clock a *tilt*. Let $\Theta_z^{j,s}$ denote this tilt, where $z \in \{T, E\}$ identifies tenure or experience, and $j \in \{w, S, \tau\}$ labels log wages, latent strain, or training effort, evaluated after optimal training. For example, $\Theta_T^{w,s} = \partial^2 \ln w^* / (\partial \Delta^s \partial T)$, where Δ^s abbreviates the fixed occupational measure Δ_o^s . Differentiation with respect to Δ^s compares occupational churn values. A positive tilt means that the outcome gradient with respect to this fixed measure becomes more positive, or less negative, at higher levels of tenure or experience, holding the other employment clock and worker and firm state fixed.

Holding experience and worker and firm state fixed, the churn–tenure tilts are

$$\begin{aligned} \Theta_T^{w,s} &= -\lambda [\kappa_s - \tau_H^* (\kappa_s + \ell_s)], \\ \Theta_T^{S,s} &= S_H^* (\kappa_s + \ell_s), \quad \Theta_T^{\tau,s} = \tau_H^* (\kappa_s + \ell_s). \end{aligned} \quad (6)$$

Holding tenure and worker and firm state fixed, the corresponding experience tilts are

$$\Theta_E^{w,s} = -\lambda(1 - \tau_H^*)\delta_s^E, \quad \Theta_E^{S,s} = S_H^*\delta_s^E, \quad \Theta_E^{\tau,s} = \tau_H^*\delta_s^E, \quad (7)$$

with $1 - \tau_H^* > 0$ in the feasible interior regime.

One education decision generates both sets of profiles. The gradient of combined demands with respect to occupational churn varies with tenure through $\kappa_s + \ell_s$, which can be positive or negative, and with experience through portable erosion, $\delta_s^E \geq 0$. The benchmark therefore permits either sign for wage–tenure tilts but implies nonpositive wage–experience tilts and nonnegative strain–experience tilts. Positive wage–experience tilts lie beyond this portable-erosion mechanism.³

Table 1: Selected joint predictions for tenure and experience profiles

Conditions	Log wages	Strain	Training
<i>A. Tenure profiles</i>			
Useful knowledge; modest implementation demands $\kappa_s < 0, \kappa_s + \ell_s < 0, \eta < 1$	+	−	−
Erosion; no additional implementation tilt $\kappa_s > 0, \ell_s = 0, \eta < 1$	−	+	+
Useful knowledge; demanding implementation $\kappa_s < 0, \kappa_s + \ell_s > 0, \eta > 1$	$+\dagger$	+	−
<i>B. Experience profiles</i>			
Erosion of portable knowledge $\delta_s^E > 0$; benchmark model (see footnote 3 for an extension)	−	+	$+, 0, -\ddagger$

Notes: Predictions concern the interior regime at fixed worker and firm state. Entries describe how gradients with respect to the time-invariant occupational churn measure vary with tenure (Panel A) or experience (Panel B), holding the other employment clock fixed. The rows illustrate selected cases, not all possible parameter combinations. [†]The wage tilt is positive when $-\kappa_s > -\tau_H^*(\kappa_s + \ell_s)$: the reduction in initial mismatch exceeds the reduction in training. Appendix OA0.1.4 gives the exact parameter region. [‡]The education interaction is positive when education relieves net strain ($\eta < 1$), zero when its net strain effect is zero ($\eta = 1$), and negative when it adds net strain ($\eta > 1$). Prescription and participation coefficients require the measurement conditions in Appendix OA0.1.6.

Conditional predictions. The framework suggests five predictions for how wage, education, and strain profiles differ across occupations with different levels of skill churn.

³ An extension could allow education to renew the productive use of accumulated experience by adding $gE_{it}\tau_{ift}$ to Equation (4), where $g > 0$ measures education–experience complementarity. While mismatch remains, the marginal wage benefit of education would then be $\lambda + gE_{it}$. After reoptimizing training, this extension could generate positive wage–experience tilts under appropriate conditions. The joint outcome profiles do not identify this mechanism, so we retain the simpler benchmark in which education raises wages by restoring task fit.

1. *Knowledge revaluation.* When changing requirements make existing firm knowledge less useful, additional education may only partly offset the loss, leaving weaker wage progression and greater strain. When incumbent knowledge helps workers adapt, wage progression can improve with less additional education and lower strain, provided implementation demands remain modest.
2. *Demanding implementation.* Workers whose knowledge is especially useful may also take on more implementation responsibilities. Favorable wage progression can then accompany greater strain. Formal education may decline if it adds more strain than it relieves, although wages improve only if the benefit of useful incumbent knowledge outweighs the productive cost of less education.
3. *Ability, firm characteristics, and upgrading.* Upgrading can strengthen the value of accumulated firm knowledge or undermine established routines. Workers whose adaptability and firm knowledge help them integrate new requirements may therefore experience stronger wage progression. Where upgrading reduces adjustment needs, less additional education and lower strain can accompany these gains; greater implementation responsibilities can instead make adaptation more demanding. These possibilities depend on both worker capabilities and the firm's production environment.
4. *Education and experience.* When changing requirements erode knowledge accumulated through experience, education helps restore task fit and limit wage losses. Training itself can nevertheless be demanding. More education may coexist with weaker wage progression and greater strain when it only partly offsets erosion. The benchmark therefore treats education as helping workers manage the loss of knowledge value.
5. *Sorting and retention.* Workers weigh wages against strain, education costs, moving costs, and available alternatives. Useful firm knowledge can make staying more attractive, while loss of its value and demanding implementation work can encourage leaving. Higher wages need not make a job more attractive when obtaining those gains also brings greater demands.

We examine these outcomes together, recognizing that registered courses capture formal participation and prescriptions capture treatment. Sorting and retention also affect which workers contribute to each profile. The Online Appendix sets out the formal conditions and measurement qualifications.

4 Empirical strategy

We estimate how digital and general occupational churn are associated with profiles of wages, formal continuing education, and stress-related prescription use over actual accumulated employment experience and firm tenure. Additional labor-market outcomes, including mobility, help assess adjustment and selection. The analysis asks how changing skill requirements affect the usefulness of accumulated knowledge and the demands of putting that knowledge to work. Reading wages, education, and prescription use together helps assess whether productive adaptation is accompanied by additional learning or health-related burdens. The estimates show how these outcome profiles differ across occupations with different levels of skill churn, after accounting for the included controls and fixed effects. They can indicate whether the joint outcome patterns are consistent with the conceptual model, but cannot establish which mechanisms cause those patterns or how much each mechanism contributes.

4.1 Joint experience and tenure profiles

We apply a common specification separately to each outcome. Let y_{ift} denote, in turn, log wages, an indicator for participation in at least one registered adult or continuing-education course during year t , or the annual indicator for stress-related prescription use. The prescription indicator records whether a worker has a prescription in any of the medication categories defined in Section 5.4. We also apply the specification to labor-market outcomes such as mobility. All coefficients and fixed effects are outcome-specific.

The two churn measures summarize changes in posting shares between 2010 and 2023 and are assigned to the worker’s current four-digit occupation, o_{it} . They are fixed characteristics of occupations over the estimation period. Experience accumulates with observed employment; non-employment does not add to it. Tenure measures continuous employment with the current firm.

Let D_{ift}^T and D_{it}^E collect category indicators for tenure and experience:

$$D_{ift,k}^T = \mathbf{1}\{\min(T_{ift}, 10) = k\}, \quad k = 1, \dots, 10, \quad (8)$$

$$D_{it,k}^E = \mathbf{1}\{\min(E_{it}, 20) = k\}, \quad k = 1, \dots, 20. \quad (9)$$

The last categories pool tenure of 10 or more years and experience of 20 or more years. Let G_{it} denote one-digit occupation-group indicators. We normalize the churn interactions for year 1 of tenure and year 1 of experience to zero and omit redundant baseline and

occupation-group columns using the usual reference-category normalizations. We estimate

$$\begin{aligned}
y_{ift} = & (D_{ift}^T)' \tau^T + (D_{it}^E)' \tau^E + (D_{ift}^T)' \Pi^T G_{it} + (D_{it}^E)' \Pi^E G_{it} \\
& + \sum_{s \in \{D, G\}} \Delta_{oit}^s [\theta^s + (D_{ift}^T)' \gamma^{T,s} + (D_{it}^E)' \gamma^{E,s}] \\
& + \alpha_i + \psi_f + \alpha_t + \varepsilon_{ift}.
\end{aligned} \tag{10}$$

Worker, firm, and year fixed effects absorb permanent worker heterogeneity, persistent firm premia, and common calendar shocks. The occupation-group interactions allow each one-digit occupation group to have its own flexible experience and tenure profiles. These controls absorb broad occupational differences in career progression, including differences in profile shape between, for example, professional and service occupations. The churn–experience and churn–tenure interactions therefore draw on differences in churn across four-digit occupations within these broad groups, conditional on the fixed effects and other regressors. Therefore, the estimated churn tilts cannot be attributed solely to differences in profile shape across major occupation groups. For binary outcomes, the specification is a linear probability model: the churn gradients describe differences in conditional probabilities, expressed in percentage points when multiplied by 100. Standard errors are clustered by four-digit occupation, the level of the churn measure.

The coefficient $\gamma_k^{T,s}$ is the difference in the churn gradient between tenure category k and year 1, holding experience fixed. An adjacent difference, $\gamma_k^{T,s} - \gamma_{k-1}^{T,s}$, measures the change in that gradient between neighboring categories. The experience coefficients have the analogous interpretation. We present both the churn–profile interaction coefficients and the corresponding average partial effects (APEs).⁴ The interaction coefficients compare churn gradients with those in year 1 of tenure or experience, holding the other dimension fixed. They therefore provide the more direct comparison with the model’s predictions about how churn gradients vary with tenure or experience.

The APEs are useful for describing the direction and magnitude of the average conditional association between churn and the outcome among workers observed in each tenure or experience category. Differences across tenure-indexed APEs reflect both the churn–tenure interactions and differences in the average churn–experience contribution across tenure groups.

⁴For each outcome, let $\mathcal{S}$ denote the estimation sample and let $\mathcal{S}_k^T = \{(i, f, t) \in \mathcal{S} : D_{ift,k}^T = 1\}$ denote the observations in tenure category k . The tenure-indexed APE for churn type s is

$$\widehat{\text{APE}}^{T,s}(k) = \hat{\theta}^s + \hat{\gamma}_k^{T,s} + \frac{1}{|\mathcal{S}_k^T|} \sum_{(i,f,t) \in \mathcal{S}_k^T} (D_{it}^E)' \hat{\gamma}^{E,s}, \quad \hat{\gamma}_1^{T,s} = 0. \tag{11}$$

The experience-indexed APE is constructed analogously, averaging the tenure contribution over observations in each experience category. Each profile therefore uses the observed distribution of the other dimension within the indicated category.

The corresponding interpretation applies to the experience-indexed APEs. A rising curve therefore indicates a more positive average churn association across the observed groups; it does not by itself isolate the tenure or experience interaction, nor does it imply that the outcome itself rises.

The churn level terms are absorbed by worker fixed effects for occupation stayers and draw their identifying variation from occupation changes. We therefore interpret absolute APE levels more cautiously than the underlying conditional interaction coefficients.

We treat continuing education as an adjustment outcome and leave it out of the wage equation. Conditioning on realized training would hold fixed a potential response to churn and could introduce additional selection.

4.2 Identifying variation and interpretation

The specification in Equation (10) allows each one-digit occupational group to have its own flexible tenure profile and its own flexible experience profile. These interactions absorb broad occupational differences in how outcomes vary with the two dimensions of employment history. Worker and firm fixed effects absorb permanent worker heterogeneity and persistent firm premia, while year fixed effects absorb common calendar shocks. The churn–tenure and churn–experience coefficients therefore describe how profiles vary with churn across four-digit occupations within these broad groups, conditional on the other employment-history dimension and the fixed effects.

Employment interruptions can cause workers from the same entry cohort to reach a given experience category in different calendar years. Employer changes reset tenure while preserving accumulated experience, and occupational changes can alter assigned churn exposure. These differences in employment histories help distinguish the experience and tenure profiles. The estimates thus use variation in the timing and composition of employment histories as well as differences in occupational skill change.

Workers who remain in the same occupation can also contribute to the interaction estimates as they move through tenure and experience categories. Their churn level is constant and absorbed by worker fixed effects, but the interactions with the profile indicators can change. Occupation changes supply additional variation for the interaction coefficients and identify the churn level terms included in the APEs.

The joint wage, continuing-education, and prescription interactions can help assess which mechanisms in Section 3 are most consistent with the observed patterns. This interpretation requires that, conditional on the included controls, other determinants of outcome growth do not generate systematic profile differences correlated with churn. Relevant concerns include unobserved occupational developments and selective mobility or retention. Comparisons with the model’s sign predictions also require that course participation and prescription use

preserve the signs of the corresponding interactions in formal training effort and latent strain, respectively, and that differences in access or recording do not drive the observed profiles.⁵

Even under these assumptions, the profiles cannot uniquely identify a mechanism or quantify its separate causal contribution, because different mechanisms can generate similar joint patterns. The sorting, heterogeneity, upgrading, match fixed-effect, occupation-stayer, and occupation-switch analyses help assess these interpretations across workers and settings.

4.3 Sorting and heterogeneous profiles

These exercises examine worker allocation across churn environments and differences in joint outcome profiles by ability and firm type. They help assess the roles of adaptation capacity, accumulated knowledge, and adjustment demands in Section 3, while recognizing that sorting and selective retention also shape the observed profiles.

We use upper-secondary GPA as a predetermined proxy for adaptation capacity. Let $H_i = 1$ indicate a graduate of general academic upper-secondary school whose GPA falls in the top two deciles, and $H_i = 0$ otherwise.⁶ The indicator captures predetermined differences in educational performance and provides an imperfect measure of workers' capacity to adapt.

For $s \in \{D, G\}$, let $\Delta_i^{s,0}$ and $\Delta_i^{s,1}$ denote churn in the first and last observed occupations. These refer to the observation window, not necessarily to labor-market entry and exit. Let G_i contain initial one-digit occupation-group indicators and Z_i contain birth-year indicators and gender. We first describe initial and final allocation using

$$\Delta_i^{s,r} = \alpha_{s,r} + \beta_{s,r}H_i + G_i'\lambda_{s,r} + Z_i'\gamma_{s,r} + u_i^{s,r}, \quad r \in \{0, 1\}. \quad (12)$$

We then condition final exposure on initial exposure:

$$\Delta_i^{s,1} = \alpha_s + \beta_s H_i + \rho_s \Delta_i^{s,0} + G_i'\lambda_s + Z_i'\gamma_s + u_i^s. \quad (13)$$

The coefficient β_s describes differences in final exposure conditional on initial exposure and controls. It can reflect movement, retention, and differences in when workers are last observed; it does not isolate a causal effect of ability on occupational choice. Table 7 reports these specifications.

A complementary specification describes the ability composition of initial–final exposure

⁵The continuing-education indicator records formal course participation rather than effective training effort; prescription use records treatment rather than latent strain. Even with stable access and recording, nonlinear measurement relationships can cause interaction signs to differ between the observed indicators and the underlying model outcomes. Appendix OA0.1.6 sets out the measurement conditions, and Section 5.4 describes the prescription indicator.

⁶Comparable GPA information for business- and technical-oriented upper-secondary programs becomes available only from 2000/01 onward.

paths:

$$H_i = \alpha + \sum_{s \in \{D, G\}} [\pi_{s,0} \Delta_i^{s,0} + \pi_{s,1} \Delta_i^{s,1}] + G'_i \lambda + Z'_i \gamma + v_i. \quad (14)$$

The coefficients describe how the probability of belonging to the high-ability group varies with each exposure measure, conditional on the other exposures and controls. They characterize the composition of observed employment histories rather than effects of churn on ability. Table 8 reports the estimates.

We also extend the dynamic sorting specification to occupation–firm environments. Let $F_i^{q,r}$ indicate whether the firm observed at endpoint r belongs to environment q , where q denotes large, old, or innovation-active firms. Define joint exposure as $X_i^{s,q,r} = \Delta_i^{s,r} F_i^{q,r}$. For each churn measure and firm environment, we estimate

$$X_i^{s,q,1} = \alpha_{s,q} + \beta_{s,q} H_i + \rho_{s,q} X_i^{s,q,0} + G'_i \lambda_{s,q} + Z'_i \gamma_{s,q} + u_i^{s,q}. \quad (15)$$

These coefficients describe differences in final occupation–firm exposure conditional on the corresponding initial exposure and controls. Because the outcome combines occupational churn and firm characteristics, it does not isolate sorting on either component. Table 9 reports the estimates. For innovation-related environments, the analysis conditions on initial and final firms being large firms with valid FUI information; missing innovation information is not treated as zero expenditure.

These sorting exercises relate to the model’s trade-off between wages, strain, education costs, moving costs, and available alternatives. They describe the resulting allocation and retention patterns, but do not reveal which component of match value drives them. The model does not impose a common direction of ability sorting across digital and general churn. Appendix OA0.1.8 formalizes these trade-offs.

We next estimate the joint profile specification in Equation (10) separately by ability. This comparison examines whether the churn–experience and churn–tenure profiles vary with measured adaptation capacity. Workers with greater adaptation capacity may learn more efficiently and make more productive use of accumulated knowledge. They may also take on more complex implementation responsibilities or select into environments with greater demands. Higher ability can therefore be associated with greater rewards alongside more learning or strain. The framework does not imply that higher-ability workers must have more favorable outcomes on every margin.

We then compare profiles across small firms, large non-innovating firms, and large innovating firms, using the same joint profile specification.⁷ These comparisons examine how

⁷In this exercise, large firms have more than 100 full-time-equivalent employees and valid FUI information. Large innovating firms report positive innovation-related expenditure; large non-innovating firms have observed zero expenditure. Missing FUI information is not classified as zero innovation. Section 5.7 describes

the usefulness of incumbent knowledge and the demands of implementation vary across production environments. Larger firms may have more extensive established systems, internal routines, and career ladders, making familiarity with the firm useful when skill requirements change. The same organizational complexity can create demanding implementation tasks. Comparing large non-innovating and large innovating firms helps assess how the joint profiles vary where new practices must be integrated with existing systems. Favorable wage progression may coexist with greater strain when useful incumbent knowledge improves task fit while its use entails demanding implementation work. Reading education alongside wages and prescriptions helps assess the adjustment cases, subject to the measurement qualifications above. These are descriptive comparisons across selected environments; firm characteristics do not directly measure the usefulness of incumbent knowledge or implementation demands.

4.4 Firm-upgrading event studies

These event studies examine how incumbent workers fare around the renewal or reconfiguration of the firm’s technologies, systems, and routines. They address the model’s prediction that changes in the production environment can make established routines less useful while creating new uses for accumulated firm knowledge in implementing change.

Innovation-related expenditure provides an observable proxy for such renewal episodes. We define T_f^U as the first observed upgrading episode, using FUI measures that include equipment, machinery, software, consulting, and other non-R&D innovation inputs. The exercise asks whether the relationship between occupational churn and outcomes changes around these episodes, particularly for incumbents with both high measured ability and substantial pre-event tenure.

We use a stacked event-study design. For an adoption cohort g , treated workers are employed at firms whose first observed episode occurs in year g ; controls work at firms that have not upgraded during the relevant event window. The risk set is defined in $g - 1$ and requires employment in the same large firm in $g - 2$ and $g - 1$. Workers are followed from $g - 3$ to $g + 3$, including after leaving the baseline firm.

Alongside wages, formal continuing education, and stress-related prescription use, we examine firm switching, occupational switching, and unemployment. These outcomes trace whether changes in wages and adjustment burdens are accompanied by movement across employers, reallocation across occupational skill environments, or non-employment. Following workers after they leave the baseline firm allows these margins to be observed rather than limiting the analysis to surviving matches. These outcomes also speak to the model’s sorting and retention prediction that favorable wages need not make staying more attractive

the innovation data and sample restrictions.

when adjustment demands also rise.

Churn exposure, occupation, industry, ability, and tenure group are fixed at $g - 1$. This prevents post-event mobility, occupational reassignment, or tenure accumulation from re-defining the worker's exposure or heterogeneity group. Baseline occupation and industry also determine the comparison cells, so those cells are not reassigned following post-event moves. Fixing the occupational assignment before the event does not make the 2010–2023 churn index itself a pre-event measure.

Let r index the adoption stack and $s \in \{D, G\}$ the skill dimension. Write C_{ir0}^s for baseline occupational churn, H_{ir0} for high ability, and J_{ir0} for high baseline tenure. For treated workers, D_{irt}^k indicates event time $k = t - g$; it equals zero for controls. The reference period is $k = -1$. For each skill dimension we estimate

$$\begin{aligned}
y_{irt} = \sum_{k \neq -1} D_{irt}^k & \left[C_{ir0}^s (\gamma_k^s + \pi_k^s H_{ir0} + \tau_k^s J_{ir0} + \rho_k^s H_{ir0} J_{ir0}) \right. \\
& \left. + \psi_k^{-s} C_{ir0}^{-s} + \ell_{0k} + \ell_{Hk} H_{ir0} + \ell_{Jk} J_{ir0} + \ell_{HJk} H_{ir0} J_{ir0} \right] \\
& + \alpha_{ir} + \lambda_{r,t,c_{ir0}} + \varepsilon_{irt}.
\end{aligned} \tag{16}$$

The fixed effects are worker-by-stack effects and stack-by-year comparison-cell effects, with cells c_{ir0} constructed from baseline occupation and industry. Standard errors are clustered by worker and baseline firm. The specification includes all lower-order event-time interactions for ability and tenure and a simple event-time adjustment for the other churn measure. Digital and general heterogeneity are estimated separately; we also consider single-churn and fully symmetric alternatives.

The coefficient ρ_k^s is the additional high-ability difference in the high-tenure churn gradient. It is distinct from the full implied gradient for an ability–tenure group:

$$\widehat{\Gamma}_k^s(a, h) = \widehat{\gamma}_k^s + a\widehat{\pi}_k^s + h\widehat{\tau}_k^s + ah\widehat{\rho}_k^s, \quad a, h \in \{0, 1\}. \tag{17}$$

Appendix OA0.1.9 formalizes upgrading as a change in the firm's production environment that need not reset workers' accumulated tenure. Such a change can shift $\kappa_s = \delta_s^T - b_s$, the balance between erosion and the usefulness of incumbent knowledge, and ℓ_s , which governs the implementation demands associated with churn and tenure. The additional ability–tenure interaction assesses whether the outcome responses associated with this changing balance differ for workers with greater adaptation capacity and longer pre-event tenure.

Workers with greater adaptation capacity and substantial pre-event tenure may be particularly well placed to connect new skill requirements with existing systems. Their wages can be preserved or increase if this contribution is sufficiently productive, even when implementation adds strain. A weaker education response can reflect less need for formal learning

or greater difficulty combining study with implementation work. The joint wage, education, and prescription responses therefore help assess whether the observed pattern fits the model’s cases of easier adaptation or demanding implementation. Employment outcomes also allow us to assess whether favorable wages among observed earners coexist with employment losses, as allowed by the model’s employment and selection discussion.

The design supplies mechanism evidence under qualified identifying assumptions. Upgrading is selected, pre-event coefficients can reveal differential dynamics, and the incumbent risk set conditions on prior attachment. For firm switching in particular, employment at the same firm in $g - 2$ and $g - 1$ mechanically restricts pre-event transitions. These features limit a causal interpretation even when the joint outcome pattern is consistent with the framework.

4.5 Match quality, occupation stayers, and occupational moves

The sorting and retention margin in Section 3 and Appendix OA0.1.8 implies that observed profiles reflect both adjustment within jobs and which workers enter and remain in them. We examine this margin through three exercises: controlling for stable worker–firm match quality, restricting attention to occupation stayers, and tracing outcomes around occupational moves that change assigned churn exposure.

4.5.1 Match fixed effects

The first exercise estimates churn-related tenure profiles with worker–firm match fixed effects. For each outcome, we estimate

$$y_{ift} = (D_{ift}^T)' \tau_M^T + \sum_{s \in \{D, G\}} \Delta_{oit}^s \left[\theta_M^s + (D_{ift}^T)' \gamma_M^{T, s} \right] + \alpha_{if} + \alpha_t + \varepsilon_{ift}, \quad (18)$$

where D_{ift}^T contains the tenure indicators defined above, α_{if} is a worker–firm match fixed effect, and α_t is a calendar-year fixed effect. Digital and general churn enter jointly. We estimate the specification separately for log wages, formal continuing education, and stress-related prescription use, with standard errors clustered by four-digit occupation. Identification of the churn level term requires occupational changes within worker–firm pairs; matches with unchanged occupation can still contribute to the interaction estimates as tenure advances.

Match fixed effects absorb permanent differences in outcome levels, including stable worker–firm complementarities. Persistence of the profiles therefore assesses whether the digital–general difference remains after accounting for these differences. Changing match

value and selective retention remain relevant. Because experience generally advances with tenure within a continuing match, this tenure-based specification does not separate their contributions.

4.5.2 Occupation stayers

The second exercise reestimates the joint tenure–experience specification in Equation (10) among workers who remain in the same four-digit occupation throughout the observation window. These workers may change employers. Writing o_i for their fixed occupation and G_i for the corresponding one-digit occupation-group indicators, we estimate

$$\begin{aligned} y_{ift} = & (D_{ift}^T)' \tau_O^T + (D_{it}^E)' \tau_O^E + (D_{ift}^T)' \Pi_O^T G_i + (D_{it}^E)' \Pi_O^E G_i \\ & + \sum_{s \in \{D, G\}} \Delta_{o_i}^s \left[(D_{ift}^T)' \gamma_O^{T,s} + (D_{it}^E)' \gamma_O^{E,s} \right] \\ & + \alpha_i + \psi_f + \alpha_t + \varepsilon_{ift}. \end{aligned} \quad (19)$$

The specification retains the baseline tenure and experience categories, occupation-group profiles, and worker, firm, and year fixed effects. Standard errors are clustered by four-digit occupation.

Because occupational exposure is constant within each worker, the churn level terms are absorbed by worker fixed effects. We therefore focus on the interaction coefficients, normalized to zero in year 1. The coefficient $\gamma_{O,k}^{T,s}$ compares the churn gradient at tenure category k with that at tenure year 1, holding experience fixed; $\gamma_{O,k}^{E,s}$ provides the analogous comparison across experience categories, holding tenure fixed.⁸

This exercise asks whether the conditional profile differences remain visible without changes in assigned occupational exposure. It allows adjustment within occupations, including through employer changes, but conditions on occupational survival. Selective retention and the occupation-specific calendar-time concerns discussed in Section 4.2 therefore remain relevant.

4.5.3 Occupational moves

The third exercise examines outcome dynamics around occupation switches. Let g_i denote the calendar year of the switch used to index worker i 's event window. For skill dimension

⁸The supplementary APE curves in Online Appendix Figure OA0.5 depend on the normalization of the absorbed churn level terms. Their absolute levels are not separately identified in the occupation-stayer sample.

$s \in \{D, G\}$, define the change in assigned exposure as

$$\Delta\Delta_i^s \equiv \Delta_{o_{i,g_i}}^s - \Delta_{o_{i,g_i-1}}^s, \quad s \in \{D, G\}, \quad (20)$$

where o_{i,g_i} is the destination occupation and o_{i,g_i-1} is the origin occupation. For event times in the estimation window, we estimate

$$\begin{aligned} y_{it} = & \alpha_i + \alpha_t + \sum_{k \neq -1} \mathbf{1}\{t - g_i = k\} [\beta_k^D \Delta\Delta_i^D + \beta_k^G \Delta\Delta_i^G] \\ & + X'_{it}\delta + \varepsilon_{it}, \end{aligned} \quad (21)$$

where t denotes calendar year, $k = -1$ is the omitted pre-switch year, and X_{it} contains time-varying controls. Worker and calendar-year fixed effects absorb permanent worker differences and common year shocks. We estimate the equation separately for log wages, continuing education, and prescription use, both for the full sample of switchers and for the high-ability subsample.

The coefficient β_k^s measures how the outcome change relative to the pre-switch year varies with a one-unit larger change in churn exposure, conditional on the other churn change and the included controls. The leads describe differential outcome dynamics before the move; the post-switch coefficients describe their subsequent evolution. These coefficients concern changes around occupational moves and therefore have a different interpretation from the baseline tenure and experience interactions or category-specific APEs.

In the model, a move changes the environment in which portable knowledge is used, while a simultaneous employer change can require rebuilding knowledge of firm-specific systems and routines. The joint outcome responses assess whether moves toward different skill environments are associated with changes in wages, formal learning, and health-related treatment consistent with these mechanisms. Because moves and destinations are chosen, the estimates remain descriptive. Pre-switch dynamics can reflect preparation and selection, and the static model does not predict the precise timing of education or prescription responses.

5 Data

We combine Danish administrative records from Statistics Denmark with occupation-level measures of skill change constructed from online job postings and individual-level prescription data from the Danish Health Data Authority. This section describes each data source, the construction of the skill-churn and mental-health measures, the definitions of tenure and experience, and the sample selection criteria.

5.1 Administrative data

Our core data come from four registers maintained by Statistics Denmark (DST), which we link at the individual level using anonymized person identifiers. The Integrated Database for Labour Market Research-Persons (IDAP) provides annual information on primary employment, including workplace identifier, 4-digit ISCO occupation code, industry, and employment status. The Integrated Database for Labour Market Research-Income (IDAN) records annual wage and salary income. The Population Register (BEF) supplies demographic characteristics such as date of birth, sex, municipality of residence, and family structure. The Education Register (UDDA) records highest completed education.

We use these registers for the period 2010–2023 and restrict attention to individuals aged 24 to 60 in a given year. The age restriction excludes the majority of students and early retirees, focusing the sample on the prime working-age population.

We supplement the register data with individual-level prescription records obtained from the Danish Health Data Authority, which we merge to the administrative records using the same anonymized identifiers. These records cover all prescriptions dispensed at Danish pharmacies and allow us to construct the stress-related morbidity indicators described in Section 5.4.

5.2 Job posting data and skill measurement

We measure occupation-level skill demand using online job postings from Jobindex, Denmark’s largest online job board. The posting data, obtained through the Danish consultancy firm Højbjerg Brauer Schultz (HBS Economics), span the period from 2006 through 2023 and cover the near universe of Danish job postings.

We classify each posting’s skill content using the framework developed in Zhu and Hardt (2025), which treats skill extraction as a multi-label classification problem solved with large language models (LLMs). The starting point is a training set of 986 Danish job postings that were manually annotated by domain experts across 17 binary skill categories. Using these annotations, Zhu and Hardt develop a prompting strategy in which the LLM reads the full posting text and returns, for each category, a binary prediction together with a supporting text snippet that grounds the classification in the source material. To reduce false positives, the framework exploits the model’s own confidence scores (log probabilities): predictions whose confidence falls below an optimized threshold are reclassified as negative. A fine-tuned version of the model achieves 93 percent classification accuracy in three-fold cross-validation, compared with 73 percent for traditional keyword-matching methods. The accuracy gain arises because LLMs can interpret context-dependent language, for instance, distinguishing a posting that requires data-analysis skills from one that merely mentions

data in passing, whereas keyword methods treat all occurrences identically. We apply the fine-tuned classifier to the full corpus of approximately 4.3 million Jobindex postings using OpenAI’s GPT-4.1 model.

We organize the resulting skill indicators into two broad groups. The first group consists of eight digital skill categories, seven of which follow the taxonomy in Nania et al. (2019): software and programming, data analysis, digital design, customer relationship management (CRM), digital marketing, machining and manufacturing technology, and productivity software. We add an eighth category, artificial intelligence (AI), to capture the rapid diffusion of AI-related requirements over the sample period. The second group consists of nine general (non-digital) skill categories following the taxonomy in Deming and Kahn (2018): cognitive, social, management, financial, character, writing, customer service, project management, and people management.

5.3 Measuring digital and general skill change

Following Deming and Noray (2020), we measure changes in skill demand within each occupation by tracking how the composition of demanded skills in job postings evolves over time. Let o index 4-digit occupations and t years. For each occupation o , year t , and digital skill $x \in \mathcal{X}^D$, we compute the share of postings requiring that skill as

$$s_{o,t}^D(x) \equiv \frac{\# \text{ postings in } o \text{ at } t \text{ requiring digital skill } x}{\# \text{ all postings in } o \text{ at } t}.$$

Analogously, for each general skill $x \in \mathcal{X}^G$ we define

$$s_{o,t}^G(x) \equiv \frac{\# \text{ postings in } o \text{ at } t \text{ requiring general skill } x}{\# \text{ all postings in } o \text{ at } t}.$$

We focus on long-run changes between 2010 and 2023. Let

$$\Delta_o^D(x) = s_{o,2023}^D(x) - s_{o,2010}^D(x) \quad \text{for } x \in \mathcal{X}^D, \quad \Delta_o^G(x) = s_{o,2023}^G(x) - s_{o,2010}^G(x) \quad \text{for } x \in \mathcal{X}^G.$$

In the spirit of Deming and Noray (2020), we summarize the overall amount of “churn” in digital and general skills within occupation o as

$$\Delta_o^D = \sum_{x \in \mathcal{X}^D} |\Delta_o^D(x)|, \tag{22}$$

$$\Delta_o^G = \sum_{x \in \mathcal{X}^G} |\Delta_o^G(x)|. \tag{23}$$

These measures capture the total change in the composition of digital and general skills

demanded within each occupation over the 2010–2023 period, counting both the appearance of new skill requirements and the disappearance of previously demanded ones. In the main analysis, we treat Δ_o^D and Δ_o^G as continuous, time-invariant occupation-level treatments.

The churn measure should therefore be interpreted as a long-run characteristic of the occupation rather than a contemporaneous year-by-year shock. When assigned to current occupation, it captures exposure to working in an occupation that is structurally more fast-changing. In the worker–firm panel, we denote by o_{it} the 4-digit occupation held by worker i in year t , and we always evaluate these measures at the worker’s current occupation, i.e. as $\Delta_{o_{it}}^D$ and $\Delta_{o_{it}}^G$.

5.4 Measurement of stress-related morbidity

Because register data do not contain subjective stress perceptions or symptom scales, we operationalize stress-related morbidity rather than stress per se. In medicine and psychosomatic research, chronic psychosocial stress is understood as a multi-system process: threats to homeostasis activate neuroendocrine and autonomic responses, and repeated or dysregulated activation can generate “wear and tear” across body systems (allostasis/allostatic load), contributing to both mental and somatic conditions (McEwen, 1998; Chrousos, 2009; Schneiderman et al., 2005; Cohen et al., 2007).

Consistent with this framework, we track prescription-based indicators spanning (i) affective and sleep-related symptoms, and (ii) common somatic manifestations of stress-system dysregulation. The included categories map to well-established stress-linked domains in the medical literature: depression/stress and sleep disturbance (Cohen et al., 2007; Han et al., 2012); cardiovascular risk including hypertension (Steptoe and Kivimäki, 2012; Liu et al., 2017); functional gastrointestinal symptoms via brain–gut mechanisms (Mönnikes et al., 2001); chronic pain pathways in which stress and pain mutually reinforce one another (Timmers et al., 2019); and alcohol/substance-use vulnerability and relapse risk (Sinha, 2008). By using a broader set of outcomes, we reduce the risk that stress-related health consequences are missed simply because they present somatically rather than as a recorded psychiatric diagnosis. This is particularly important if some groups are less likely to enter psychiatric diagnosis or treatment for comparable symptoms; for example, Franco et al. (2026) provide evidence that men are less likely than women to recognize depression and seek specialist help for equivalent depressive symptoms.

We obtain the underlying prescription records from the Danish Health Data Authority and construct a composite extensive-margin indicator that equals one if an individual is prescribed any medication in any of the above categories within a year.⁹ In the full sample,

⁹We identify drug categories using ATC codes: anxiolytics (ATC3 = N05B), depression medications (ATC3 = N06A), sleep medications (ATC3 = N05C), gastrointestinal medications (ATC3 = A03B or ATC2

the mean of this composite indicator is approximately 0.30, indicating that nearly one in three worker-year observations involves at least one prescription in a stress-linked category.

5.5 Tenure and experience measures

We distinguish between firm-specific tenure and accumulated labor-market experience, following the distinction between general and firm-specific human capital in the wage literature (e.g., Topel, 1991).

We define firm tenure as the number of years a worker has been continuously employed with the same firm. Changing firms resets tenure. In the estimation, we top-code tenure at $K^T = 10$ years, so the highest category includes workers with ten or more years of tenure.

We define labor-market experience as actual accumulated employment experience in the administrative records, regardless of occupation or employer. Periods of non-employment do not add to this measure, while experience accumulated in previous jobs is retained following firm or occupation changes. In the estimation, we top-code experience at $K^E = 20$ years, so the highest category includes workers with twenty or more years of accumulated employment.

These employment-history measures serve as proxies for distinct dimensions of human capital: experience captures opportunities to accumulate portable knowledge and skills across jobs, while tenure captures opportunities to develop knowledge and skills specific to the current firm.

5.6 Continuing education

We measure participation in adult and continuing education using the VEUV registers from Statistics Denmark. VEUV records individuals' participation in formal adult and continuing education courses, including external education activities that are publicly financed, governed, or organized. The register is recorded at the individual-course level and contains information on the person participating in the course, the educational institution, the course or education code, the start and end dates of the course, the activity scope, and the way in which the course was completed.

We use VEUV to construct measures of continuing education and retraining during the worker's employment history. In the main analysis, we define an indicator for whether worker i participates in at least one adult or continuing education course in year t . In supplementary specifications, we use the number of course spells and course intensity to capture the extensive and intensive margins of training. When relevant, we distinguish courses by education or course type using the register's course and education classifications.

= A03), pain medications (ATC2 = N02), alcohol and substance abuse treatments (ATC4 = N07BB), and hypertension medications (ATC2 = C02–C09).

Because VEUV covers formal adult and continuing education, these measures do not capture informal on-the-job training or firm-internal learning activities that are not registered as formal course participation.

5.7 Firm Innovation Data

We measure firm-level innovation activity using the Danish register/survey data on firms' research, development, and innovation activities, FUI/FORSK (Virksomheders forskning, udvikling og innovation), maintained by Statistics Denmark. The FUI data are collected to measure research and development (FoU) and innovation activity in the Danish business enterprise sector. The survey follows the international Frascati framework for business sector R&D statistics and covers private-sector business enterprises, excluding private non-profit organizations. Public-sector research institutions, higher education institutions, and private non-profit research units are covered by separate public-sector R&D statistics rather than the business-sector FUI file.

A central feature of FUI/FORSK is that it is not a universal administrative register of all Danish firms. Instead, firms are sampled from the business population according to firm size and industry. Large firms are selected with certainty conditional on belonging to the eligible FUI sampling frame. In the recent documentation, Statistics Denmark describes the certainty-sampling rule as covering firms with at least 100 employees or turnover above DKK 1 billion, while smaller firms are sampled with probabilities that decline with firm size and vary across industries. FUI-intensive industries receive higher sampling coverage than industries with lower expected R&D or innovation activity.

Our analysis focuses on firms for which the FUI data provide a credible firm-level measure of innovation activity. We therefore restrict the firm sample to large firms that respond to FUI. Specifically, we retain firms with more than 100 full-time-equivalent employees and a valid FUI response in the relevant year. This restriction has two advantages. First, it focuses the analysis on firms that are close to the certainty-sampled part of the FUI frame, reducing concerns that observed FUI participation is driven by endogenous survey selection. Second, it ensures that the innovation measure is observed rather than inferred. In our data, approximately 90 percent of firms satisfying the large-firm criterion respond to FUI, so the analysis is conducted within the part of the firm population where FUI coverage is high.

The key firm-level innovation variable is `INNO_U`. Statistics Denmark defines `INNO_U` as innovation expenditures excluding expenditures on the firm's own R&D. Thus, `INNO_U` captures resources devoted to innovation activities outside own R&D expenditures. Conceptually, this variable is useful for our purposes because it identifies firms that undertake innovation-related upgrading even when the upgrading is not recorded as own R&D. In the empirical analysis, we use `INNO_U` to define a firm-level innovation-upgrading event.

Let $INNO_{ft}$ denote whether firm f reports positive innovation expenditures excluding own R&D in year t . We define the innovation-upgrade year, T_f^U , as the first year in which firm f records positive innovation expenditures according to this measure, subject to the firm being observed as a large FUI respondent. In the event-study analysis below, this first observed upgrade year anchors the timing of the firm innovation event. Workers employed at firm f are assigned event time relative to this firm-level upgrade year.

Because $INNO_U$ is observed only for FUI respondents, our estimates should be interpreted as effects for large FUI-responding firms rather than for the universe of Danish firms. This is a deliberate design choice. It avoids treating missing FUI responses as zero innovation activity and restricts the analysis to firms for which the innovation-upgrade measure is directly observed.

5.8 Sample selection

The estimation sample is constructed by merging the administrative records, job-posting-based skill measures, and prescription data described above. We impose the following restrictions. First, we restrict to individuals aged 24 to 60 in each year, focusing on the prime working-age population and excluding most students and early retirees. Second, we require that individuals hold wage employment as their primary labor market status in the IDAP register, excluding the self-employed and individuals outside the labor force. Third, we require that the individual’s 4-digit occupation can be matched to the job-posting data, so that both digital and general skill churn measures are available. Occupations with too few postings to compute reliable skill shares are excluded. Fourth, we require non-missing wage information in the IDAN register.

After these restrictions, the full sample contains approximately 24.2 million worker-year observations covering roughly 2.9 million workers at 256 thousand firms over the period 2010–2023. The private-sector subsample, which excludes public-sector employment, contains approximately 14.4 million observations, 2.1 million workers, and 247 thousand firms. When we consider exercises that involve ability, defined from high school grades, we restrict the population to those born after 1959.

5.9 Summary statistics

Table 2 reports means and standard deviations for the full sample and the private-sector subsample. Mean annual wages are approximately 371,000 DKK in the full sample and 394,000 DKK in the private sector, with substantially larger dispersion in the latter (SD 342,000 vs. 296,000). Workers average roughly 18 years of labor market experience and between 4.6 and 4.8 years of firm tenure. The two samples differ most in demographic

composition: the full sample is 51 percent female, whereas the private-sector subsample is 38 percent female, reflecting the concentration of women in public-sector employment. Educational attainment is slightly lower in the private sector (14.3 vs. 14.7 years).

The churn measures, evaluated at the worker level, confirm the patterns described in Section ‘5.3’. General churn is roughly four times as large as digital churn (means of 0.87 and 0.20 in the full sample), partly because general skills span more categories and have higher baseline prevalence in postings. The private-sector subsample exhibits the same pattern at comparable magnitudes, with slightly higher digital churn (0.22 vs. 0.20) and slightly lower general churn (0.82 vs. 0.87). We focus on private-sector employees in the empirical analysis.

Tables 3 and 4 illustrate variation in digital and general churn across four-digit occupations by listing the occupations with the highest and lowest values of each measure. High digital churn is not confined to information-technology occupations. It also appears in technical, production, military, sales, administrative, and scientific occupations, indicating changes in digital skill requirements across a broad set of work environments. High general churn identifies a different set of occupations, including military, production, mechanical, service, safety, and technical occupations, where non-digital skill requirements change substantially over the measurement window.

The comparison between the two rankings also shows that digital and general churn capture distinct dimensions of occupational change. Some occupations with very low digital churn have high general churn, and some occupations with low general churn have non-negligible digital churn. The low-churn occupations should therefore be interpreted as low-churn benchmarks for the specific dimension used in the ranking, not as occupations with stable skill requirements in all respects.

Tables 5 and 6 repeat this exercise for professional occupations. This restriction is useful because it shows that meaningful variation remains within a more comparable segment of the labor market. The professional occupation tables therefore help rule out the concern that the main variation is driven only by broad differences between professional and non-professional work, or between manual and non-manual jobs. This variation is relevant to the specification in Section 4.1, which includes one-digit occupation-group-specific experience and tenure profiles. The descriptive evidence therefore supports the claim that the identifying variation comes from differences in exposure to digital and general skill churn across detailed occupations, rather than only from composition differences across major occupational groups.

6 Results

6.1 Profiles

The baseline results are consistent with the usefulness of accumulated firm knowledge depending on which occupational skill requirements change. In Figure 1, the association between occupational digital skill churn and log wages generally becomes more positive across tenure categories, while the association with general skill churn becomes more negative, holding accumulated employment experience fixed. These differences emerge across the tenure range. For workers with ten or more years of tenure, the interaction coefficients are approximately 0.04 and -0.014 , respectively, both statistically significant. To put these magnitudes on a comparable scale, we use occupation-level standard deviations of approximately 0.22 for digital churn and 0.75 for general churn. After scaling by these standard deviations, the wage difference associated with higher occupational churn is approximately 0.009 log points more positive for digital churn and 0.010 log points more negative for general churn than in the first tenure year.

Useful incumbent knowledge could help workers meet changing requirements with less additional formal learning. This interpretation fits the positive wage interactions and generally negative course-participation interactions between digital skill churn and tenure. Familiarity with existing systems and workflows may help workers incorporate new requirements into their jobs. For general skill churn, negative wage interactions accompany increasingly positive education interactions at longer tenure. Within the framework, this combination can arise when formal learning partly offsets the declining usefulness of existing knowledge. Greater course participation may therefore reflect investment in maintaining task fit, with benefits appearing as losses avoided.

The prescription evidence is less decisive about the demands accompanying these adjustments. Interactions between digital skill churn and tenure are imprecisely estimated for prescription use. The corresponding interactions for general skill churn are positive and statistically significant at several intermediate tenure durations. The results therefore provide clearer evidence about differences in wages and formal learning than about differences in strain. The framework allows useful incumbent knowledge to improve task fit while putting that knowledge to work entails demanding implementation. More favorable wage associations consequently need not imply less demanding adjustment.

The APEs in Figure 2 provide complementary evidence about observed groups. Among longer-tenure workers, greater digital skill churn in their occupation is associated with higher wages, less formal-education participation, and lower prescription use. Using the occupation-level standard deviations stated above, a one-standard-deviation difference in digital churn is associated with approximately 0.6 percent higher wages at low tenure and 1.1 percent higher

wages at high tenure. General skill churn displays the opposite associations: at high tenure, a one-standard-deviation difference is associated with approximately 0.7 to 0.8 percent lower wages, although the general-churn wage APEs are imprecisely estimated. In several longer-tenure categories, a one-standard-deviation difference in occupational digital skill churn is associated with stress-related prescription use approximately 0.1 to 0.2 percentage points lower; the corresponding estimates for general skill churn indicate use approximately 0.2 to 0.3 percentage points higher. These associations are consistent with different adjustment demands among observed workers, while the conditional prescription interactions leave their relationship with tenure less firmly established. The evidence concerning portable knowledge is weaker. Wage interactions between occupational churn and accumulated employment experience are imprecise, and the predominantly negative prescription interactions do not follow the benchmark’s prediction of nonnegative strain–experience tilts. This comparison remains subject to the distinction between treatment use and latent strain discussed in Section 4.2. The clearest baseline evidence concerns the joint wage and education associations over firm tenure.¹⁰ Sorting, selective retention, and occupation-specific calendar developments remain possible contributors to these patterns.

6.2 Sorting across occupations and firm environments

The sorting results suggest that workers’ measured adaptation capacity is related to the occupational skill changes they encounter. Conditional on the included controls, workers in the high-ability group have greater digital skill churn and lower general skill churn in both their first and last observed occupations (Table 7). The association with final digital churn remains after conditioning on initial exposure: the high-ability coefficient is 0.0142, approximately 0.06 of the occupation-level standard deviation. The corresponding general-churn coefficient is -0.0238 and is not statistically significant at the 5 percent level.

Initial allocation therefore does not fully account for the association between measured ability and final digital churn. The remaining association can reflect which occupations workers move to and which they remain in during the observation window. Table 8 provides complementary evidence: higher initial and final digital churn are each associated with a higher conditional probability of belonging to the high-ability group, while the associations with general churn are negative. These patterns are consistent with adaptation capacity influencing which occupational environments workers enter and remain in. They do not establish whether this allocation reflects greater productive opportunities, lower adjustment costs, or differences in available alternatives.

¹⁰Appendix Figures A.2 and A.3 illustrate how the estimated tenure and experience contributions combine along continuing employment spells. Figure OA0.3 reports APEs without the broad occupational profile controls.

The firm-environment results are compatible with adaptation capacity being particularly useful where changing requirements must be integrated with established systems and routines. In Table 9, the high-ability coefficients for final digital-churn exposure combined with large-firm and old-firm status are 0.0153 and 0.0102, respectively, both statistically significant conditional on the corresponding initial exposure. The general-churn coefficients are small and imprecisely estimated. These outcomes combine occupational churn with firm type, so the estimates describe joint allocation across occupations and firms. Firm size and age also provide only indirect information about the production environments in which adaptation takes place.

The restricted sample with valid innovation information provides less decisive evidence. The high-ability coefficients for exposure combining occupational churn with innovation-active firm status are small and statistically insignificant for both skill types. Their signs alone do not establish an additional sorting pattern associated with innovation activity.

The sorting evidence makes worker allocation and retention relevant to interpreting the preceding outcome profiles. Workers with different measured capabilities encounter different combinations of occupational skill change and firm environment, potentially shaping both adjustment demands and the usefulness of accumulated knowledge. The following subsection examines whether the associations between occupational churn and worker outcomes also differ across ability groups and firm environments.

6.3 Heterogeneous churn profiles

Familiarity with the current firm may help workers meet changing occupational requirements with less additional formal learning. In Figure 3, this interpretation fits the results for workers outside the high-ability group: the association between occupational digital skill churn and wages becomes more positive across tenure categories, holding experience fixed, while the association with course participation becomes more negative. The prescription interactions remain comparatively close to zero. For scale, at ten or more years of tenure, the digital-churn interactions multiplied by its standard deviation are approximately 0.010 log points for wages and -0.6 percentage points for course participation, relative to the first tenure year.¹¹

For the high-ability group, the more pronounced wage pattern appears over accumulated employment experience. Positive interactions between occupational digital skill churn and experience emerge across much of the career, accompanied by greater formal-education participation over the middle experience categories. At twenty or more years of experience, the wage interaction corresponds to approximately 0.031 log points for a one-standard-deviation

¹¹The corresponding APEs are reported in Online Appendix Figures OA0.2 and OA0.1.

difference in digital churn, relative to the first experience year and holding tenure fixed. Formal learning may therefore complement portable capabilities along this dimension. The positive wage interactions extend beyond the benchmark’s erosion-only treatment of portable knowledge in Equation (7), pointing to possible learning complementarities or sorting across career paths. The estimates do not identify education’s contribution to wages.

General skill churn is associated with a different role for formal learning, particularly among workers outside the high-ability group. Negative wage interactions with tenure accompany positive education and prescription interactions across the later tenure categories. This combination fits adjustment in which learning helps maintain task fit while the usefulness of existing knowledge declines. Greater course participation can therefore signal the demands of preserving productive capacity, even where relative wage outcomes weaken.¹²

The firm comparisons indicate why useful incumbent knowledge need not imply adjustment with fewer demands. In Figure 4, the positive wage interactions between occupational digital skill churn and tenure generally have larger point estimates in the two large-firm groups. This pattern is consistent with greater scope for familiarity with established systems and workflows to help workers meet new requirements. However, in large innovating firms, positive wage interactions often accompany positive prescription point estimates, with less precisely estimated prescription responses across the tenure range. At ten or more years of tenure, the interactions for a one-standard-deviation difference in digital churn correspond to approximately 0.015 log points for wages and 0.4 percentage points for prescription use, both relative to the first tenure year.

Together with the generally negative education point estimates, this pattern is consistent with the demanding-implementation case in Table 1. Useful firm knowledge can reduce mismatch while putting that knowledge to work adds strain. If formal education also adds net strain, implementation demands can make further training less attractive; a positive wage interaction remains possible when the usefulness of incumbent knowledge outweighs the productive cost of reduced training. The estimates do not establish these mechanisms, but they show why the wage association alone cannot characterize adjustment demands. For general skill churn, the combination of negative wage and positive education and prescription interactions is most evident in small firms.

These comparisons suggest that the roles of accumulated knowledge and formal learning depend on both worker characteristics and the production environment. Differences between groups remain descriptive, sorting and retention can contribute to the profiles, and prescriptions measure treatment rather than latent strain. The following event studies examine whether outcome changes around firm upgrading vary with workers’ pre-event occupational

¹²Figure 3 also shows increasingly positive interactions between occupational digital skill churn and tenure for occupational switching in both ability groups. Adjustment may therefore include occupational reallocation; remaining with a firm need not mean remaining in the same occupation.

churn, measured ability, and tenure.

6.4 Firm upgrading event study

Figure 6 points to relative wage preservation among high-ability workers with longer pre-event tenure. In the later post-event years, greater digital skill churn in workers' pre-event occupations is associated with negative wage changes among high-ability workers with shorter tenure, while the corresponding estimates for longer-tenure workers are closer to zero. These responses are measured relative to the year before upgrading and the comparison firms, using the design in Section 4.4. High tenure denotes at least five years with the baseline employer.

Figure 7 reports the additional ability–tenure interaction: the high- versus low-tenure difference in the outcome response associated with occupational digital churn among high-ability workers, net of the corresponding difference among other workers. For wages, this interaction is positive after upgrading, with the clearest evidence two years after the event. At $k = 2$, the coefficient is approximately 0.6, equivalent to 0.13 log points for a 0.22 difference in digital churn, and its 95% confidence interval excludes zero. It remains positive but less precise at $k = 3$. The group-specific estimates show that this relative advantage partly reflects more adverse wage responses among high-ability workers with shorter tenure.

Relative wage preservation accompanies a negative additional ability–tenure interaction in continuing education from the upgrading year onward. At $k = 1$, this interaction corresponds to approximately -5.5 percentage points for the same churn difference, with a 95% confidence interval below zero. These joint differences are consistent with incumbent knowledge helping workers meet new requirements with less additional formal retraining. Learning outside registered courses or implementation demands that make further coursework costly could also contribute. The prescription interactions are imprecise throughout the post-event period, leaving the associated strain response unresolved. The joint outcomes therefore support a role for useful incumbent knowledge without identifying how learning contributes to wage outcomes.

Employment outcomes place an important limit on this interpretation. Greater occupational digital churn is associated with higher post-event unemployment within the high-ability, high-tenure group itself. The additional ability–tenure interaction is also positive, reaching approximately 1.8 percentage points at $k = 3$ for the same churn difference, with a 95% confidence interval above zero. Relative wage preservation among observed earners can therefore coexist with employment losses within this group. Changes in who remains employed may contribute to the wage pattern alongside any value of incumbent knowledge. The imprecise firm- and occupation-switching interactions also leave the contribution of reallocation unresolved.

The general-churn estimates in Figure 8 vary across groups and event years, without

a clear joint pattern across wages, education, and employment. Some wage estimates are economically sizeable despite their imprecision, so the results leave room for meaningful responses. Comparisons with the digital-churn findings remain descriptive: establishing differences between the two would require a formal test of the standardized ability–tenure interactions.

The qualifications discussed in Section 4.4 also constrain interpretation. Upgrading episodes are selected, and some pre-event estimates depart from zero. Moreover, workers are followed after leaving the baseline employer, so subsequent wage observations can reflect earnings at other firms. These features limit how directly the observed relative wage preservation can be attributed to the value of incumbent knowledge within the upgrading firm.

6.5 Match quality, occupation stayers, and occupational moves

The three exercises described in Section 4.5 examine how match quality, occupational retention, and mobility shape the interpretation of the baseline profiles.

6.5.1 Match fixed effects

The APEs in Figure 5, estimated using Equation (18), broadly preserve the baseline joint pattern. The association between occupational digital churn and wages becomes more positive over the early tenure years and remains positive at longer tenure, while general churn is negatively associated with wages over much of the tenure range. The education and prescription APEs tend to move in the opposite direction: more negative with tenure for digital churn and more positive for general churn.

These patterns remain visible after absorbing permanent worker–firm differences in outcome levels. They are consistent with useful incumbent knowledge easing adjustment under digital churn, while formal learning partly offsets knowledge erosion under general churn. However, this specification does not separate tenure from experience accumulation, so the profiles cannot be attributed specifically to firm knowledge. Changing match value and selective retention also remain relevant.

6.5.2 Occupation stayers

The opposing wage–tenure patterns are less evident among workers who remain in the same four-digit occupation throughout the observation window. Appendix Figure A.4 reports the interactions from Equation (19). Holding experience fixed, the digital-churn wage interactions are modestly positive at longer tenure but imprecisely estimated, while the general-churn interactions remain close to zero.

Differences in formal learning and prescription use remain more visible. Relative to the first tenure year, the education interactions become negative for digital churn at longer tenure and are positive for general churn. The prescription point estimates mostly follow the same directions, although their precision varies. Occupational continuity therefore leaves room for different adjustment demands even where wage differences are muted. Workers can learn or change employers without changing occupation.

These estimates do not distinguish knowledge erosion from the continued usefulness of incumbent knowledge. Moreover, remaining in an occupation is itself selected. The weaker wage evidence in this sample therefore does not establish that occupational moves generate the stronger full-sample patterns. The calendar-time concerns in Section 4.2 also remain relevant.

6.5.3 Occupational moves

Figure 9 relates outcome changes relative to the pre-switch year to changes in occupational churn at the move, using Equation (21). Larger increases in digital churn are associated with more positive wage changes over the first few years after entry into the destination occupation, with the association persisting thereafter. The point estimates are larger among high-ability workers. The corresponding general-churn wage coefficients are weak or negative.

The education results suggest that adjustment can precede the move. Among high-ability workers, education differences associated with the change in digital churn are most visible several years before the switch and fade around entry. The subsequent wage pattern therefore develops without a sustained increase in observed formal education. Earlier education could reflect preparation or selection into destinations; these estimates do not identify its contribution to later wages.

Prescription outcomes also qualify the interpretation of wage improvements. In the full sample, the positive wage associations accompany declining prescription coefficients. Among high-ability workers, several post-switch prescription point estimates are positive, with varying precision. The framework permits improved task fit alongside greater implementation demands, so higher wages need not indicate lower strain. This provides one possible interpretation of the joint outcomes, while prescriptions measure treatment rather than strain directly.

The pre-switch coefficients are not uniformly flat, leaving preparation and endogenous destination choice central to the interpretation. These patterns describe adjustment around chosen occupational moves; they do not isolate the contributions of improved task fit, implementation demands, and selection.

6.6 Model implications and empirical evidence

Table 10 summarizes how the findings relate to the framework. The tenure results support a role for employees’ knowledge of their firm’s systems, routines, and workflows in adapting to new skill requirements. The digital results support the model’s prediction that changing requirements can create new uses for employees’ knowledge of existing firm systems and routines. Within the benchmark, the joint wage and education pattern implies that this contribution to meeting new requirements more than offsets the loss in relevance of previously acquired knowledge. Under general churn, the opposite pattern is consistent with erosion dominating and formal learning partly compensating for the declining relevance of existing knowledge.¹³

The firm-environment comparisons also support the model’s distinction between maintaining task fit and bearing the demands of implementation. In large innovating firms, positive digital wage–tenure interactions coexist with positive prescription point estimates and generally negative education point estimates. This combination is consistent with familiarity with the firm helping employees remain productive, while responsibilities for configuring systems, revising workflows, or helping colleagues adopt new tools add strain.

The framework fits the tenure evidence more closely than the experience evidence. Its benchmark treatment of portable knowledge allows churn to erode that knowledge but cannot explain the positive wage–experience interactions. The upgrading results impose a further qualification: favorable wages among observed earners can coexist with employment losses, so wage preservation alone does not establish successful adjustment for the affected workers. The findings support a role for firm-specific knowledge and implementation demands without identifying their separate contributions or resolving selection. These interpretations remain subject to the identification and measurement assumptions discussed in Section 4.2.

7 Robustness

This section examines the measurement underlying our comparisons with the conceptual framework. We distinguish increases from decreases in recorded skill requirements, then examine demographic composition and separate medication categories within the prescription outcome. These exercises clarify which changes in requirements and which treatment outcomes account for the observed profile patterns.

¹³If the conditional profiles reflect the benchmark’s fixed-state interior tenure responses, and participation preserves the signs of training-effort interactions, their joint signs imply $\kappa_D < 0$ and $\kappa_G > 0$. These restrictions concern the net balance $\kappa_s = \delta_s^T - b_s$; they neither identify its components separately nor establish that $b_D > b_G$. Opposing training responses are compatible with the same worker–firm state and common training parameters: for example, with $\eta < 1$, they arise when $\kappa_D + \ell_D < 0 < \kappa_G + \ell_G$.

7.1 Directionality in the churn index

The baseline churn measure sums absolute changes in skill shares, following Deming and Noray (2020), and therefore treats increases and decreases symmetrically. To distinguish these directions of change, as in Acemoglu et al. (2022), we separate each index into expansion and contraction components. For skill dimension $s \in \{D, G\}$, define

$$\Delta_o^{s,+} = \sum_{x \in \mathcal{X}^s} \max\{s_{o,2023}^s(x) - s_{o,2010}^s(x), 0\},$$

and

$$\Delta_o^{s,-} = \sum_{x \in \mathcal{X}^s} \max\{s_{o,2010}^s(x) - s_{o,2023}^s(x), 0\}.$$

These components sum increases and decreases in posting shares between 2010 and 2023. Their sum equals the baseline index:

$$\Delta_o^s = \Delta_o^{s,+} + \Delta_o^{s,-}.$$

We replace the baseline churn measures with their directional components, retaining the experience and tenure interactions and controls in Equation (10).

The components describe changes in the prevalence of recorded requirements. Because a posting can require several skills, the shares need not sum to one: an increase in one category does not mechanically require a decrease in another. Changes may also reflect the composition of vacancies or how requirements are described. Expansions and contractions therefore do not directly measure technology adoption or the erosion of workers' knowledge.

Figures 10 and 11 report the corresponding APEs. The appropriate baseline comparison is Figure 2. As explained in Section 4.1, each tenure-indexed APE averages over the experience distribution observed in that tenure category, and conversely for experience-indexed APEs. Differences across categories therefore do not isolate the conditional tenure or experience interactions.

For digital expansions, wage APEs are positive across tenure categories and generally become more positive at longer tenure. Education and prescription APEs are negative along the tenure profile, although precision varies. These patterns resemble the baseline digital APEs. Digital contractions yield less precise wage estimates, with point estimates rising from negative values at short tenure toward zero or positive values at longer tenure. Their education APEs are mostly close to zero along tenure, while prescription APEs become positive in the longest-tenure categories. Thus, the contraction profiles do not reproduce the full joint pattern observed for digital expansions.

For general expansions, wage APEs become more negative across tenure categories, while

education APEs are positive and generally larger at longer tenure. Prescription APEs are also positive beyond the first tenure category. General contractions produce wage estimates close to zero and mostly imprecise prescription estimates. Their education APEs, however, are positive across tenure categories. The evidence therefore does not support describing contraction-related associations as uniformly weaker across outcomes.

The expansion profiles reproduce the main digital–general contrast in the baseline APEs. In particular, the adverse wage associations for general churn also appear when measured requirements expand. This is compatible with the framework in Section 3: new requirements can reduce the relevance of previously acquired knowledge, while also creating new uses for employees’ knowledge of existing firm systems and routines. Declining posting shares are therefore not necessary for knowledge erosion. The directional decomposition clarifies the changes associated with the observed patterns, but does not separately identify knowledge erosion, the contribution of incumbent knowledge, or implementation demands.

7.2 Stress-related prescriptions: composition checks and clinical components

We next examine the interpretation of prescription use as an indicator of the model’s latent strain. The broad outcome records prescription use in any of the categories defined in Section 5.4. We examine whether demographic composition varies along the churn-related profiles and whether the prescription patterns extend across medication groups.

For the composition exercises, we use age and an indicator for women as outcomes in Equation (10), omitting individual fixed effects. Sex is time invariant, while age is absorbed jointly by individual and year fixed effects. The specification retains the churn terms, experience and tenure profiles, occupation-group profile controls, and firm and year fixed effects. These regressions describe conditional demographic composition.

Figure 12 reports the interaction coefficients relative to year 1. Digital age–tenure interactions remain close to zero, while general age–tenure interactions become modestly positive at longer tenure. The age–experience estimates are less precise. For the female indicator, digital churn–experience interactions become negative at longer experience, and general churn–tenure interactions are negative beyond the reference category. Digital churn–tenure interactions are modestly positive over several intermediate categories.

External evidence helps interpret the direction of the demographic patterns. Danish register evidence documents higher antidepressant use among women (Møller, 2023), while prescription data from Denmark, Norway, and Sweden show higher tramadol use among women and generally increasing use with age (Schelde et al., 2020). To the extent that these sex differences also characterize our prescription indicators, the relative shift toward women

associated with digital churn at several intermediate tenure categories would, all else equal, tend to raise prescription use. It therefore offers no straightforward explanation for the negative digital somatic-prescription interactions through greater representation of workers with lower baseline treatment rates. Conversely, the relative shift away from women along the general-churn tenure profile would tend to lower prescription use, whereas the somatic interactions are positive.

The age diagnostics provide a more qualified picture. Digital age-tenure interactions remain close to zero, offering little indication that the negative somatic-prescription interactions reflect a substantial relative shift toward younger workers. General age-tenure interactions become modestly positive. Where prescription use increases with age, this pattern could contribute in the direction of higher prescription use. Although the implied age differences are small when scaled by a standard deviation of churn, their contribution cannot be quantified from the composition regressions alone. The age-experience estimates are less precise and provide weaker guidance about demographic composition along that dimension.

These comparisons are directional diagnostics. Individual and year fixed effects in the prescription regressions already absorb stable worker differences and a common linear age effect. Remaining demographic influences would involve nonlinear or sex-specific health trajectories, or selection associated with those trajectories. The diagnostics therefore help assess simple composition explanations without establishing that demographic influences are absent or that the prescription estimates are conservative. We then estimate the baseline specification separately for three prescription outcomes: psychiatric medications, comprising sleep medication, antidepressants, and anxiolytics; somatic medications, comprising the hypertension, gastrointestinal, and pain categories; and alcohol-dependence medications, defined by ATC category N07BB. Each regression includes individual fixed effects. The indicators can overlap, so their coefficients are not additive contributions to the broad prescription indicator.

Figure 13 reports the churn interactions relative to year 1. Tenure interactions hold accumulated employment experience fixed, while experience interactions hold tenure fixed.

The somatic component displays the clearest opposing digital and general tenure patterns. Digital interactions are negative over intermediate tenure categories, but do not become steadily more negative; the estimate at 10+ years is close to zero and imprecise. General interactions are positive beyond the reference category, with several confidence intervals excluding zero. The contrast is therefore evident over parts of the tenure distribution rather than widening uniformly with tenure. Along experience, somatic point estimates are predominantly negative for both churn measures, although many are imprecise.

The psychiatric component does not reproduce this opposing tenure pattern. Digital tenure interactions are generally nonnegative and become more positive in some later cate-

gories, while general tenure interactions are small and imprecise. Along experience, general interactions are mostly negative, whereas digital estimates are predominantly positive but imprecise. The broad indicator therefore combines medication groups with different profiles and should not be interpreted as a measure of psychiatric treatment alone.

The alcohol-dependence prescription estimates provide less systematic evidence. Tenure interactions vary in sign and are often imprecise. Some digital experience interactions are negative, but these results do not reproduce the digital–general tenure contrast observed for somatic prescriptions.

These findings locate the clearest opposing tenure interactions in somatic prescription use. The framework does not assign remaining mismatch, education demands, and implementation demands to distinct medication categories, so the component estimates cannot distinguish these sources of strain. Nor do medication categories establish the clinical cause of treatment. Relating prescription interactions to latent-strain interactions continues to require the measurement conditions in Appendix OA0.1.6, including restrictions on how morbidity and treatment translate strain into recorded prescription use.

Online Appendix Figures OA0.7 and OA0.6 report the corresponding APEs. These average churn gradients over the workers observed in each tenure or experience category and incorporate the contribution of the other employment-history dimension. Their shapes can therefore differ from the conditional interaction profiles. The exercises clarify the composition and scope of the prescription evidence, subject to the identification and measurement concerns discussed in Section 4.2.

8 Conclusion

This paper examines how changing occupational skill requirements are associated with workers’ career progression and the demands of adaptation. Using Danish employer–employee records for 2010–2023, we distinguish actual accumulated employment experience from firm tenure and examine wages, formal continuing education, prescription use, and employment outcomes. The clearest baseline evidence concerns tenure. Holding accumulated experience fixed, digital churn is associated with steeper wage–tenure profiles, while general churn is associated with flatter profiles. The associations with formal course participation generally become more negative for digital churn and more positive for general churn at longer tenure.

These joint patterns support a role for incumbent knowledge in meeting changing requirements. Under digital churn, stronger wage progression with less additional formal education is consistent with familiarity with existing systems, routines, and workflows helping employees adapt. Under general churn, greater formal learning accompanies weaker wage progression, consistent with education partly compensating for the declining relevance of

existing knowledge. The findings therefore extend an account of career progression based on learning and obsolescence: changing requirements can also create new productive uses for what employees already know. The education estimates do not identify the contribution of courses to earnings, however. Greater participation can reflect the effort required to prevent losses, while a weaker response in registered courses can coexist with substantial informal learning.

The prescription findings qualify what favorable wage progression implies for workers. This evidence is less decisive than the wage and education evidence. The clearest opposing digital and general tenure interactions occur in somatic prescriptions; psychiatric prescriptions do not reproduce the same contrast. Firm environments also matter. In large innovating firms, positive digital wage–tenure interactions coexist with positive prescription point estimates. This combination is consistent with the framework’s distinction between maintaining task fit and bearing the demands of implementation. Knowledge of the firm can help employees remain productive, while configuring systems, revising practices, and supporting colleagues creates additional responsibilities. The estimates do not directly measure those responsibilities or establish their health consequences, but they show why earnings alone provide an incomplete assessment of adjustment.

Worker heterogeneity also limits a single account of career progression. Outside the high-ability group, the favorable digital wage pattern is clearest over tenure. Among high-ability workers, positive digital wage interactions are more prominent over accumulated employment experience. This latter pattern extends beyond the benchmark’s treatment of portable knowledge as subject to erosion and leaves room for productive uses of portable capabilities, learning complementarities, and selection across career paths. Sorting and occupational moves reinforce the importance of allocation: high-ability workers encounter greater digital churn, and moves involving larger increases in digital churn accompany more positive subsequent wage changes. Preparation and chosen destinations remain relevant to these patterns.

The firm-upgrading evidence adds an important employment qualification. Under digital churn, high-ability workers with longer pre-event tenure exhibit relative wage preservation, partly reflecting more adverse wage responses among their shorter-tenure counterparts. The additional ability–tenure interaction in formal education is negative, while prescription responses remain imprecise. Greater digital churn is nevertheless associated with higher post-event unemployment within the high-ability, high-tenure group itself. Favorable wages among observed earners can therefore coexist with employment losses. Selected upgrading episodes, some differential pre-event dynamics, and wage observations after departure from the baseline firm limit attribution of this relative wage preservation to incumbent knowledge within the upgrading firm.

The estimates describe conditional outcome profiles rather than structural returns to

knowledge. Worker, firm, and match fixed effects address stable differences, but cannot eliminate changing match value, selective retention, or unobserved occupational developments. The broad digital-general patterns remain visible with match fixed effects, although that specification does not separate tenure from experience accumulation. Wage-tenure differences are weaker among occupation stayers. These exercises help assess the interpretation without isolating the separate contributions of knowledge erosion, useful incumbent knowledge, learning, and implementation demands. Continuing education and prescriptions also capture particular dimensions of learning and health: the former omit informal learning, while the latter reflect treatment as well as morbidity.

The broader implication is that technological change reshapes careers through the changing usefulness of knowledge accumulated within firms. Alongside displacement and retraining for new jobs, adjustment takes place within continuing employment relationships, where new requirements can give existing expertise new uses or make it less relevant. Our findings are consistent with digital change creating productive uses for incumbent knowledge, while continuing education under general skill change partly compensates for its declining relevance. The type of skill change and the firm environment therefore matter for understanding adaptation. Favorable earnings, however, need not mean that adjustment is less demanding or employment more secure. Incumbent knowledge is not merely at risk from technological change: for some workers, changing requirements can make it more valuable. Preserving that value need not eliminate the strain involved in putting it to use.

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Tables

Table 2: Descriptive statistics

	<i>All workers</i>		<i>Private sector</i>	
	Mean	SD	Mean	SD
Wage (1,000 DKK)	371.233	(296.044)	394.087	(342.133)
Age	42.662	(10.402)	42.022	(10.409)
Tenure	4.577	(5.935)	4.748	(6.181)
Experience	17.917	(11.144)	18.089	(11.292)
Years of education	14.654	(2.285)	14.326	(2.252)
Δ General skills	0.867	(0.548)	0.824	(0.476)
Δ Digital skills	0.204	(0.160)	0.216	(0.152)
Public sector	0.406	(0.491)	0.000	(0.000)
Female	0.510	(0.500)	0.380	(0.485)
Mental health prescriptions	0.318	(0.466)	0.293	(0.455)
Continuing education	0.123	(0.328)	0.116	(0.321)
Observations	24.2 million		14.4 million	
Workers	2,893,616		1,772,271	
Firms	255,863		246,488	

Table 3: Top and bottom occupations by **digital** skill churn

Highest churn occupations	Digital	General	Lowest churn occupations	Digital	General
Management of agricultural and forestry production	1.20	1.97	Food and beverage production work	0.00	4.52
Meteorology work	1.14	1.98	Sports and fitness work	0.00	4.00
Internet technician work	1.11	0.89	Waiters and bartenders	0.00	0.89
Marine fishing work	1.11	2.33	Service and sales work	0.01	1.77
Information and communications technology technician work	1.07	4.20	Waiting staff work	0.02	0.86
Mechanic work	1.05	4.45	Manual food preparation work	0.02	0.73
Military work at non-commissioned officer level	1.02	5.84	General service work	0.03	0.65
Operation of packing, filling, and labeling machinery	1.00	1.50	Social and health care work in private homes (incl. nursing homes)	0.03	1.02
Artistic work in the visual arts	0.95	1.42	Train driving work	0.03	0.00
Technical and medical sales work (excluding ICT)	0.92	3.58	Cleaning work in private homes	0.04	1.89
Sales, marketing, and PR work	0.89	0.98	Butchery, fishmongering, and related food production work	0.04	0.72
Pre-press work and graphic form production	0.86	1.03	General office work in statistics, financial transactions, and insurance	0.04	0.93
Military work at officer level	0.85	1.79	General receptionist work, excl. hotel receptionist work	0.04	0.68
Finishing and binding of printed products	0.83	1.91	Cook work (excl. head chef work)	0.04	1.08
Operation of pulp and paper product manufacturing machinery	0.83	1.39	Plumbing work	0.05	1.26
Physical science and engineering technician work	0.76	0.64	Medical imaging and treatment equipment technician work	0.05	1.25
Philosophy, history, and political science work	0.74	1.13	Biochemistry, biology, botany, zoology, and related work	0.05	1.46
Tax and duty legislation administration	0.74	1.97	Bartender work	0.05	0.89
Washing machine operator work	0.73	1.73	Dental care work	0.06	1.07
Public benefits administration	0.73	1.61	Kitchen assistance and related work	0.06	1.25

Notes: Occupations are ranked by the occupation-level digital skill churn measure within the estimation sample and for those occupations with at least 100 observations throughout the period 2010-2023. The left panel reports the occupations with the highest values of digital churn, and the right panel reports the occupations with the lowest values. General churn is reported for comparison but is not used for the ranking.

Table 4: Top and bottom occupations by **general** skill churn

Highest churn occupations	Digital	General	Lowest churn occupations	Digital	General
Military work at non-commissioned officer level	1.02	5.84	Train driving work	0.03	0.00
Military work, other ranks	0.66	5.01	Executive and management secretarial work	0.10	0.35
Food and beverage production work	0.00	4.52	Mechanical engineering work	0.11	0.19
Mechanic work	1.05	4.45	Cosmetology work and related functions	0.11	0.30
Information and communications technology technician work	1.07	4.20	Research, development, and advisory work in teaching methods	0.11	0.33
Meter reading and vending machine emptying	0.52	4.11	Auditing and accounting controller work	0.13	0.22
Sports and fitness work	0.00	4.00	Pharmaceutical work	0.16	0.23
Technical and medical sales work (excluding ICT)	0.92	3.58	Management of other business services and administrative functions	0.19	0.19
Telecommunications technician work	0.43	3.43	Industrial and production engineering work	0.20	0.23
Passenger travel service work	0.37	3.33	Web and multimedia development	0.22	0.23
Rubber product manufacturing operator work	0.50	3.25	Management work	0.24	0.35
Occupational health and safety work	0.60	2.87	Senior management in legislative authorities, companies, and organisations	0.25	0.33
Management of core activities in pedagogical work with and care for children	0.08	2.85	Corporate strategy/policy work	0.28	0.18
Customer service and cashier work in banks	0.42	2.75	Credit and lending work	0.31	0.33
Maritime technician work	0.50	2.58	Management in public administration and corporate strategy/policy	0.31	0.30
Metal forming and casting work	0.23	2.57	System administration	0.35	0.34
Air traffic control work	0.38	2.52	Other engineering work (excluding electrical engineering)	0.38	0.21
Marine fishing work	1.11	2.33	Systems analyst work	0.38	0.33
Judicial work	0.18	2.14	Product and fashion design work	0.48	0.23
Manual laundry and pressing work	0.35	2.13	Advertising and PR management	0.60	0.27

Notes: Occupations are ranked by the occupation-level general skill churn measure within the estimation sample and for those occupations with at least 100 observations throughout the period 2010-2023. The left panel reports the occupations with the highest values of general churn, and the right panel reports the occupations with the lowest values. Digital churn is reported for comparison but is not used for the ranking.

Table 5: Professionals: Top and bottom occupations by **digital** skill churn

Highest churn occupations	Digital	General	Lowest churn occupations	Digital	General
Meteorology work	1.14	1.98	Biochemistry, biology, botany, zoology, and related work	0.05	1.46
Artistic work in the visual arts	0.95	1.42	Religious work	0.08	1.31
Technical and medical sales work (excluding ICT)	0.92	3.58	Dentistry work	0.08	1.15
Sales, marketing, and PR work	0.89	0.98	Artistic work in music and singing	0.08	0.86
Philosophy, history, and political science work	0.74	1.13	Primary school teaching (incl. 10th grade)	0.09	0.99
Advertising and marketing work	0.62	0.50	Special education work	0.10	0.46
Journalistic work	0.62	0.52	General medical work	0.10	0.75
Sociology, anthropology, and related work	0.61	1.43	Mechanical engineering work	0.11	0.19
Occupational health and safety work	0.60	2.87	Research, development, and advisory work in teaching methods	0.11	0.33
Architecture, infrastructure, and design work	0.60	0.66	Analysis, product development, and maintenance work in finance and insurance	0.11	0.36
Engineering work (excluding electrical engineering)	0.59	0.88	Veterinary work	0.12	0.78
Teaching and pedagogical work	0.59	1.20	Pedagogical work	0.12	0.88
Graphic and multimedia design work	0.58	0.49	General teaching above primary school level	0.13	0.63
Physics and astronomy work	0.56	1.17	Auditing and accounting controller work	0.13	0.22
Complementary and alternative medicine work	0.54	1.74	Paramedical work	0.13	1.70
Database design and administration	0.53	0.45	Other teaching and pedagogical work	0.15	1.04
Landscape architecture work	0.51	1.65	Pharmaceutical work	0.16	0.23
Business administration work – private and public	0.49	0.67	Other music and singing teaching	0.17	0.78
Product and fashion design work	0.48	0.23	Acting work	0.17	0.84
Other teaching in creative subjects	0.47	1.87	Judicial work	0.18	2.14

Notes: Occupations are ranked by the occupation-level digital skill churn measure within the estimation sample and for those occupations with at least 100 observations throughout the period 2010-2023. The left panel reports the occupations with the highest values of digital churn, and the right panel reports the occupations with the lowest values. General churn is reported for comparison but is not used for the ranking.

Table 6: Professionals: Top and bottom occupations by **general** skill churn

Highest churn occupations	Digital	General	Lowest churn occupations	Digital	General
Technical and medical sales work (excluding ICT)	0.92	3.58	Corporate strategy/policy work	0.28	0.18
Occupational health and safety work	0.60	2.87	Mechanical engineering work	0.11	0.19
Judicial work	0.18	2.14	Other engineering work (excluding electrical engineering)	0.38	0.21
Teaching and pedagogical work not elsewhere classified	0.33	2.13	Auditing and accounting controller work	0.13	0.22
Meteorology work	1.14	1.98	Industrial and production engineering work	0.20	0.23
Other teaching in creative subjects	0.47	1.87	Web and multimedia development	0.22	0.23
Complementary and alternative medicine work	0.54	1.74	Pharmaceutical work	0.16	0.23
Paramedical work	0.13	1.70	Product and fashion design work	0.48	0.23
Landscape architecture work	0.51	1.65	Systems analyst work	0.38	0.33
Other work in arts and creative fields	0.36	1.53	Research, development, and advisory work in teaching methods	0.11	0.33
Midwifery work	0.26	1.47	System administration	0.35	0.34
Biochemistry, biology, botany, zoology, and related work	0.05	1.46	HR analysis and advisory work	0.35	0.36
Sociology, anthropology, and related work	0.61	1.43	Analysis, product development, and maintenance work in finance and insurance	0.11	0.36
Artistic work in the visual arts	0.95	1.42	Electronics engineering work	0.27	0.37
Optician/optometrist work	0.25	1.37	Chemical engineering work	0.25	0.37
Chemistry work	0.44	1.34	Staff development and training work	0.36	0.37
Religious work	0.08	1.31	Building architecture work	0.36	0.38
Teaching and pedagogical work	0.59	1.20	Electrical engineering work	0.27	0.38
Translation and other linguistic work	0.19	1.19	Software and applications development and analysis	0.32	0.39
Physics and astronomy work	0.56	1.17	Environmental engineering work	0.30	0.40

Notes: Occupations are ranked by the occupation-level general skill churn measure within the estimation sample and for those occupations with at least 100 observations throughout the period 2010-2023. The left panel reports the occupations with the highest values of general churn, and the right panel reports the occupations with the lowest values. Digital churn is reported for comparison but is not used for the ranking.

Table 7: Sorting across occupational churn

	Initial exposure		Final exposure		Final exposure initial exposure	
	Digital	General	Digital	General	Digital	General
High ability	0.0193*** (0.00544)	-0.0422*** (0.0108)	0.0200** (0.00739)	-0.0341* (0.0166)	0.0142* (0.00593)	-0.0238 (0.0140)
Initial exposure	–	–	–	–	0.296*** (0.0265)	0.244*** (0.0379)
Initial 1-digit occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Female control	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,374,990	1,374,990	1,374,990	1,374,990	1,374,990	1,374,990
R^2	0.101	0.121	0.121	0.158	0.202	0.209

Notes: Standard errors in parentheses. The dependent variable is listed in the column heading. High ability is an indicator for being in the top two deciles of the high-school grade distribution. In columns (5)–(6), initial exposure is the corresponding initial digital or general churn exposure. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Ability composition of occupational churn exposure paths

	Dependent variable: high ability
Initial digital churn exposure	0.0451*** (0.0120)
Initial general churn exposure	-0.0131*** (0.00279)
Final digital churn exposure	0.0534** (0.0206)
Final general churn exposure	-0.0130* (0.00521)
Initial 1-digit occupation FE	Yes
Birth-year FE	Yes
Female control	Yes
Observations	1,374,990
R^2	0.070

Notes: Standard errors in parentheses. This specification places ability on the left-hand side. The coefficients describe the ability composition of initial–final exposure paths, conditional on the other exposure measures and controls. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Dynamic sorting by ability across firm environments

	Large firm		Old firm		Innovation-active FUI firm	
	Digital churn (1)	General churn (2)	Digital churn (3)	General churn (4)	Digital churn (5)	General churn (6)
High ability	0.0153*** (0.00331)	-0.00599 (0.0126)	0.0102*** (0.00200)	0.00488 (0.00548)	0.00269 (0.00198)	-0.00185 (0.0111)
Initial exposure	0.353*** (0.0183)	0.337*** (0.0167)	0.419*** (0.0273)	0.390*** (0.0196)	0.141*** (0.0118)	0.144*** (0.0217)
Initial 1-digit occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender control	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	Full	Full	FUI large firms	FUI large firms
Observations	1,556,919	1,556,919	1,556,919	1,556,919	402,555	402,555
R^2	0.140	0.111	0.097	0.083	0.065	0.074

Notes: Standard errors are in parentheses. The dependent variable is the final-period occupation-firm exposure indicated in the column heading. The coefficient of interest is the coefficient on the high-ability indicator, defined as having an upper-secondary GPA in the top two deciles. Each specification controls for the corresponding initial occupation-firm exposure, initial 1-digit occupation fixed effects, birth-year indicators, and gender. Columns (1)–(4) are estimated in the full ability sample. Columns (5)–(6) are estimated only among workers whose initial and final firms are large firms with valid FUI innovation information. Within this restricted sample, innovation-active FUI status indicates positive innovation-related expenditures. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Joint outcome profiles and their interpretation

Profile or exercise	Joint pattern in the evidence	Model interpretation and limits
<i>A. Joint tenure and experience profiles</i>		
Digital: tenure	Wage interactions become more positive with tenure, while education interactions are negative. Prescription interactions are mostly negative or near zero and imprecise.	Useful knowledge with modest implementation demands, $\kappa_D + \ell_D < 0$, and $\eta < 1$ produces a positive wage tilt and negative education and strain tilts. Existing knowledge reduces the need for additional formal training.
Ability	Outside the high-ability group, wage interactions rise and education interactions decline with tenure; prescription estimates are fairly flat. High-ability education and prescription point estimates turn positive in some later tenure categories, with a less clear wage pattern.	Useful firm knowledge can support adaptation outside the high-ability group. Rising combined demands can generate positive education and strain tilts when $\eta < 1$. These patterns do not rank incumbent knowledge benefits across groups.
Firm type	Wage interactions are larger in point estimates in large firms. Education interactions tend to be negative at longer tenure. In large innovating firms, prescription point estimates are also positive at longer tenure.	Useful knowledge and demanding implementation can coexist when $\kappa_D < 0 < \kappa_D + \ell_D$ and $\eta > 1$. A positive wage tilt requires the knowledge benefit to exceed the productive cost of reduced training. Implementation has no direct wage payoff.
General: tenure	Wage interactions become more negative, while education interactions turn positive. Prescription interactions are positive across several intermediate tenure categories.	One compatible erosion case has $\kappa_G > 0$, $\ell_G = 0$, and $\eta < 1$. Education restores some task fit while erosion continues to weaken wage progression and raise strain.
Ability	Negative wage interactions and positive education and prescription interactions are more systematic outside the high-ability group. The high-ability profiles are less clear.	Erosion and adjustment demands can outweigh incumbent benefits. The profiles do not establish whether differences across ability groups reflect knowledge benefits, implementation, training costs, or selection.
Firm type	Wage point estimates are negative at longer tenure across firm types, while education interactions tend to be positive. Positive prescription evidence is clearest in small firms.	Formal learning can help maintain task fit without fully offsetting erosion. Differences across firms can reflect incumbent benefits, implementation demands, training costs, and selection into employment relationships.

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Table 10: Joint outcome profiles and their interpretation (*continued*)

Profile or exercise	Joint pattern in the evidence	Model interpretation and limits
Digital: experience	Wage interactions are negative but imprecise. Education interactions show a midcareer hump, while prescription point estimates are mostly negative.	Negative wage interactions are compatible with portable-knowledge erosion. Neither the education hump nor negative prescription interactions follows directly from the benchmark's fixed-state experience predictions.
Ability	High-ability wage interactions become positive with experience, alongside positive education interactions over much of midcareer and mostly negative prescription estimates. Other workers have negative wage interactions and little sustained education increase.	Positive wage–experience interactions lie beyond the benchmark. The optional education–experience complementarity discussed in footnote 3 could generate them under suitable conditions. Sorting and selection could also contribute.
Firm type	Large firms show negative wage and prescription point estimates alongside a midcareer education hump. Small-firm education interactions are mostly negative, with weaker wage and prescription patterns.	Cross-firm experience profiles can reflect different erosion and training parameters or composition. In the fixed-state interior benchmark, incumbent benefits and implementation demands enter tenure tilts without a direct churn–experience term.

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Table 10: Joint outcome profiles and their interpretation (*continued*)

Profile or exercise	Joint pattern in the evidence	Model interpretation and limits
General: experience	Wage interactions are small, positive, and imprecise. Education interactions become more positive later in the career, while prescription interactions are mostly negative.	Portable erosion can induce more education when $\eta < 1$, but the benchmark predicts nonpositive wage and nonnegative latent-strain tilts. Imprecise positive wage estimates do not establish a departure from that benchmark.
Ability	High-ability education point estimates are mostly positive, with less systematic wage and prescription patterns. Among other workers, education interactions become more positive later in the career, alongside mostly negative prescription interactions.	Training costs and education's net strain effect shape learning responses. Positive course interactions alone do not establish wage gains, lower strain, or complementarity between education and accumulated experience.
Firm type	Large innovating firms show negative wage and positive prescription point estimates, with uneven education responses. Small firms show positive wage and negative prescription point estimates.	The large-innovator wage and prescription signs are compatible with portable erosion. The other signs are not direct fixed-state predictions of the benchmark; uncertainty, treatment measurement, selection, or additional mechanisms remain relevant.
<i>B. Match quality, sorting, and event-time evidence</i>		
Match fixed effects	Tenure-specific churn APEs broadly preserve the joint digital-general patterns after including worker-firm match fixed effects (Figure 5).	The patterns persist after absorbing permanent worker-firm differences in outcome levels. This specification does not separate tenure from experience accumulation; changing match value and selective retention remain relevant.
Occupation stayers	Wage-tenure interactions are muted and imprecise. At longer tenure, education and prescription interactions are generally negative for digital churn and positive for general churn (Appendix Figure A.4).	Occupational continuity permits learning and employer changes. Selection into staying and calendar-time confounding limit attribution to knowledge preservation or erosion. Muted wage estimates do not establish preserved incumbent value.

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Table 10: Joint outcome profiles and their interpretation (*continued*)

Profile or exercise	Joint pattern in the evidence	Model interpretation and limits
Sorting	High ability is associated with higher digital and lower general occupational churn. Conditional on initial exposure, the final-exposure association remains positive for digital churn; the general-churn coefficient is negative but imprecise (Table 7).	Sorting can reflect wages, strain, education costs, moving costs, and outside options. The model does not impose the observed digital–general sign pattern or identify the separate contribution of adaptation capacity.
Occupational moves	Larger increases in digital churn at a move accompany more positive subsequent wage changes, with larger point estimates among high-ability workers. In this group, education differences precede the move and some post-switch prescription coefficients are positive (Figure 9).	Preparation and chosen destinations matter. Improved task fit can coexist with demanding implementation. The static framework does not predict the timing of these responses, and the event-time estimates do not identify causal effects of occupational mobility.
Firm upgrading	The additional ability–tenure interaction is positive for wages, negative for education, and imprecise for prescriptions. Group-specific estimates indicate relative wage preservation and positive associations between digital churn and post-event unemployment among high-ability, high-tenure workers (Figures 6 and 7).	Useful knowledge can reduce mismatch, while demanding implementation can discourage education when $\eta > 1$. Employment selection and wages observed after departure limit attribution of relative wage preservation to incumbent knowledge within the upgrading firm.

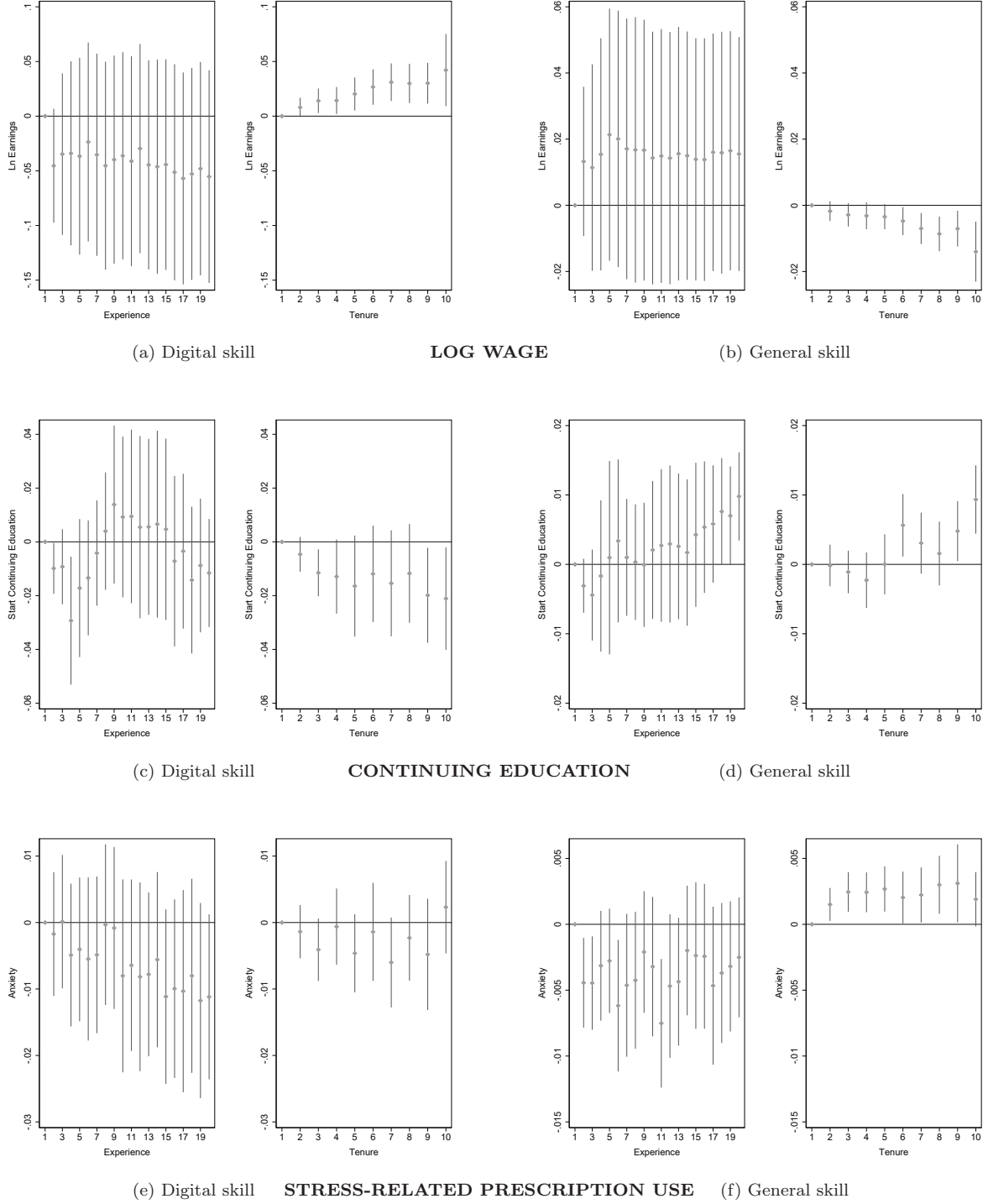
Notes: Panel A summarizes conditional interactions between occupational skill churn and tenure or actual accumulated employment experience, relative to the first year and holding the other employment-history dimension fixed (Figures 1, 3, and 4). Signs describe interaction coefficients rather than outcome levels. Precision varies, and comparisons across ability groups and firm types are descriptive.

Model statements describe possible cases at fixed worker and firm state with an interior training choice. Here $\kappa_s = \delta_s^T - b_s$ is firm-specific erosion net of incumbent knowledge benefits; $\ell_s \geq 0$ captures the tenure component of implementation demands; and η is education’s direct strain cost per unit of mismatch removed. Education relieves net strain when $\eta < 1$ and adds net strain when $\eta > 1$. The term $gE\tau$ belongs only to the optional extension in footnote 3; it is absent from the maintained benchmark.

Panel B combines distinct estimands. For firm upgrading, the additional interaction compares the high-versus low-tenure difference in the response associated with churn among high-ability workers, net of the corresponding difference among other workers. Prescriptions measure treatment and courses measure registered participation; mapping their interactions to latent strain and training requires the qualifications in Appendix OA0.1.6. The listed mechanisms are possible interpretations and do not identify structural parameters or causal effects of education or implementation.

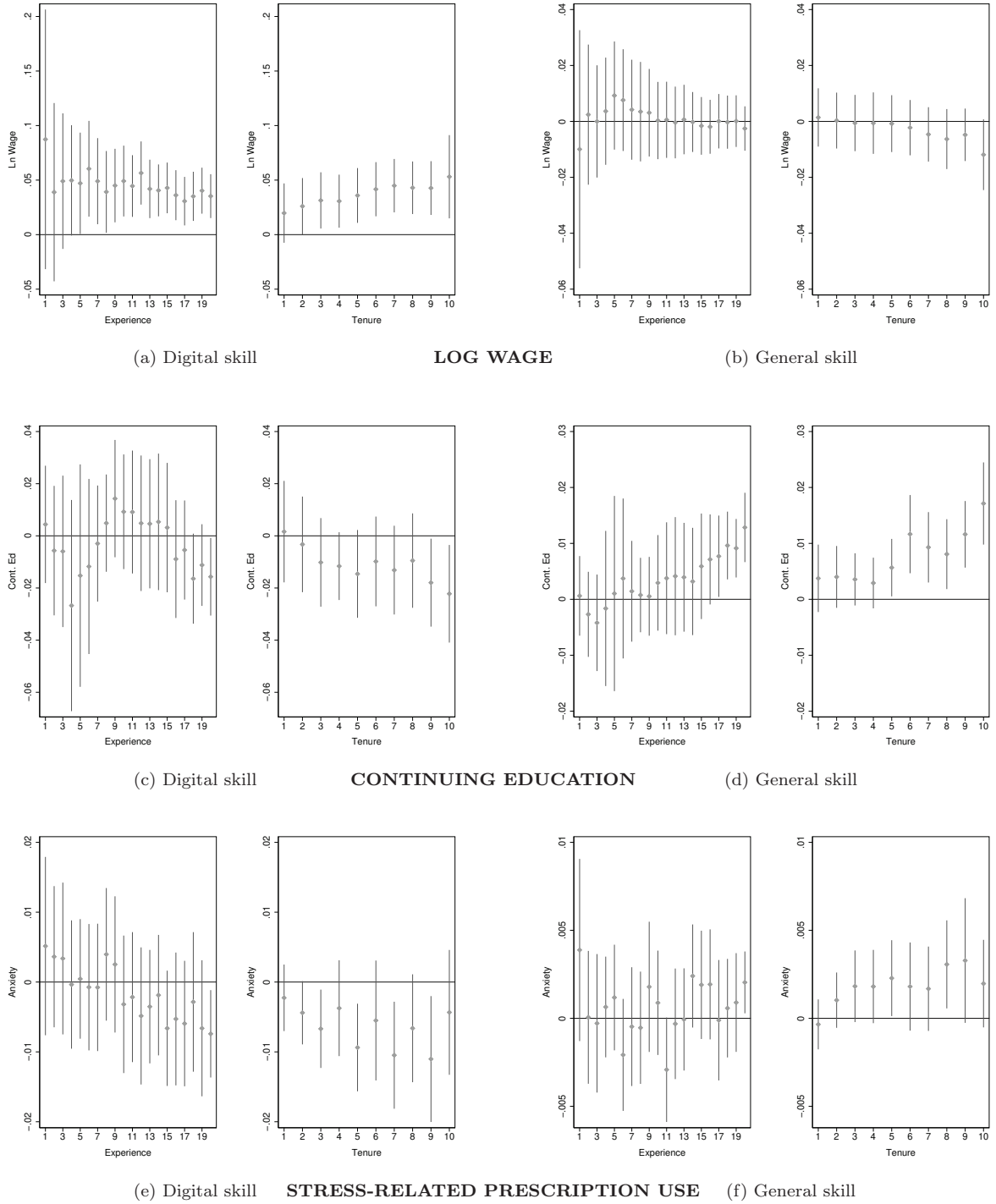
Figures

Figure 1: Skill-churn interactions with tenure and experience



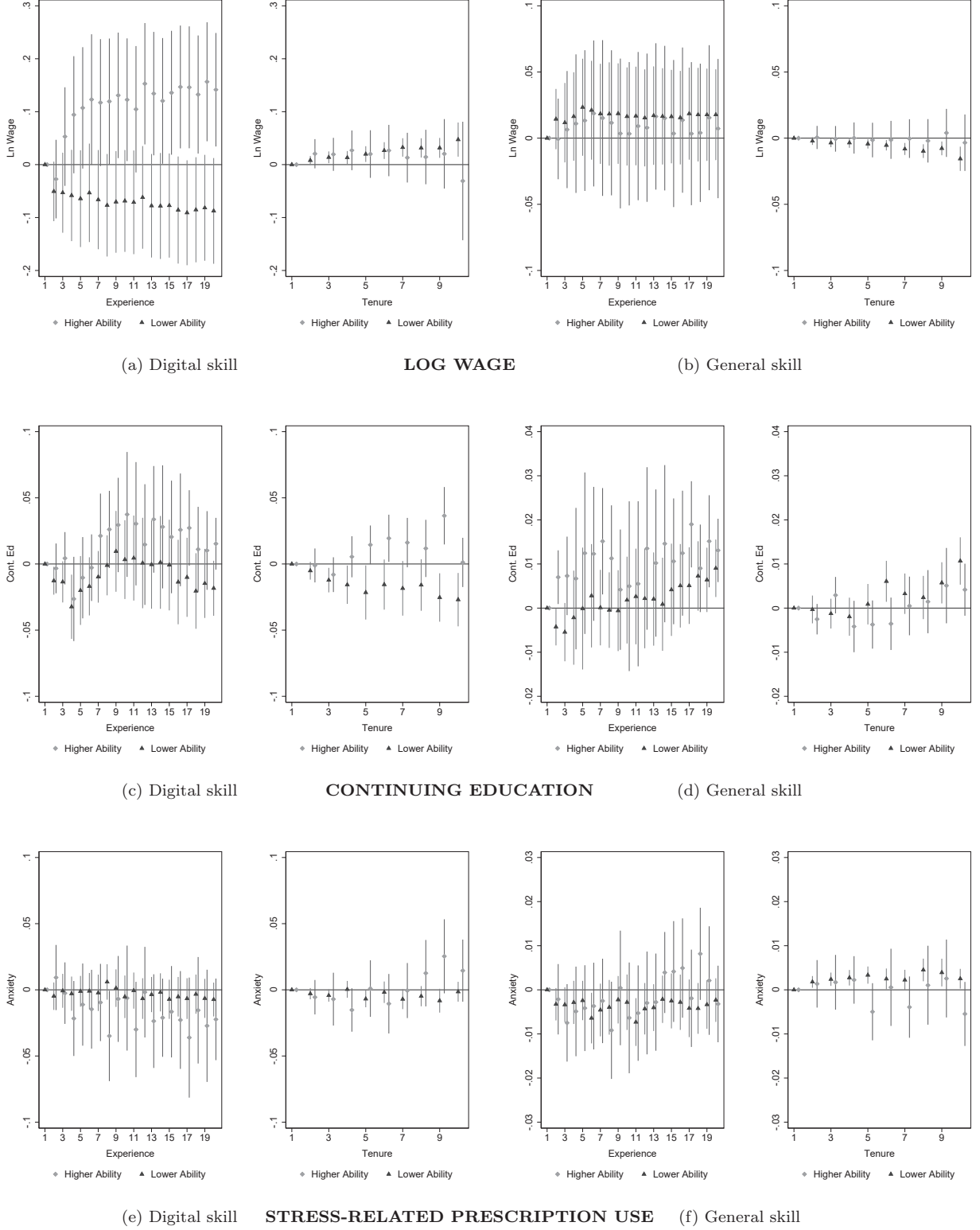
Notes: Each panel plots churn–tenure or churn–experience interaction coefficients from Equation (10), measured per unit of the corresponding churn measure. The first year is the omitted category, with its interaction normalized to zero. A tenure coefficient is the difference in the fitted churn gradient relative to one year of tenure, holding experience fixed; an experience coefficient holds tenure fixed. The upper categories pool tenure of 10+ and experience of 20+. Vertical bars show 95% confidence intervals, with standard errors clustered by four-digit occupation.

Figure 2: Average partial effects of skill churn across outcomes, tenure and experience profiles



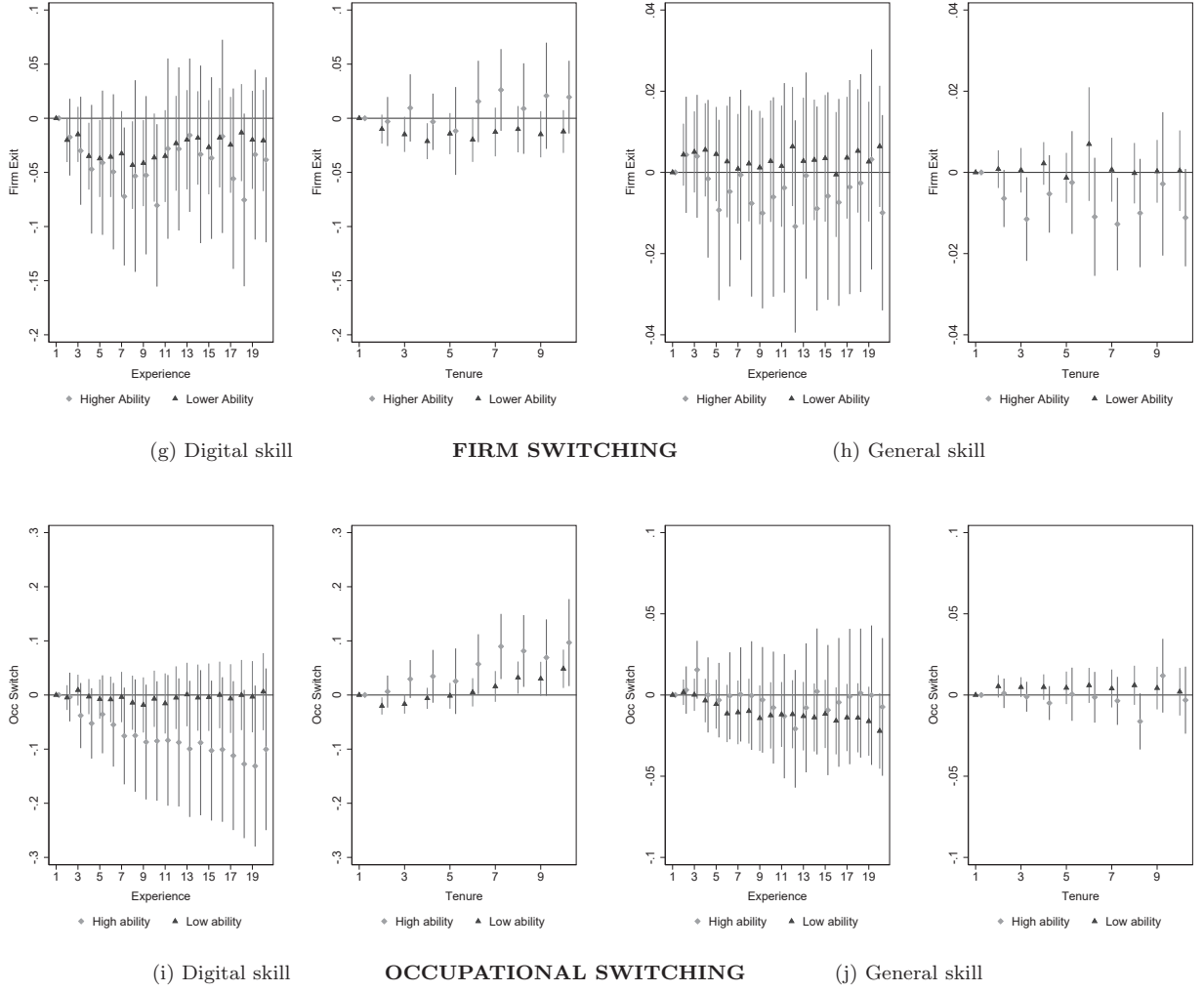
Notes: The left-hand panels report average partial effects of digital churn and the right-hand panels report average partial effects of general churn from Equation (10). At each tenure category, the fitted churn gradient is averaged over observations in that category using their observed experience distribution. At each experience category, it is averaged over observations in that category using their observed tenure distribution; see Equation (11). The rows report log wages, continuing-education participation, and stress-related prescription use, respectively. Estimates are per unit of the corresponding churn measure. Tenure is top-coded at 10+ and experience at 20+. Vertical bars show 95% confidence intervals, with standard errors clustered by four-digit occupation.

Figure 3: Skill-churn interactions with tenure and experience **by ability**



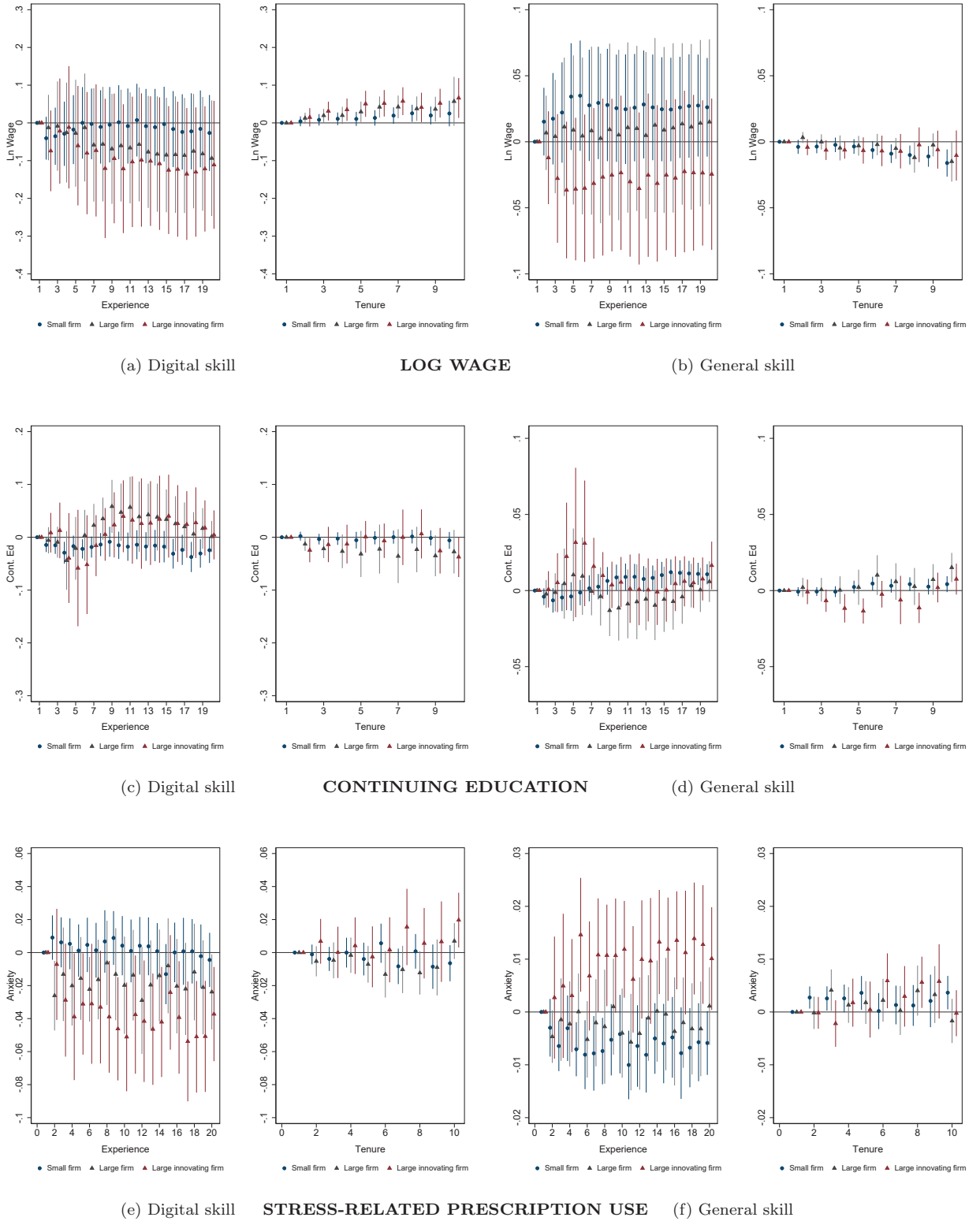
Notes: Points are ability-specific churn–experience (left) and churn–tenure (right) coefficients relative to year 1, conditional on the other profile dimension. The first year is normalized to zero; final categories pool 20+ experience years and 10+ tenure years. Bars show the supplied 95% confidence intervals. Higher ability denotes general academic upper-secondary graduates with GPA in the top two deciles; lower ability denotes all other sample workers. Binary outcomes are in probability units; “Anxiety” denotes aggregate stress-related prescription use.

Figure 3: Skill-churn interactions with tenure and experience **by ability** (continued)



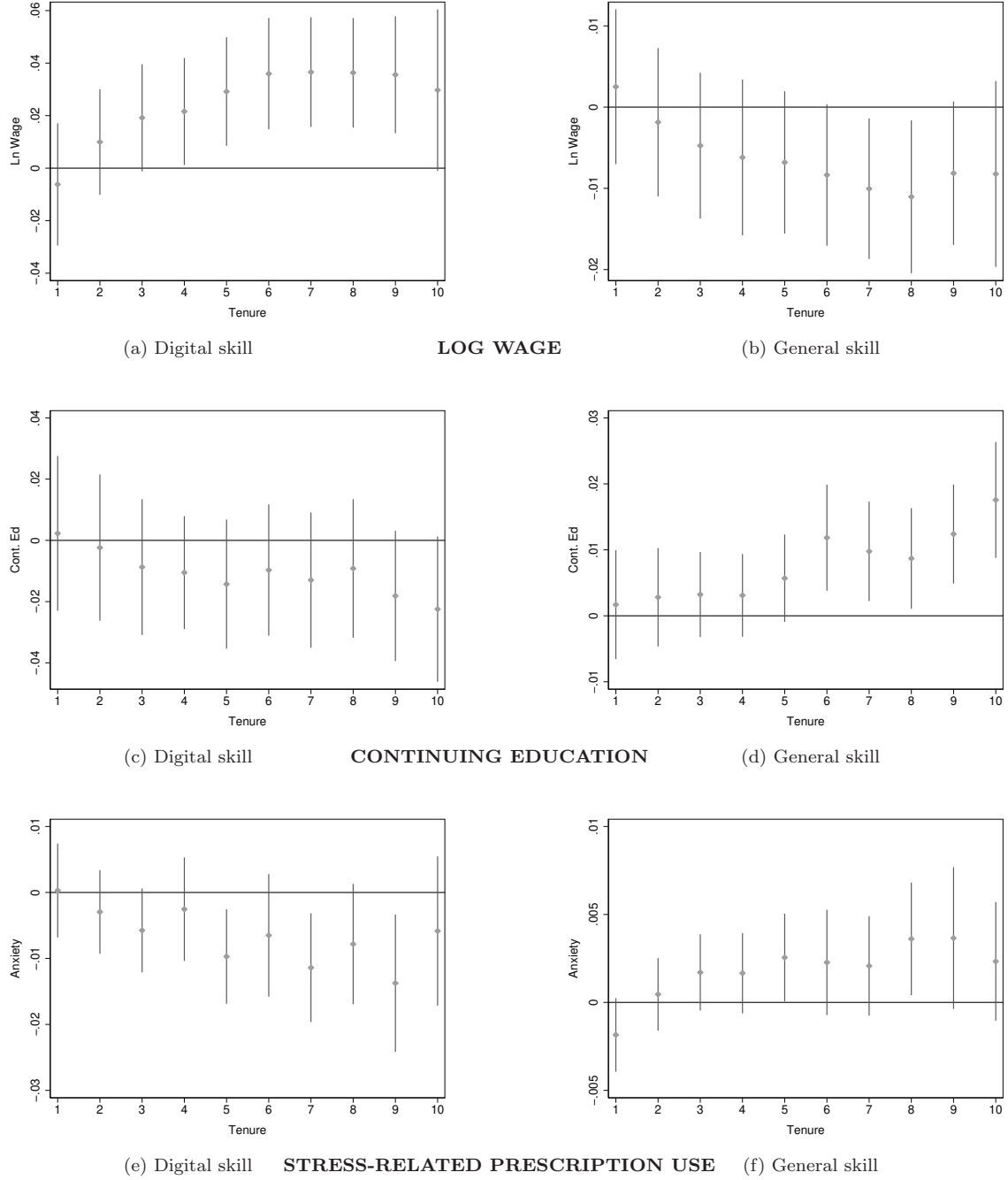
Notes (continued): The sample, ability groups, normalization, coefficient units, and confidence intervals are as described in the first part of Figure 3. Experience coefficients hold tenure fixed, and tenure coefficients hold experience fixed.

Figure 4: Skill-churn interactions with tenure and experience **by firm type**



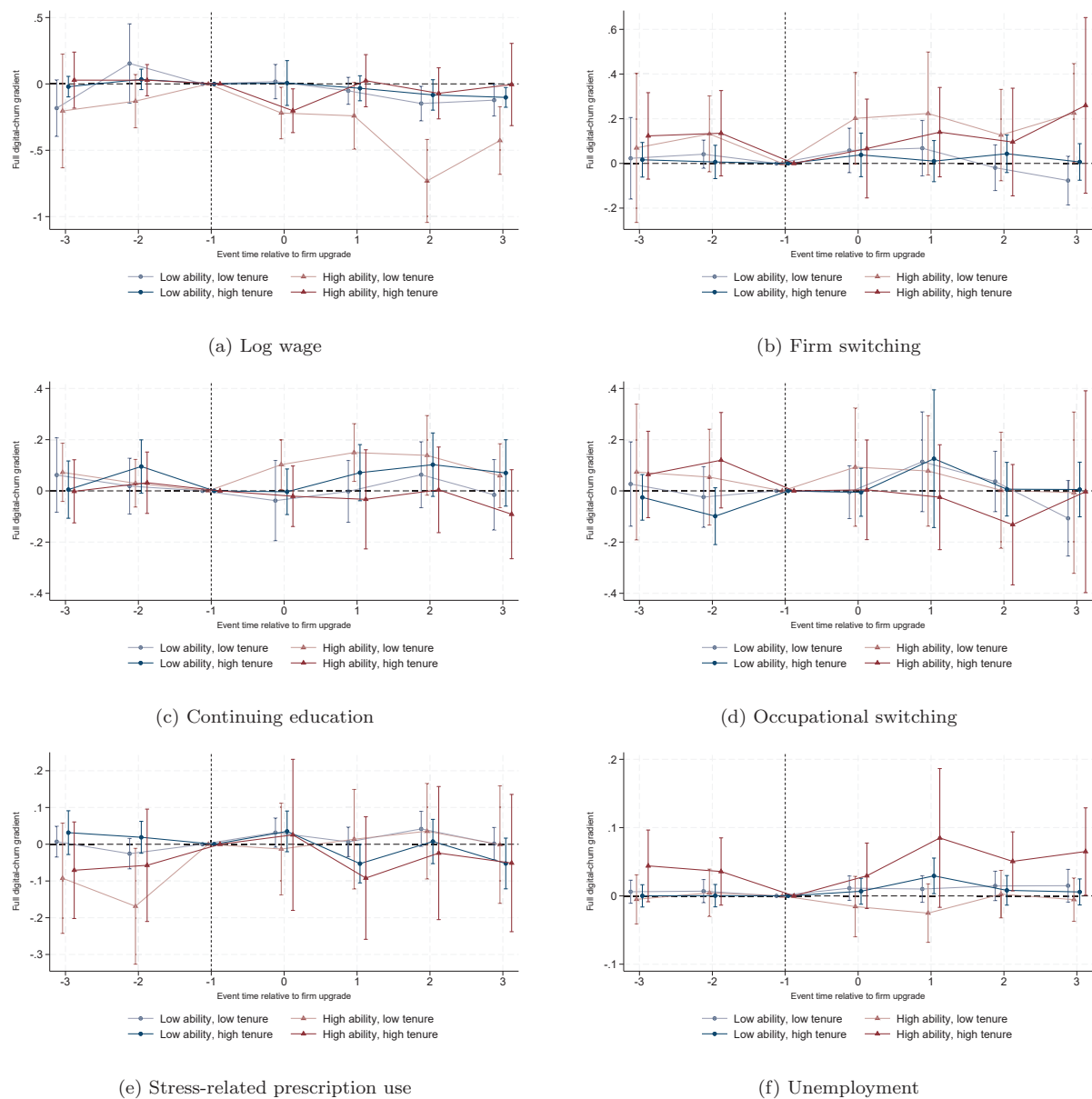
Notes: Points are firm-type-specific churn–experience (left) and churn–tenure (right) coefficients relative to year 1, conditional on the other profile dimension. Year 1 is normalized to zero; final categories pool 20+ years of experience and 10+ years of tenure. Bars show approximate 95% intervals (coefficient $\pm 1.96 \times$ standard error). Binary outcomes are in probability units; “Anxiety” denotes aggregate stress-related prescription use. “Large firm” denotes large non-innovating firms.

Figure 5: Average partial effects of skill churn by tenure, individual–firm and year fixed effects



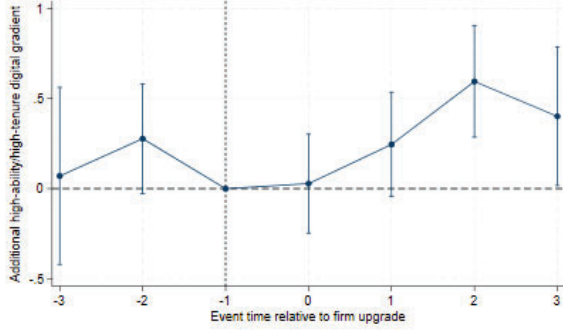
Notes: The figure reports average partial effects of occupation-level digital and general skill churn on log wage, continuing education, and stress-related prescription use. Panels (a), (c), and (e) show digital skill churn; panels (b), (d), and (f) show general skill churn. All effects are evaluated across tenure indicators in a specification with individual–firm match fixed effects, year fixed effects, and tenure dummies. The plotted objects are average partial effects of churn, not unconditional outcome profiles. Shaded areas indicate 95% confidence intervals based on standard errors clustered at the occupation level.

Figure 6: Firm innovation expenditure event study: marginal effects of digital skill churn by incumbent type

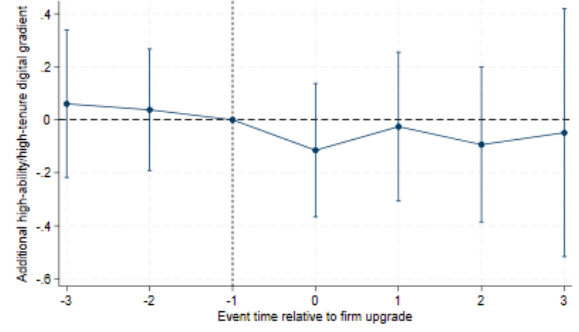


Notes: Each panel plots the implied marginal effect of digital skill churn following firm innovation expenditure events, separately by measured ability and tenure group. The high-ability group consists of workers who graduated from high school with a GPA in the top 20 percent of the high-school GPA distribution. The comparison group consists of all other workers in the estimation sample. Employees with 5 or more years in the firm are considered high tenure. Vertical bars show 95% confidence intervals.

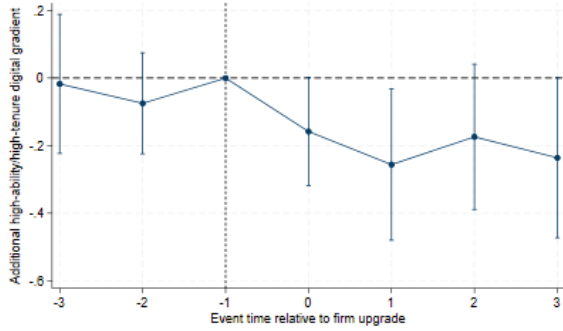
Figure 7: Firm innovation expenditure event study: high-ability difference in the high-tenure digital skill-churn gradient



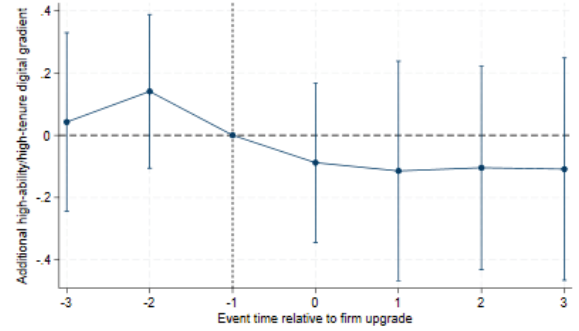
(a) Log wage



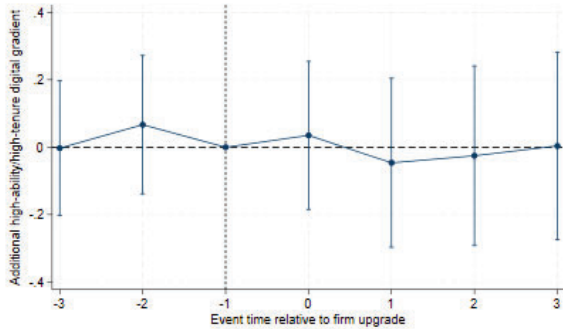
(b) Firm switching



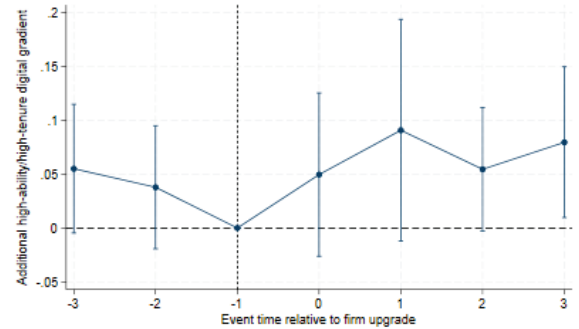
(c) Continuing education



(d) Occupational switching



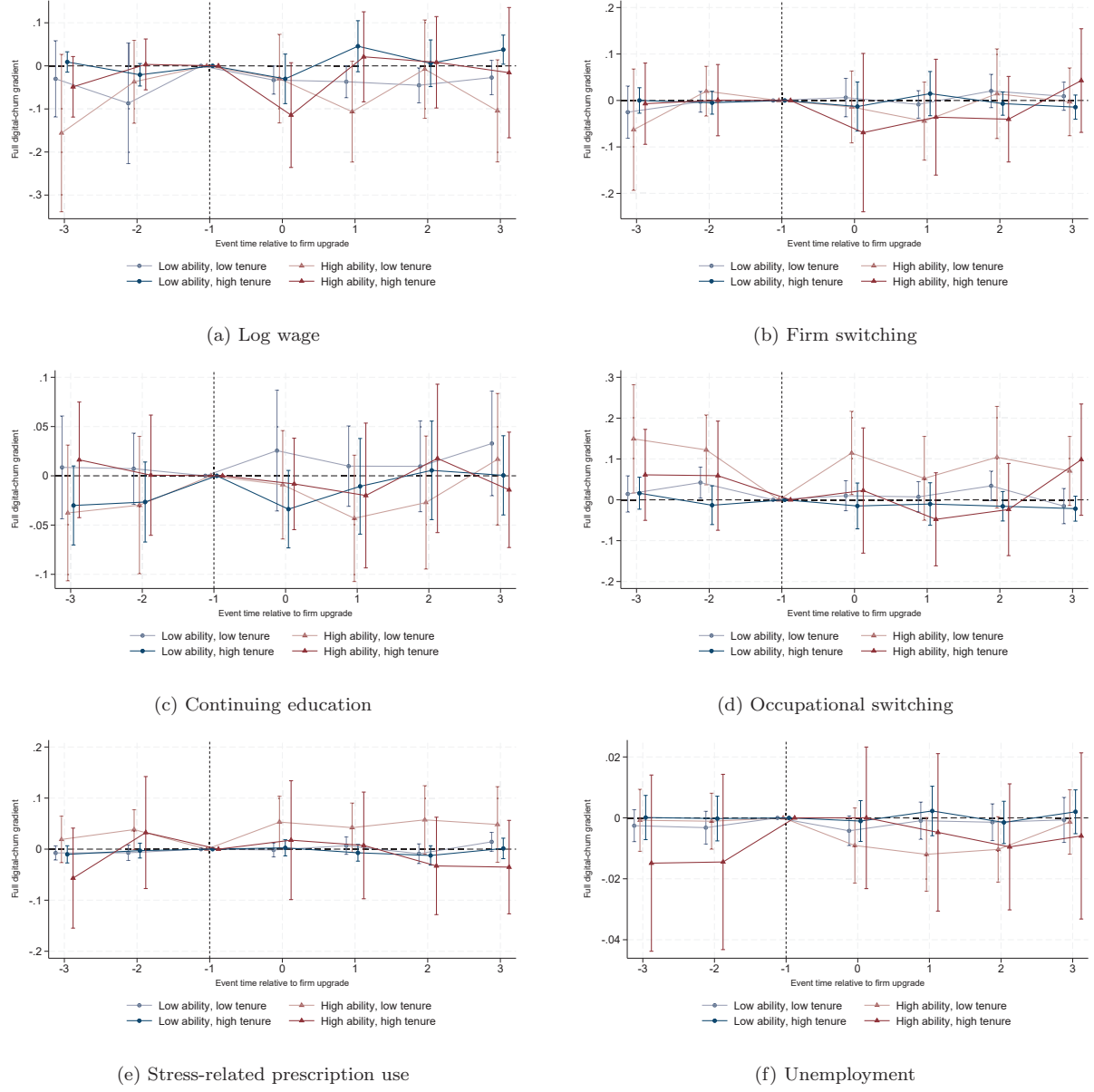
(e) Stress-related prescription use



(f) Unemployment

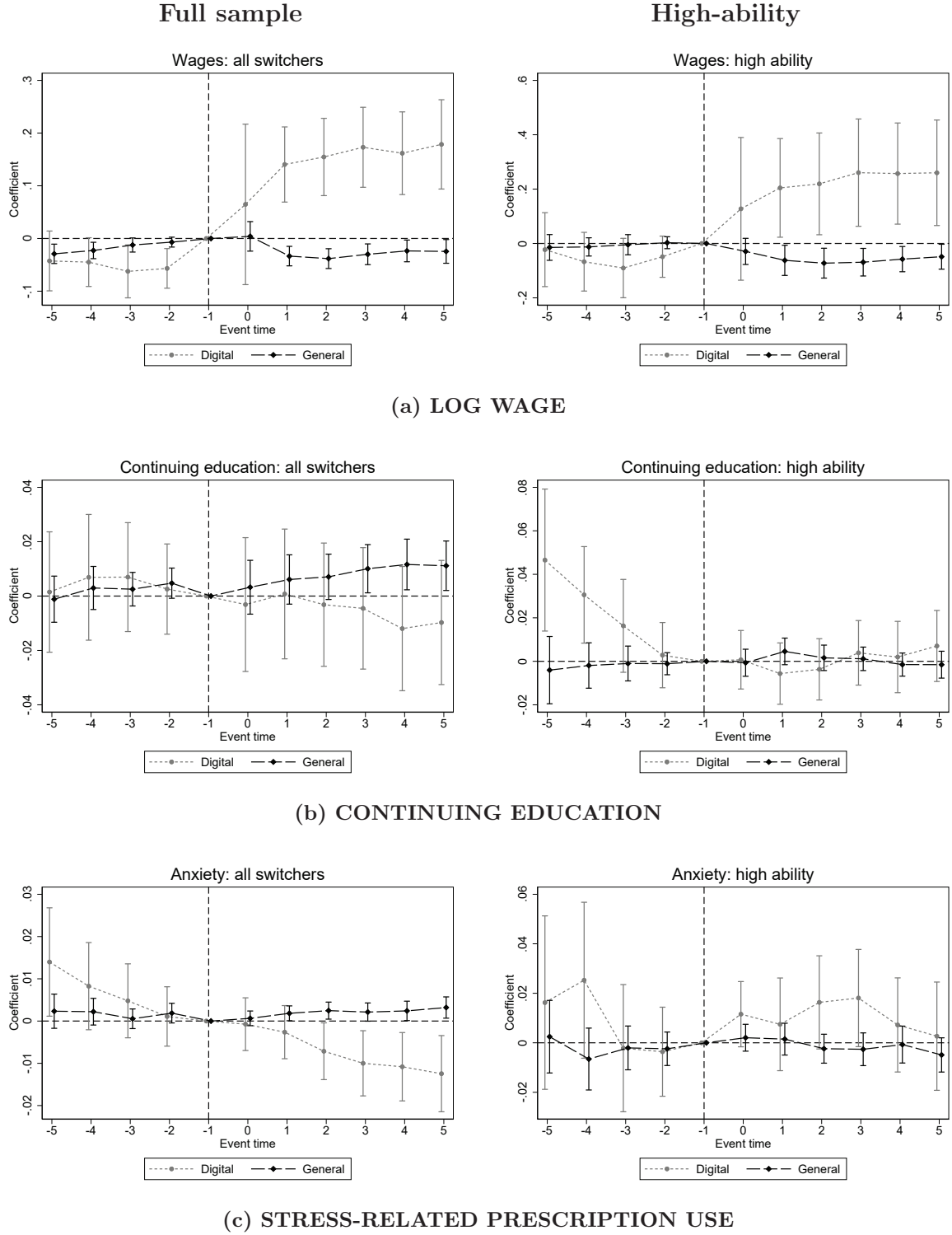
Notes: Each panel plots the event-study coefficient on the interaction between digital skill churn, high ability, and high tenure from the digital-churn specification with a simple general-churn adjustment. These coefficients capture how the high-tenure difference in the digital skill-churn gradient varies between high-ability and lower-ability workers. Equivalently, the plotted coefficient is the difference between the high-tenure and low-tenure digital-churn gradients among high-ability workers, net of the corresponding high-tenure versus low-tenure difference among lower-ability workers. The high-ability group consists of workers who graduated from high school with a GPA in the top 20 percent of the high-school GPA distribution. Employees with 5 or more years in the firm are classified as high tenure. Vertical bars show 95% confidence intervals.

Figure 8: Firm innovation expenditure event study: marginal effects of general skill churn by incumbent type



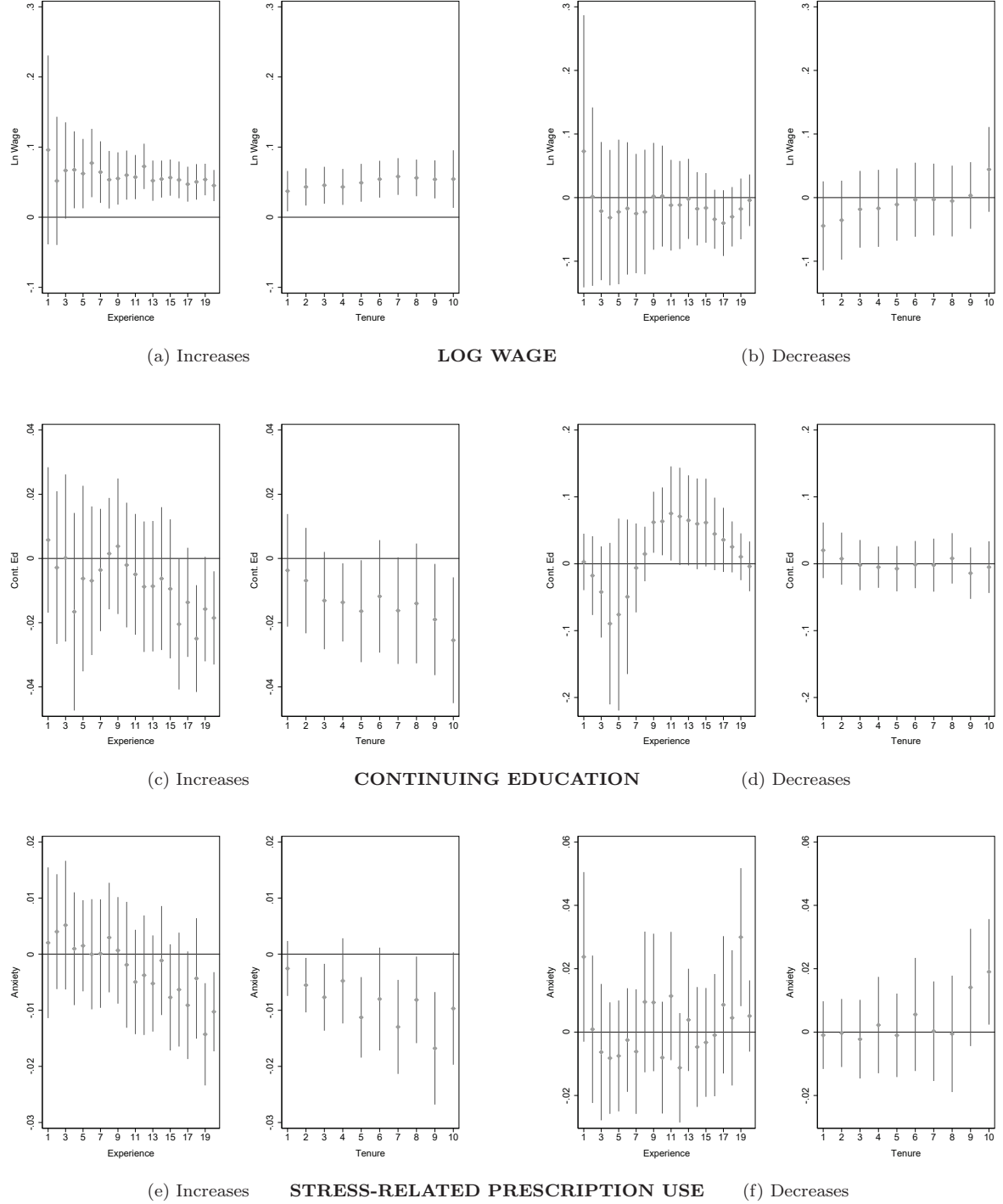
Notes: Each panel plots the implied marginal effect of general skill churn following firm innovation expenditure events, separately by measured ability and tenure group. The high-ability group consists of workers who graduated from high school with a GPA in the top 20 percent of the high-school GPA distribution. The comparison group consists of all other workers in the estimation sample. Employees with 5 or more years in the firm are considered high tenure. Vertical bars show 95% confidence intervals.

Figure 9: Event-time evidence around occupation switches: full sample and high-ability workers



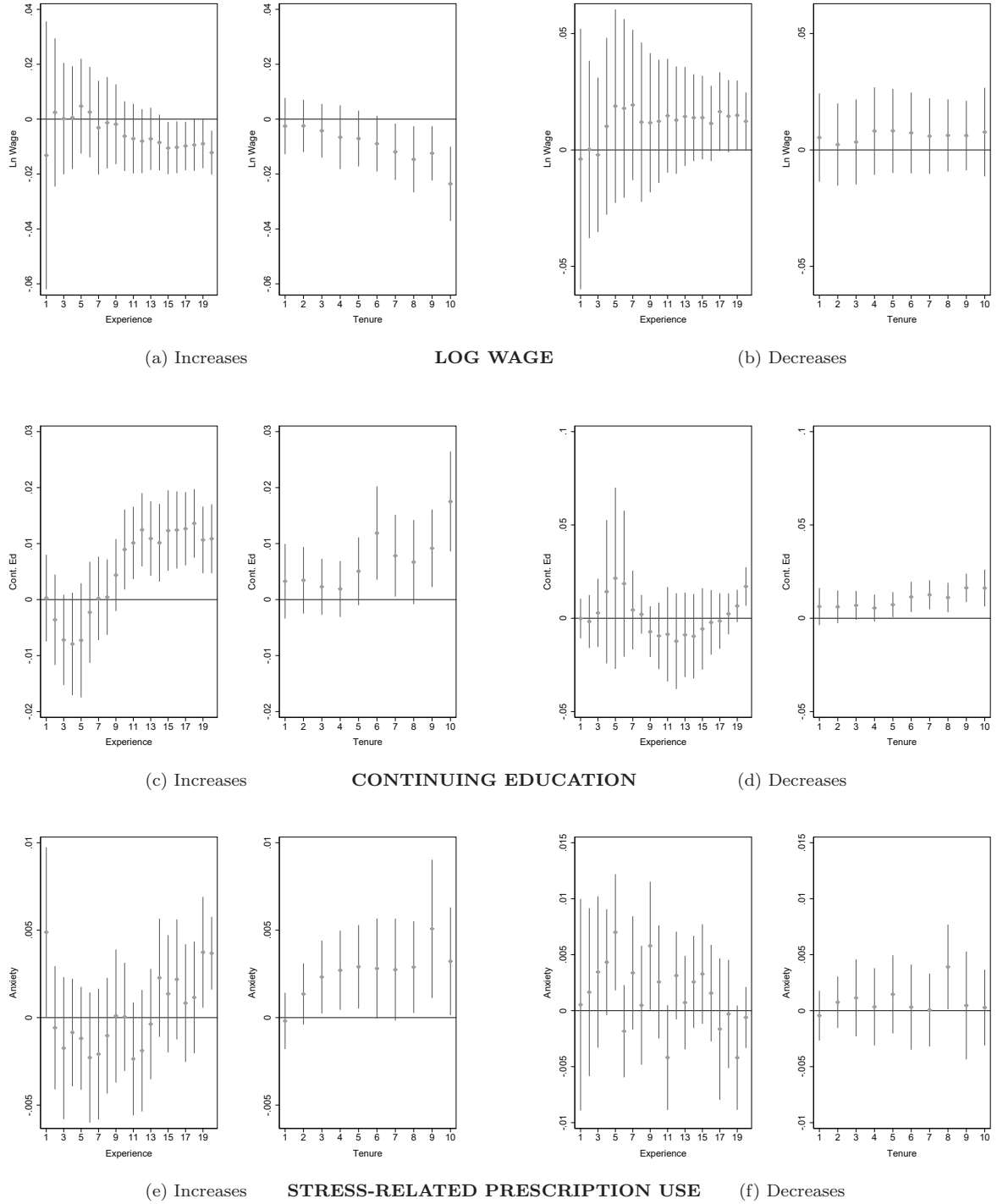
Notes: The figure reports event-time coefficients from Equation (21). The left column reports estimates for the full sample, while the right column reports estimates for high-ability workers. Coefficients trace outcome dynamics around occupation switches that change exposure to digital or general skill churn. The omitted event year is $k = -1$. Ninety-five percent confidence intervals are shown.

Figure 10: Average partial effects of increases vs decreases in digital skill demand across outcomes, tenure and experience profiles, conditional on 1-digit occupation experience and tenure profiles



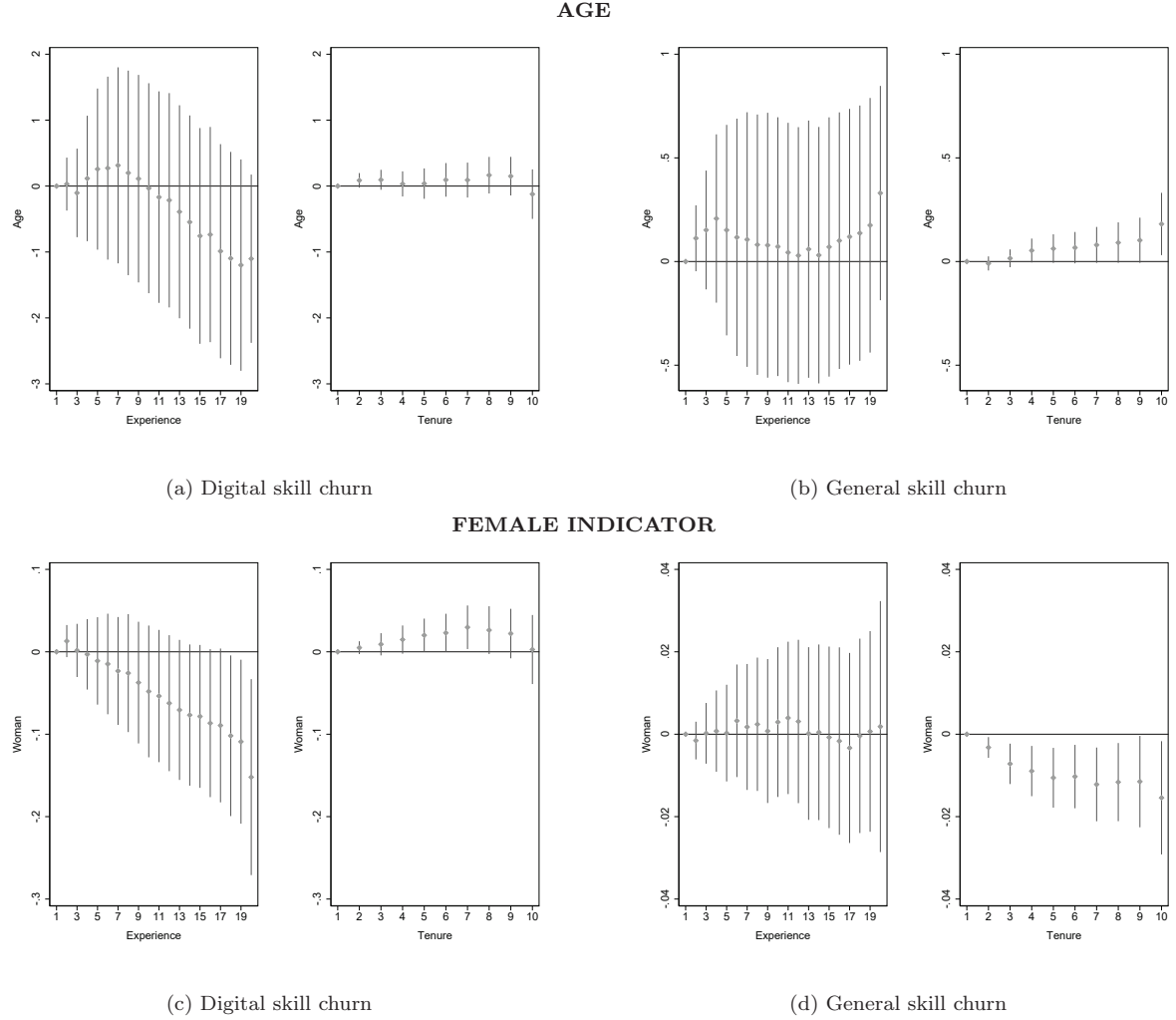
Notes: The left-hand panels show average partial effects of increases in digital skill demand, and the right-hand panels show average partial effects of decreases in digital skill demand. Effects are evaluated across the experience and tenure distributions after estimating Equation 10. The top row reports log wages, the middle row reports continuing-education participation, and the bottom row reports stress-related prescription use. All panels use the same regression specification as in the main results. Vertical bars show 95% confidence intervals.

Figure 11: Average partial effects of increases vs decreases in general skill demand across outcomes, tenure and experience profiles, conditional on 1-digit occupation experience and tenure profiles



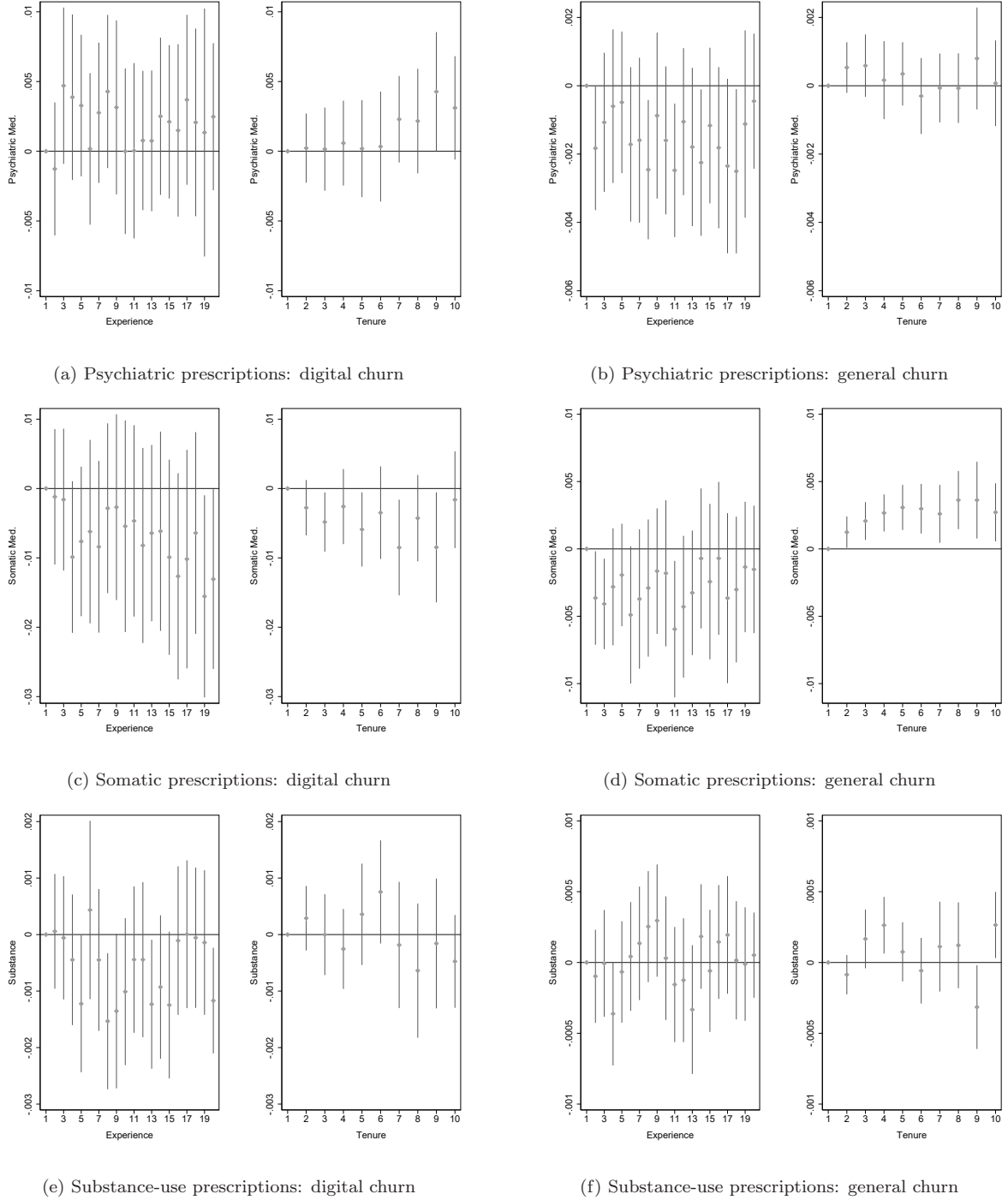
Notes: The left-hand panels show average partial effects of increases in general skill demand, and the right-hand panels show average partial effects of decreases in general skill demand. Effects are evaluated across the experience and tenure distributions after estimating Equation 10. The top row reports log wages, the middle row reports continuing-education participation, and the bottom row reports stress-related prescription use. All panels use the same regression specification as in the main results. Vertical bars show 95% confidence intervals.

Figure 12: Age and sex composition: skill-churn interactions with tenure and experience



Notes: Panels report churn–tenure and churn–experience interaction coefficients using age in years or an indicator equal to one for women as the outcome. The specification follows Equation (10), retaining firm and year fixed effects and broad occupation-group profile controls, but omitting individual fixed effects. Coefficients are measured per unit of the corresponding churn measure. Category 1 is omitted, with its interaction normalized to zero. Tenure coefficients hold experience fixed; experience coefficients hold tenure fixed. The upper categories pool tenure of 10+ and experience of 20+. Vertical bars show 95% confidence intervals, with standard errors clustered by four-digit occupation. Online Appendix Figure OA0.7 reports the corresponding APEs.

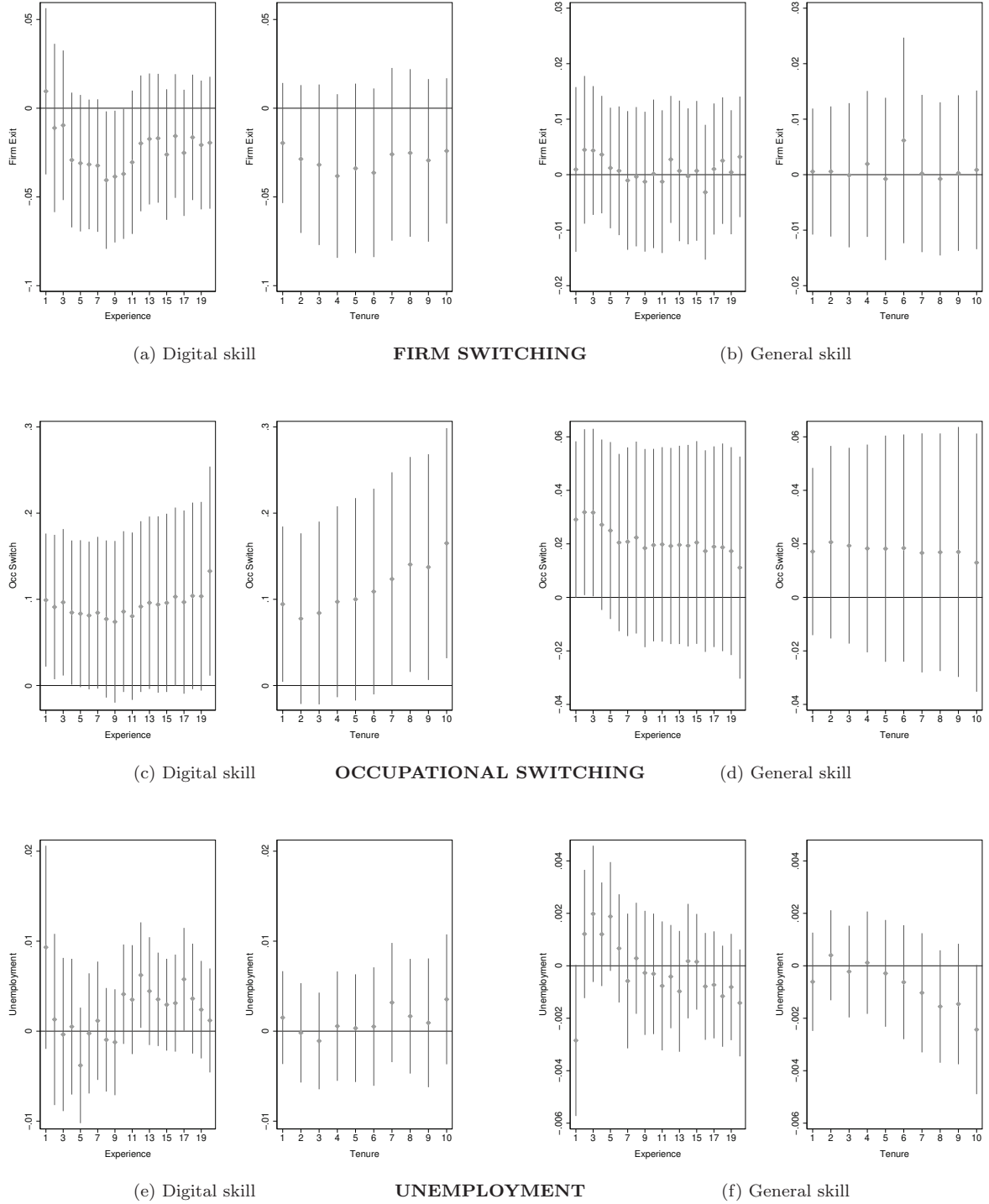
Figure 13: Prescription-component interactions with tenure and experience



Notes: Panels report churn–tenure and churn–experience interaction coefficients from Equation (10), per unit of the corresponding churn measure. Category 1 is omitted, with its interaction normalized to zero. Tenure coefficients hold experience fixed; experience coefficients hold tenure fixed. The upper categories pool tenure of 10+ and experience of 20+. Vertical bars show 95% confidence intervals, with standard errors clustered by four-digit occupation. Online Appendix Figure OA0.6 reports the corresponding APEs.

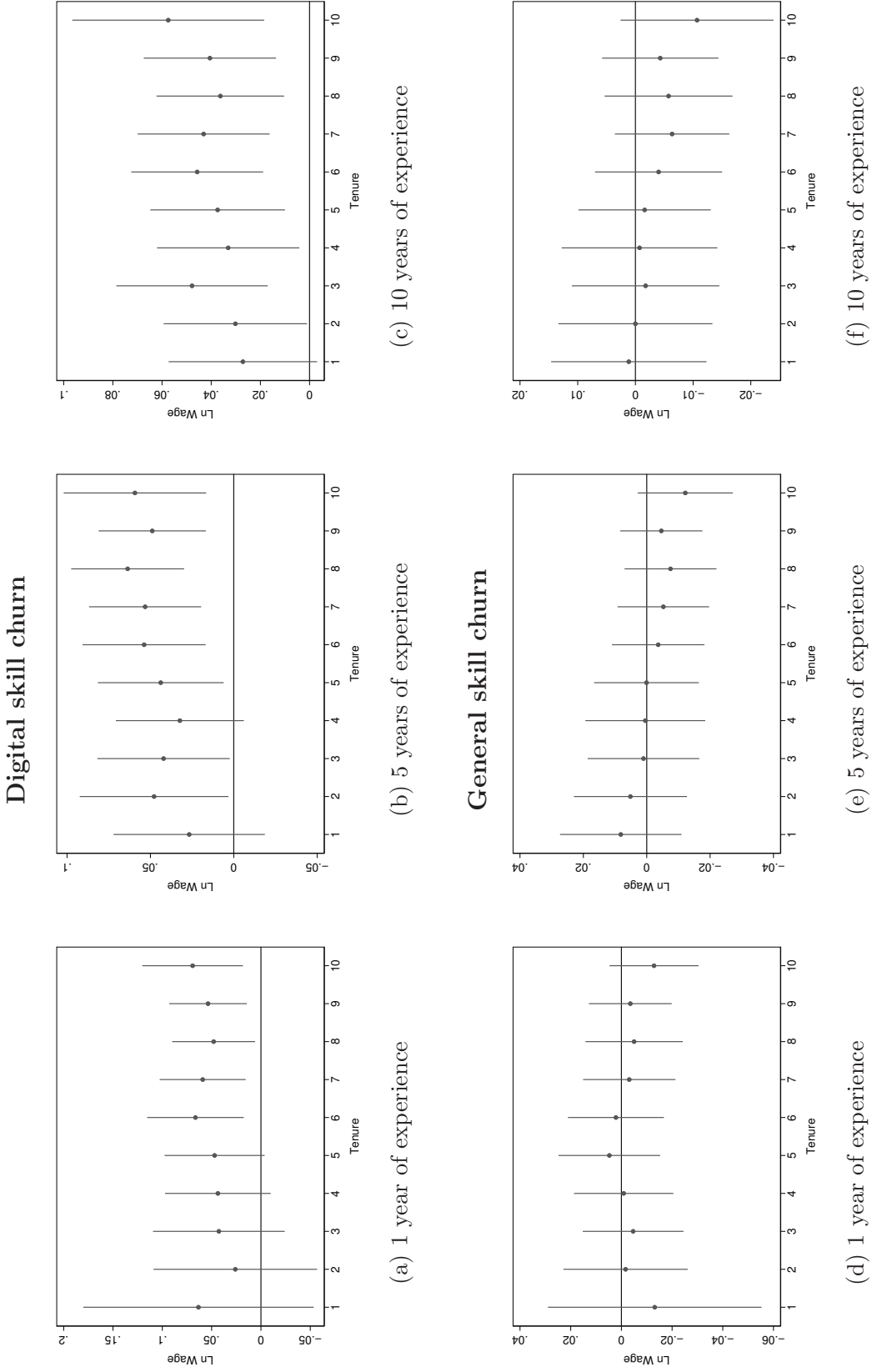
Appendix A Appendix

Figure A.1: Average partial effects of skill churn across firm, occupation and employment status switching, conditional on 1-digit occupation experience and tenure profiles



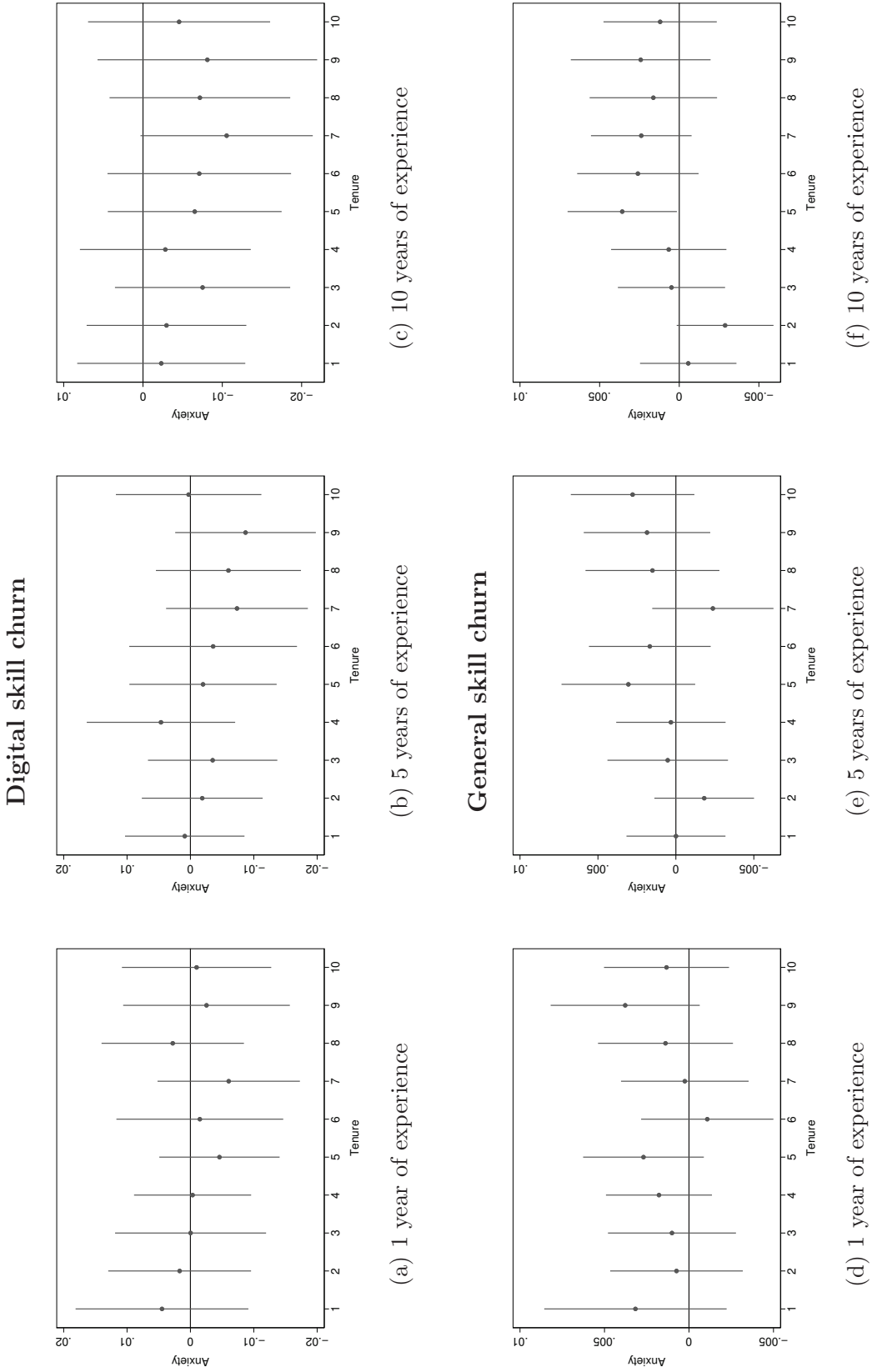
Notes: The left-hand panels report average partial effects of digital churn and the right-hand panels report average partial effects of general churn from Equation (10). At each tenure category, the fitted churn gradient is averaged over observations in that category using their observed experience distribution. At each experience category, it is averaged over observations in that category using their observed tenure distribution; see Equation (11). The plotted APEs are not contrasts relative to category 1. The rows report firm switching, occupational switching, and unemployment, respectively. Tenure is top-coded at 10+ and experience at 20+. Vertical bars show 95% confidence intervals, with standard errors clustered by four-digit occupation.

Figure A.2: Path-specific marginal effects of digital and general skill churn on log wages



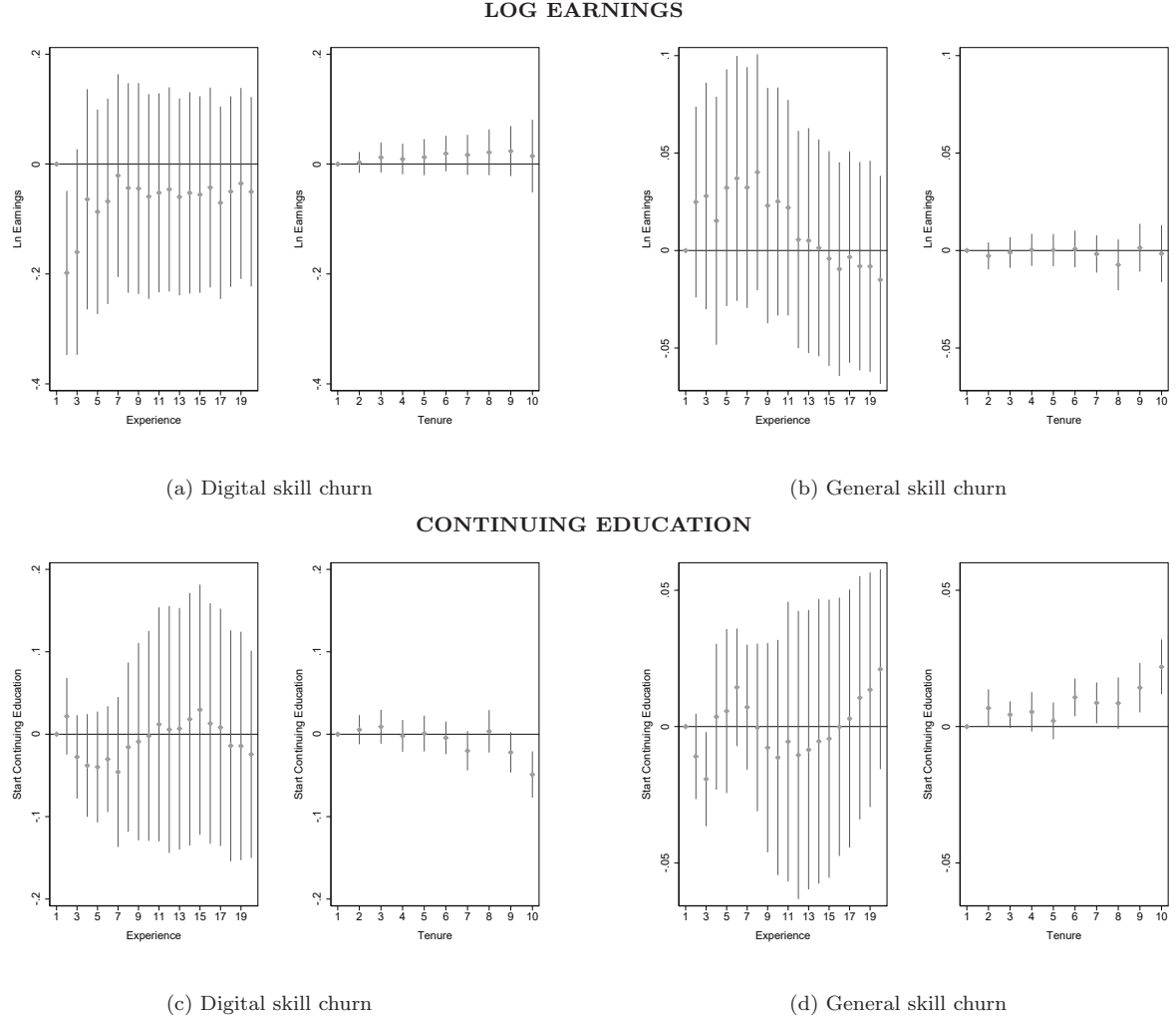
Notes: Each panel reports the fitted partial effect of occupational skill churn on log wages at specified tenure–experience pairs. The top row reports digital churn and the bottom row general churn. Paths start at tenure 1 with experience $e_0 \in \{1, 5, 10\}$ and evaluate $(T, E) = (1, e_0), (2, e_0 + 1), (3, e_0 + 2), \dots$, using the estimation top codes of 10+ for tenure and 20+ for experience. Both employment dimensions are specified at each point; the curves do not average over the experience distributions observed in different tenure categories. Because tenure and experience advance together, changes along a path combine the two sets of churn interactions and are not separate conditional tenure contrasts. Shaded areas show 95% confidence intervals, with standard errors clustered by four-digit occupation.

Figure A.3: Path-specific average partial effects of digital and general skill churn on stress-related prescription use



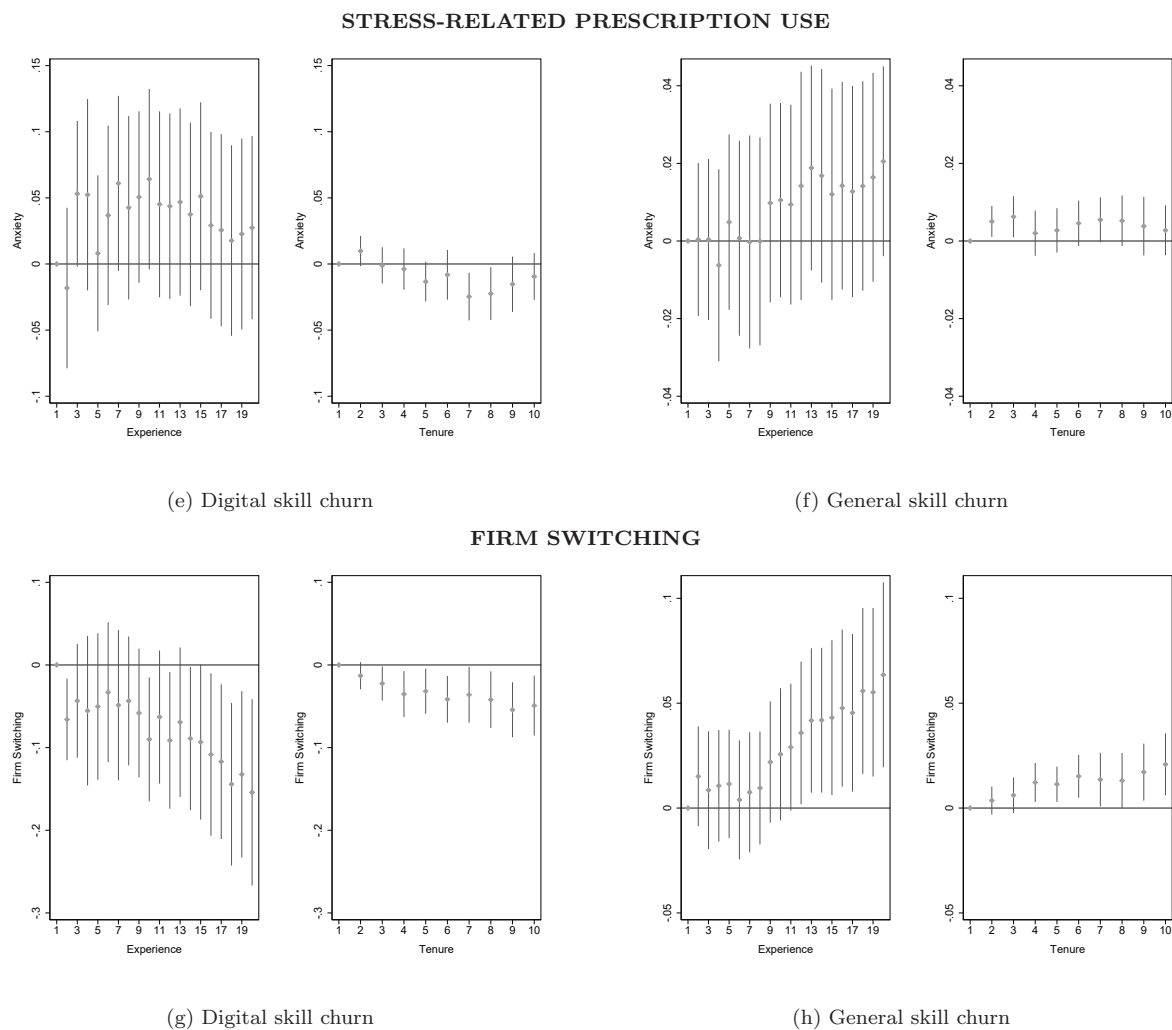
Notes: Each panel reports the fitted partial effect of occupational skill churn on the probability of stress-related prescription use at specified tenure–experience pairs. The top row reports digital churn and the bottom row general churn. Paths start at tenure 1 with experience $e_0 \in \{1, 5, 10\}$ and evaluate $(T, E) = (1, e_0), (2, e_0 + 1), (3, e_0 + 2), \dots$, using the estimation top codes of 10+ for tenure and 20+ for experience. Both employment dimensions are specified at each point; the curves do not average over the experience distributions observed in different tenure categories. Because tenure and experience advance together, changes along a path combine the two sets of churn interactions and are not separate conditional tenure contrasts. Shaded areas show 95% confidence intervals, with standard errors clustered by four-digit occupation.

Figure A.4: Skill-churn interactions with tenure and experience among occupation stayers



Notes: Each panel plots churn–tenure and churn–experience interaction coefficients from Equation (10), estimated on workers who remain in the same four-digit occupation throughout the observation window. Coefficients are measured per unit of the corresponding churn measure. Category 1 is omitted, with its interaction normalized to zero. Tenure coefficients compare the fitted churn gradient with that at tenure 1, holding experience fixed; experience coefficients compare it with that at experience 1, holding tenure fixed. The upper categories pool tenure of 10+ and experience of 20+. Vertical bars show 95% confidence intervals, with standard errors clustered by four-digit occupation. Online Appendix Figure OA0.5 reports the corresponding category-specific APEs.

Figure A.4: Skill-churn interactions with tenure and experience among occupation stayers (continued)



Notes (continued): The sample, normalization, coefficient units, and confidence intervals are as described in the first part of this figure. Tenure coefficients hold experience fixed, and experience coefficients hold tenure fixed.