REORGANIZING WORK INSIDE THE FIRM: TASK CHANGE AFTER TECHNOLOGY ADOPTION*

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Abstract

We study how an incumbent workforce adapts to technological change using panel data at the worker-task level from a Latin American bank with roughly 450 branches and 10,000 workers. We exploit two sequential interventions that separately shift production technology and organizational design, without displacing labor: the staggered rollout of a mobile banking app that automates routine transactions, and a subsequent redefinition of roles and performance criteria that prioritizes complex tasks such as SME lending. While automation creates substantial productive capacity—raising output per worker by roughly 20 percent—it does not, on its own, lead to task upgrading. Workers continue to concentrate on routine tasks, rather than shifting toward high-value complex tasks. Task reallocation occurs only after the firm explicitly reallocates priorities. Even then, adjustment is markedly slower among high-tenure workers, consistent with firm-specific human capital generating inertia in task change. High-productivity managers complement adaptation, but unevenly: they accelerate upgrading primarily among low-tenure workers, amplifying inequality within teams.

Keywords: technology adaptation; task reallocation; organizational design; managerial quality; firm productivity

JEL: J24; M54; O33

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1. Introduction

The successful adoption of new technologies, a main driver of firm productivity, depends critically on how incumbent workers adjust. When hiring and firing are costly and production relies on firm-specific human capital, labor behaves as a quasi-fixed factor (Oi, 1962). As a result, firms often cannot implement technological change primarily through rapid workforce replacement, but instead must do so through their internal labor market —reallocating tasks, redefining roles, and overall re-directing worker effort within the existing workforce.

In a frictionless environment, models of automation with task complementarities predict a natural reallocation following technological adoption: automating routine components frees worker time and increases the returns to remaining bottleneck tasks, inducing workers to shift effort toward higher-value activities (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022; Gans and Goldfarb, 2026). Firms often confront substantial departures from this frictionless prediction, whereby task reallocation requires complementary organizational investments that lag behind technological capacity and tend to be poorly measured (Brynjolfsson et al., 2021). Understanding these organizational complementarities and how they impact incumbent workers behavior, within-firm task reallocation and, in turn, firm productivity remains an open question.

We leverage detailed administrative data from a large Latin American bank to study how an incumbent workforce adapts to technological change. The Bank operates roughly 450 branches and employs about 10,000 workers. In 2017, it launched a mobile-first digital transformation strategy. While customers already had access to online channels, these services were largely limited to basic payments and transfers. The new strategy aimed to enable a fully digital customer journey by expanding functionality through a new banking app—launched in June 2018—that allows clients to open accounts and purchase selected products digitally.

Uniquely, we observe and study a *sequence* of interventions rather than a single technological change: first, a labor-saving digital tool (a mobile app) is introduced (the *"Tech Intervention"*); then, two years later, the firm implements a coordinated effort to restructure performance expectations and KPIs (the *"Task Intervention"*). This rare two-step rollout allows us

to separate the direct impact of the technology from the organizational complements needed to translate new capacity into sustained productivity gains. Throughout, the bank's objective was to expand output without materially changing the composition of its existing workforce.

The Tech Intervention takes place in 2018 and introduces a customer-facing mobile app enabling customers to seamlessly open, purchase, and manage selected simple financial products such as consumer loans and debit cards. The app automates critical steps like ID verification and compliance checks, making transactions faster and more efficient. To integrate the technology into daily operations and address potential resistance, the bank embeds the rollout within branches: employees assist with app onboarding and receive monetary rewards for in-app transactions through an employee-ID crediting system.

By automating routine processes and reducing the cost of serving retail clients, the app frees up substantial worker time. Yet, this freed capacity did *not* translate into upgrading toward more complex tasks.[1] To drive the transition toward complex services, the bank deployed a targeted Task Intervention in January 2021. Distinct from altering monetary incentives, it explicitly restructured performance evaluation to prioritize complex activities, and, in particular, SME lending. The HR and product teams changed workers' KPIs so that their performance would be primarily assessed against SME lending and visited branches to communicate the change in meetings with managers and frontline workers.

We study the impact of these two interventions on the organization of work and workers inside bank branches. The Tech Intervention leads to significant productivity gains, with workers increasing total trades by approximately 18 percentage points. However, workers do not transition toward more complex (non-automated) tasks, concentrating productivity improvements in routine activities. Beyond these productivity effects, the Tech transformation increases the client base. The app generates a sharp increase in new client acquisitions, particularly in areas with previously low penetration, indicating that digital technologies can expand the reach of financial services rather than merely substitute for branch activity.

The disconnect between expanded capacity and task upgrading reveals the central friction:

[1] Incentives for all complex products remain unchanged throughout the period, and demand for complex services rises following the app rollout, indicating that neither pay nor market conditions explain the lack of upgrading.

technology creates productive slack but does not direct its deployment. The Task Intervention addresses this friction by reweighting performance criteria to prioritize SME lending. Following this explicit reprioritization, workers increase SME production, with upgrading concentrated precisely where evaluation criteria were adjusted. Importantly, neither intervention operates through workforce adjustment—worker exits and hiring remain stable throughout.

The heterogeneous response to both interventions reveals two main sources of organizational frictions. Workers with higher tenure reallocate more slowly, suggesting that experience accumulated under the previous production regime creates rigidity that hinders adjustment. High-productivity managers—measured by manager fixed effects on branch productivity—do not differentially affect reallocation during the technology intervention when performance evaluation remains unchanged. However, they accelerate task reallocation once the task intervention restructures performance weights.

Moreover, the gains from high-productivity managers are uneven across workers. High-productivity managers raise task upgrading primarily for low-tenure workers, while provide minimal additional benefit to high-tenure workers. This pattern is consistent with evidence that managerial actions can increase dispersion in performance (Bandiera et al., 2007; Gibbons and Henderson, 2012). In particular, in our setting, high-productivity managers affect *which* workers upgrade tasks following organizational change, concentrating gains among workers with lower adjustment costs.

In principle, a counterfactual regime with greater willingness to separate workers could attenuate the tenure gradient we document through selection—by inducing exit among workers who face the highest switching costs. Such a response would change the composition of the workforce and may mechanically reduce observed tenure-based differences in adjustment. Our setting instead isolates within-worker adaptation operating solely through the incumbent workforce, allowing us to identify tenure-based frictions in task reallocation without confounding selection through hiring and firing.

To interpret the results, we develop a simple two-period model in which workers allocate time between current production and the acquisition of skills for higher-value tasks. The worker invests in the tasks where the discounted marginal returns to skill outweigh the op-

portunity cost of foregone current revenue, and invests less when learning is time-inefficient (Ben-Porath, 1967). The Task Intervention, by increasing the relative payoff to SME work, shifts learning effort (and output) toward SME tasks, with stronger responses among lower-tenure workers who have a higher effective weight of the future and lower opportunity cost of learning. Managers matter because they can either make learning more efficient (lower the time cost per unit of skill) or make it more attractive (raise perceived future returns, e.g. by clarifying expectations, outlining career trajectories, and communicating priorities).

This study contributes to two main strands of the literature. First, it adds to research on how technological change reshapes jobs and tasks (Acemoglu and Autor, 2011; Autor and Handel, 2013; Acemoglu and Restrepo, 2020) While prior work primarily focuses on economy-wide effects, this paper provides a firm-level perspective, highlighting the heterogeneity in adaptation across workers within the same organization. As Autor et al. (2002) document in their study of check processing automation, computerization typically automates tasks that can be described in terms of "rule-based" logic, but management decisions play a key role in determining how remaining tasks are organized into jobs. As a result, automation can expand capacity without changing task content if firms do not reorganize the residual tasks into new roles.

Second, we contribute to the literature on organizational design and managerial quality as determinants of technological adaptation (Bresnahan et al., 2002; Bloom et al., 2014). A growing parallel literature demonstrates that managers significantly influence worker productivity, learning, and task allocation (Adhvaryu et al., 2023; Metcalfe et al., 2023; Minni, 2025). Our findings bridge these two perspectives. The mobile app creates slack at lower layers of the hierarchy, but without complementary organizational adjustments, workers do not upgrade into more complex tasks. Moreover, high-productivity managers shape which workers successfully reallocate tasks: high-productivity managers help reduce the adjustment costs associated with new tasks, yet these gains accrue mainly to low-tenure workers.

2. Context

A contribution of this paper is the richness of the institutional environment and data we observe. Unlike most empirical settings where researchers only see wages or aggregate performance, our data allow us to track the *full task portfolio* of each worker over time. For every worker and every branch, we observe both routine, easily automated trades (e.g., savings accounts) and complex, skill-intensive trades (e.g., SME loans). This visibility into the task mix is essential for understanding how technology reshapes work inside firms.

2.1. The bank

We partner with one of the largest and longest-established banks in a Latin American country. With more than 50 years of operations, the bank serves individuals, SMEs, and rural clients, employing over 10,000 workers and roughly 3 million customers.

In 2017, the bank initiated a mobile-first digital transformation strategy. Although customers already have access to online channels, available services are limited to basic payments and transfers. The new strategy aims to create a fully digital customer journey, allowing clients to open accounts and purchase selected products via a new banking app launched in June 2018. The stated goals include (i) increasing productivity in routine tasks, (ii) reallocating branch workers toward more complex, higher value-added products, and (iii) reducing operational frictions. During 2017–2023, the bank facilitated over 15 million new trades and became one of the largest institutions in the country by financial assets.[2]

Importantly, despite the scale of the transformation, no workers are laid off. The bank commits to maintaining employment, and subsequent expansion makes workforce reductions unnecessary—our empirical analysis confirms this pattern. This no-layoff constraint shapes how technological change unfolds in our setting: the bank must achieve its transformation goals by inducing incumbent workers to reallocate effort across tasks rather than through workforce turnover.

[2]Throughout the paper, a *trade* denotes a major event in the management of a financial product, such as opening a credit line or a checking account.

2.2. Workers, roles, and the task structure

A typical branch is led by a manager and staffed primarily by account managers (our focus). Account managers are responsible for most trades, with compensation closely tied to performance-based commissions. While all account managers share the same formal role, some concentrate more heavily on specific activities—such as SME lending or other complex products—reflecting informal specialization.

We classify the work performed by account managers into three distinct categories based on product characteristics and digitization potential. Simple trades include routine, simple transactions, such as basic account openings and consumer loans. Complex trades encompass sophisticated financial products requiring substantial personal interaction, such as investment products and mortgage loans. SME trades consist of lending to small and medium-sized enterprises, which requires relationship management and credit evaluation.

These task categories differ considerably in their skill requirements. Figure 1 (Panel (a)) shows standardized O*NET-based skill measures following Autor et al. (2003), revealing that both SME and complex tasks require higher analytical and interpersonal skills than simple tasks, while relying less on routine cognitive abilities and manual work. Beyond these measurable skill differences, SME lending involves a qualitatively different mode of production. Compared to retail transactions, SME work requires active sourcing of local firms, sustained relationship building with owners and managers, and diagnostic effort to assess business models, cash-flow cycles, and supply-chain exposure. Effective SME lending also relies on local market knowledge that cannot be inferred from standardized product features or transaction histories.

2.3. Two interventions

The bank's digital transformation unfolds through two centrally coordinated and sequential interventions that differ sharply in their organizational logic. The first intervention ("Tech Intervention") introduces a new technology that alters production processes and expands productive capacity. The second intervention ("Task Intervention") explicitly redesigns roles

and performance evaluation, thereby governing how this newly created capacity is allocated across tasks. Together, these reforms allow us to separate the creation of productive slack from its subsequent deployment within the organization and to quantify the departures from the frictionless benchmark—revealing the organizational frictions that prevent natural reallocation and the deliberate redesign required to overcome them.

Figure 1, Panel (b), provides a stylized representation of the interventions. Prior to any intervention, branch activity is dominated by simple retail products, with a smaller share of complex tasks and limited SME lending. The Tech rollout expands total throughput by automating routine transactions, but leaves the composition of activity largely unchanged. In contrast, the Task Intervention reshapes the allocation of this expanded capacity: simple products remain stable, while effort is reallocated toward complex, high-value SME lending. The figure highlights that productivity gains materialize fully only once organizational design explicitly directs how newly created capacity is deployed across tasks.

1. Tech Intervention: Introduction of the mobile app. The first intervention introduces a customer-facing mobile app that automates routine, non-complex (simple) retail transactions. The app digitizes tasks such as account opening, small consumer loans, and credit card applications, transforming workflows that were previously completed manually inside branches. As a result, routine transactions become substantially faster and less time-intensive for account managers.

A key feature of this intervention is that the app affects *how* tasks are performed but not *which* tasks are prioritized. Only simple products are included in the app, while complex, high-value services—like SME loans and other advisory-intensive products—remain exclusively branch-based. The rollout of the app is rapid and universal, reaching all branches within four months, allowing us to study how workers respond when productive capacity expands without changes to performance evaluation.

2. Task Intervention: Reallocation toward SME lending. Consistent with Autor et al. (2002), our setting highlights that the key margin after automation is not only which tasks are digitized, but how the organization re-bundles the remaining tasks and responsibilities into jobs. Begin-

ning in January 2021, the bank implements a Task Intervention that operates through changes in performance evaluation rather than new technology. The reform has two main elements. First, for branch managers, the bank leadership explicitly communicates a clear operational focus: to shift attention from routine volume toward increasing in complex products, with SME lending as the centerpiece. Second, for workers (the account managers), it re-weights performance criteria toward SME loan transactions, raising KPIs tied to SME lending and making SME loans their primary responsibility. While overall monetary incentives remain unchanged, performance evaluation criteria are explicitly re-weighted toward SME lending, while other complex activities are not reprioritized.

To implement the reform, headquarters communicated the new objectives directly to branch managers, including through in-person visits to branches. The rollout was staggered and reached approximately 70% of branches by March 2023, the end of our sample.

To clarify the changes for account managers, consider a simple representation of worker incentives. Account managers maximize a total performance score S that aggregates output across tasks:

$$S = w_s \cdot \text{SimpleTasks} + w_c \cdot \text{ComplexTasks} + w_{\text{SME}} \cdot \text{SMETasks}$$

where w_s, w_c and w_{SME} capture the weights placed on routine, complex, and SME activities in performance evaluation. The Tech Intervention reduced the effort cost of simple tasks, creating additional capacity. However, performance weights remained unchanged, so workers continued allocating effort according to the original weights, expanding simple task volume rather than reallocating toward complex activities. The Task Intervention restructures the performance function by implicitly increasing w_{SME} specifically, while leaving w_c unchanged and reducing w_s. Only SME lending is explicitly prioritized—other complex activities receive no additional weight in performance evaluation. This selective restructuring raises the marginal return to effort spent on SME lending relative to both routine volume and other complex tasks, making SME activities significantly more valuable in determining performance outcomes while leaving the incentives for non-SME complex products unchanged.

Taken together, the two interventions sharply contrast the effects of technology-driven ca-

pacity creation with those of deliberate organizational design. The technology intervention generates slack by lowering the effort cost of routine work, while the task intervention provides the organizational complement required to redirect that slack toward high-value activities.

3. Empirical strategy

Our empirical strategy relies on detailed administrative records that allow us to trace, at high frequency, how branches and workers respond to the introduction of new technology and task assignments. Because the structure and granularity of the data shape both the definition of outcomes and the timing of treatment exposure, we begin by outlining the construction of the datasets before turning to the identification framework.

3.1. Data

We combine four complementary data sources—trade-level production records, personnel files, manager characteristics, and survey-based assessments of leadership—to build consistent branch-week and worker-week panels for both interventions. The richness of these datasets allows us to measure production, task allocation, mobility, and manager value added in a unified framework.

Trades data. Our primary dataset contains the universe of financial trades completed between 2015 and 2023. A trade corresponds to a major client-facing transaction (e.g., account openings, loans, credit cards) and is linked to a product, date, branch, and worker. Because the bank's performance system is based on trade volume rather than revenue at the time of sale, we use trade counts as our preferred measure of output and productivity. Mobile transactions are fully integrated into this dataset, allowing us to observe app-enabled trades that occur inside branches. To examine the broader financial effects of the interventions, we merge monthly branch-level balance sheet information (2018–2022), noting that these data are aggregated across products and therefore cannot distinguish complex from simple trades.

Personnel records. Annual HR files (2017–2022) provide information on job titles, tenure, wages, gender, and work locations. These records are essential for measuring employment outcomes, identifying account managers and branch managers affected by the interventions, and tracking worker movements across branches and tasks. The extended HR coverage through 2023 allows us to construct precise exit dates by combining HR rosters with the last observed trade executed by a worker.

Leadership surveys. Beginning in 2020, the company administers annual surveys that evaluate workers' assessments of their managers along dimensions such as leadership style, alignment with organizational values, and ability to set objectives. These data allow us to construct manager-level measures—such as leadership quality and value alignment—that serve as key heterogeneity dimensions in our analysis.

Sample coverage. Table 1 summarizes the data used to assess the Tech and Task Interventions. It reports the time periods covered, the number of branches and workers, and the composition of the workforce for each intervention. The table highlights key differences in scale and product scope across the two phases of the digital transformation. The Task Intervention sample covers a longer horizon, includes a larger number of branch-week observations, and features an expanded set of complex products relative to the technology intervention. These differences reflect both the evolution of the bank's product mix and the broader organizational scope of the task intervention.

Final branch-week panel datasets. We integrate all sources to produce two harmonized branch-week and worker-week panels. The first covers the tech intervention from January 2017 to December 2019, excluding pre-2017 data due to limited HR coverage and because the digital-first strategy had not yet begun. The second covers the Task Intervention from January 2019 to March 2023, starting after the app rollout was completed; the first branch receives the Task Intervention in January 2021. Both interventions operate at the branch level; worker-level analyses are constructed to examine within-branch adjustments.

Outcome variables. Our analysis focuses primarily on worker-level outcomes, which directly capture individual behavioral responses to the interventions. Worker-level measures include the total number of trades completed per worker-week, the composition of these trades across task categories, and transitions across branches or business units. All trade-based measures are expressed in inverse hyperbolic sine (IHS). Task reallocation is measured as the first time a worker performs a trade in a new category after at least three months of tenure, ensuring that we capture genuine shifts in responsibilities rather than onboarding.

Certain outcomes are measured at the branch level, as they reflect organizational decisions made by branch managers or aggregate client portfolio measures. These include hirings, worker exits, total balances, and the number of active accounts.[3]

3.2. Empirical framework

We estimate the effects of the two interventions using a staggered event-study design, complemented by generalized difference-in-differences specifications. This empirical framework allows us to trace the dynamic adjustment of branches and workers following each intervention, while also recovering average effects and examining how organizational heterogeneity shapes adaptation. Rather than focusing solely on whether outcomes change, our approach characterizes how production processes, task composition, and productivity evolve over time.

Roll-out. Figure 2 documents the staggered rollout of both interventions and provides a first view of aggregate trade dynamics. The figure shows substantial variation in treatment timing across branches, which underpins our identification strategy. Following the Tech Intervention, total trade volume rises at the aggregate level, whereas complex trades remain flat, foreshadowing the central puzzle of why automation-generated slack does not translate into spontaneous upgrading. By contrast, the Task Intervention coincides with a pronounced increase in SME-related activity.

Tables 2 and 3 report branch-level and worker-level descriptive statistics for the samples used in the analysis. At the branch level (Table 2), the tech intervention sample covers 69,465

[3]Worker exits are identified using the last observed trade week combined with HR separation records.

branch-week observations across 449 branches, while the task intervention sample includes 77,830 observations across 355 branches. Average productivity, measured as IHS(trades per employee), is substantially higher during the task intervention period (2.77) than during the tech intervention (1.85), reflecting both organizational changes and the expansion of complex products over time. Worker-level statistics (Table 3) show similar patterns: average total trades and complex trades differ across periods, consistent with changes in task scope and organizational design rather than differences in sample composition.

A branch is considered treated by the Tech Intervention in the first week in which a product is sold through the mobile app, indicating a change in production processes. Consistent with institutional information from the bank, treatment began in June 2018, when the app became available to customers. A branch is considered treated by the Task Intervention once an account manager completes an SME loan, reflecting the reassignment of responsibilities and the introduction of SME-focused KPIs; this process begins in January 2021.

To assess whether treatment timing is correlated with pre-intervention characteristics, Table 4 compares branches that adopt the technology early with those that adopt later. Early adopters are smaller and exhibit lower pre-treatment trade volumes and employment. However, there is no statistically significant difference in pre-treatment productivity, measured as IHS(trades per employee), between early and late adopters (difference = -0.012, s.e. 0.020). This balance supports a causal interpretation of the event–study estimates. Throughout the analysis, time-invariant branch characteristics—such as size, customer base, and local market conditions—are absorbed by branch fixed effects.

Event-study design. We estimate dynamic treatment effects using a staggered event–study specification with worker (or branch) and week fixed effects. For each outcome y_{bt} measured at the worker-week (or branch–week) level, we estimate:

$$y_{bt} = \sum_{\underline{C} \leq s \leq \overline{C}, s \neq -1} \beta_{j,s} D_{b,t}^{j,s} + \alpha_b + \xi_t + \epsilon_{bt}, \tag{1}$$

where $D_{b,t}^{j,s}$ is a relative time to treatment indicator for intervention j, in period $t - s$, defined as

$D_{b,t}^{j,s} = \mathbb{1}[t = \tau_b^j + s]$ for $s \in (\underline{C}, \overline{C})$, $D_{b,t}^{j,\underline{C}} = \mathbb{1}[t \leq \tau_b^j + \underline{C}]$, and $D_{b,t}^{j,\overline{C}} = \mathbb{1}[t \geq \tau_b^j + \overline{C}]$, where $\mathbb{1}[\cdot]$ is the indicator function, s indexes the set of time indicator variables, and τ_b^j is the first monthly period in which the intervention j starts at worker's branch, α_b denote worker (or branch) fixed effects, and ξ_t denote week fixed effects. Coefficients $\beta_{j,s}$ capture the average treatment effect on treated units s periods relative to treatment. For the technology intervention, we consider an event window from eight weeks before to twenty-six weeks after adoption; for the task intervention, we use a longer window reflecting its more gradual rollout.

Difference-in-differences specifications. In addition to the event–study estimates, we recover average treatment effects using generalized difference-in-differences models with branch and week fixed effects. While these specifications abstract from dynamics, they provide a parsimonious framework for studying heterogeneity by branch, worker, and manager characteristics. Together, the event–study and difference-in-differences approaches provide a consistent and complementary view of how technology and organizational design interact to shape productivity and task reallocation.

4. Interventions: main effects

We analyze the impact of the mobile banking app on productivity, task composition, and worker reallocation between January 2017 and December 2019, followed by the effects of the SME incentive intervention. The Tech Intervention generates an immediate increase of up to 20pp in productivity, yet this technological improvement does not translate into greater production of complex tasks. Instead, the introduction of the app creates organizational slack that branches do not convert into higher-value activities. The subsequent task intervention addresses this allocation problem by redefining performance evaluation criteria.

4.1. Impacts of the banking app

Figure 3 (Panel (a)) documents the first-order effects of the mobile banking app on worker output. Event-study estimates show a clear and persistent increase in total trades following

adoption.

Rather than exhibiting a sharp discontinuity at implementation, worker output rises gradually in the weeks after adoption, with effects that accumulate over time.

The absence of differential pre-trends and the smooth post-adoption dynamics are consistent with progressive learning and integration of the new technology into daily workflows, rather than a one-time jump in activity driven by automation alone.[4] Table A.1 Panel A shows the results by estimating a differences-in-differences model. We find that the intervention increases orker-level total trades by approximately 18.4 percentage points.

Mechanisms: Client base expansion. Figure 4 sheds light on how workers absorb the productivity gains generated by the Tech Intervention. Individual account managers serve more clients overall and attract significantly more first-time clients after adoption. These patterns indicate that the additional processing capacity created by automation is primarily used to expand the client base rather than to deepen engagement with existing customers. Appendix Figure A.2 further clarifies this mechanism by separating consumption by old and new clients. Consumption by existing clients remains stable, while new clients account for the bulk of the expansion in activity. This reassures that the increase in throughput is not driven by overserving or intensifying transactions with incumbent customers.

Importantly, the expansion in routine activity does not come at the expense of relationship quality. Figure 5 shows that both total balances and the number of active accounts increase following the app rollout.[5] Both balances and active accounts increase, indicating that branches maintain—and in some cases deepen—client relationships rather than churning low-quality transactions.

Figure 6 (Panels (a)–(b)) shows no evidence of adjustment along employment margins. Hiring and separation rates remain statistically flat throughout the post-adoption period.

[4]Results are consistent when aggregating to the branch level. Appendix Figure A.1 shows that both total trades and productivity (trades per worker) increase at the branch level following the technology intervention.

[5]Given that these financial measures aggregate client portfolios managed by branch teams rather than individual workers, they are measured at the branch level.

4.2. Worker task upgrading

Figure 7 (Panels (a)-(c)) examines how the Tech Intervention affects the composition of production across simple, complex, and SME trades at the worker level. Individual workers substantially increase the volume of simple trades they perform following adoption (Panel (a)), but show no meaningful change in complex trades (Panel (b)) or SME trades (Panel (c)). This pattern reveals an organizational friction: the Tech Intervention creates organizational slack but does not direct its deployment. The app freed worker time by automating routine transactions, yet unchanged performance weights led workers to intensify simple tasks that still contributed significantly to evaluation and became easier to complete, rather than upgrading toward complex activities.

4.3. Impact of SME loans incentives

Figure 3 (Panel (b)) presents event-study estimates for total trades at the worker level following the Task Intervention. Similar to the Tech Intervention, activity increases sharply at implementation and remains persistently higher. Table A.1 Panel B quantifies that branch-level trades increase by 15.4 percentage points and worker-level trades increase by about 11.3 percentage points. Figure 6 (Panels (c)-(d)) confirms that hiring and exits remain flat, indicating these productivity gains reflect within-worker reallocation rather than employment adjustments. The Task Intervention achieves this by restructuring performance evaluation to make SME lending the primary criterion for assessment, thereby changing the returns to effort across tasks even though monetary incentives and production technology remain unchanged.

Targeted reallocation to SME lending. Figure 7 (Panels (d)-(f)) reveals where this reallocation occurs: SME trades increase sharply and persistently, while complex trades show little response. Account managers respond narrowly to the specific task whose weight in the performance function increased, rather than broadly upgrading toward all complex activities.

To characterize how this adjustment reshapes task portfolios, Figure 8 examines changes in the Herfindahl–Hirschman Index, which increases under both interventions, indicating greater worker-level task concentration. Figure 9 uses task composition ratios to reveal the

direction of this concentration, distinguishing shifts toward lower- versus higher-value activities. Under the Tech Intervention, increases in specialization reflect concentration in simpler tasks: the ratio of complex to simple trades declines, indicating that expanded capacity is disproportionately allocated to routine activities. This pattern corresponds to "misdirected" specialization—greater focus on tasks that are easier to scale but lower in value. By contrast, under the Task intervention, specialization takes a sharply different form. The ratio of complex to simple trades shows little movement, but the ratio of SME to non-SME complex trades rises sharply. Workers reallocate within the set of complex tasks, specializing narrowly in SME lending while other complex activities remain flat.

This targeted response provides identifying evidence. If the Task Intervention operated as a generalized productivity shock, all complex tasks would rise in parallel. Instead, SME increases sharply while non-SME complex trades remain stable, confirming that reallocated effort responds specifically to restructured performance evaluation rather than broad increases in capacity or motivation.

5. Organizational frictions

The heterogeneous effects of the Tech Intervention and the task-based incentive intervention point to two organizational forces that shape adjustment: *tenure-based rigidity* and *manager effects*. The Tech shock creates slack and the Task Intervention raises the return to SME effort, but both may fail to produce broad task upgrading when workers face switching costs and when implementation varies across managers.

In the remainder of this section, we proceed in three steps. First, we examine how worker tenure constrains task reallocation. Second, we estimate manager fixed effects from pre-intervention branch productivity and assess its role in facilitating upgrading. Third, we study how high-productivity managers interact with worker tenure in shaping adjustment to both interventions.

5.1. Worker tenure

We examine worker tenure as a central source of organizational friction constraining task reallocation.[6] Tenure proxies for accumulated routines, task-specific human capital, and established work practices—all of which increase the costs of reallocating effort in response to organizational changes. Figure A.3 displays the distribution of worker tenure, with a mean tenure of 8.89 years and a median of 8 years.

Table 5 shows heterogeneous treatment effects by tenure to both interventions using a binary high/low tenure median split. Under the Tech Intervention (Panel A), high tenure substantially reduces responses across all task categories. Under the Task Intervention (Panel B), high tenure similarly dampens responses across most trade categories, with particularly strong attenuation for total trades and complex trades.

Figure 10 decomposes these patterns by examining heterogeneity across the tenure distribution. Under the Tech Intervention (Panels (a)–(c)), effects exhibit a clear negative tenure gradient for both simple and complex trades, with responses declining steadily as tenure increases. By contrast, SME lending displays small and statistically muted responses across all tenure groups, indicating limited adjustment along this margin.

For the Task Intervention, the effects on simple and complex trades (Panels (d)–(e)) also decline with tenure: low-tenure workers experience sizable increases, while effects attenuate rapidly and approach zero among high-tenure workers. In contrast, SME lending (Panel (f)) is roughly stable across the tenure distribution, with high-tenure workers exhibiting increases comparable in magnitude to those of low-tenure workers.

Workers with higher tenure appear to shift effort within a fixed amount of time and attention—doing more SME lending while scaling back simple tasks and other complex activities. By contrast, less tenured workers increase activity more broadly across task categories. This pattern is consistent with the idea that established routines and responsibilities limit how much high-tenure workers can expand overall, whereas lower-tenure workers have more room to increase total output rather than mainly reallocating effort.

[6] Throughout the paper, whenever we refer to tenure we mean worker tenure measured at the time of the intervention at the branch level. Tenure is thus time-invariant and fixed at the moment of the shock.

Figures A.4-A.6 present the non-parametric plots by tenure group and task type across additional heterogeneity dimensions: worker age, ability and share of high tenure peers in the branch. The negative tenure gradient following both interventions is robust to conditioning on worker age, ability, and peer tenure composition, suggesting that tenure itself operates as a organizational friction rather than merely proxying for differences in age, ability, or peer composition.

These results show that tenure generates persistent organizational rigidity that limits adaptation to both technological change and explicit task redefinition. The close similarity of tenure gradients across interventions, task types, and levels of aggregation underscores the role of tenure as a binding constraint on organizational adaptation.

5.2. High-productivity managers

We next examine whether high-productivity managers mitigate organizational frictions that constrain task reallocation. To measure high-productivity managers, we estimate manager value-added (θ_m) from the following specification using pre-intervention data starting in January 2017:

$$\text{asinh(branch productivity)}_{bmt} = \theta_m + \eta_b + \tau_t + \varepsilon_{bmt} \tag{2}$$

where branch productivity is total number of trades per employee, and b indexes branches, m indexes managers, and t indexes time. The specification includes manager fixed effects (θ_m), branch fixed effects (η_b), week fixed effects (τ_t), and and idiosynchratic error term ε_{bmt}.

Figure A.7 presents the AKM variance decomposition and shows that managers account for a substantial share of productivity variation, comparable in magnitude to worker effects.

Motivated by this evidence, we ask whether differences across branch managers translate into differential adjustment to the two interventions. In particular, we examine whether high-productivity managers are better able to facilitate task reallocation when organizational change alters either productive capacity or performance priorities. Table 6 examines heterogeneity by high-productivity managers across both interventions.

Tech Intervention. Panel A shows that the interaction between the technology intervention and high-productivity managers is small and statistically insignificant across total trades, simple trades, and complex trades. While the banking app generates a large increase in overall output (total trades rise by about 18 pp), the interaction between the technology shock and high-productivity managers is small and statistically insignificant across all outcomes, indicating that high-productivity managers do not induce differential task upgrading when technological change expands capacity but leaves task priorities unchanged.

Task Intervention. By contrast, under the Task Intervention (Panel B), high-productivity managers play a role in shaping worker responses. Total trades increase by roughly 9 pp in the initial post period and 14 pp thereafter under high-productivity managers, and SME lending—the task explicitly prioritized by the redesign—rises by about 5–6 pp. Effects on complex trades remain small and statistically insignificant. These results suggest that high-productivity managers mitigate organizational frictions and enable targeted task reallocation only when organizational objectives are clearly aligned through performance evaluation.

5.3. Worker tenure and high-productivity managers

Lastly, we examine whether high-productivity managers amplify task reallocation following the interventions, and whether these effects differ systematically by worker tenure.

Technology intervention. Figure 11 (Panels (a)-(d)) reports heterogeneity by worker tenure and high-productivity managers during the technology intervention. The dominant pattern across total trades, simple trades, and complex trades (Panels (a)-(c)) is a negative tenure gradient: low-tenure workers respond substantially more than high-tenure workers. Importantly, this gradient is similar under high- and low-quality managers, indicating that high-productivity managers improve worker productivity uniformly but does not differentially overcome tenure-related frictions when performance weights remain unchanged.

Task intervention. Figure 11 (Panels (e)-(h)) reveals how high-productivity managers and worker tenure jointly shape reallocation once performance evaluation is restructured. Total trades respond less uniformly across tenure groups, highlighting that the intervention does not primarily operate through scale. Instead, task-level responses reveal reallocation

that is mediated by high-productivity managers. Under high-productivity managers, simple trades stagnate or decline, while complex trades and SME lending increase substantially. This pattern is particularly pronounced among low- and mid-tenure workers but is also evident among higher-tenure workers, indicating that high-productivity managers play an important role in overcoming adjustment frictions once task priorities are explicitly aligned.

This heterogeneity reflects how high-productivity managers allocate scarce attention across workers. Low-tenure workers present higher expected returns from managerial investment: they have fewer entrenched routines, lower switching costs, and longer remaining horizons over which skill investments compound—consistent with Ben-Porath logic, as formalized in our model in Section 6. High-productivity managers therefore invest disproportionately in these workers through coaching, shadowing, and targeted assignment to complex and SME-related activities. In contrast, highly tenured workers' established task bundles and client relationships are costlier to reconfigure, reducing the returns to guidance. This mechanism explains why high-productivity managers amplify task upgrading primarily among newer workers and why adjustment remains uneven even when task priorities are explicitly re-aligned.

Mechanisms and wage effects Why are high-productivity managers effective in facilitating re-allocation once incentives are aligned? Survey evidence provides insight. Table 7 shows that manager AKM fixed effects are strongly correlated with leadership traits such as trust, inspiration, and clarity of objectives, but only weakly correlated with demographic characteristics. This pattern indicates that AKM captures persistent leadership and coordination capacity rather than sorting or branch-level composition.

Figure 12 shows that tenure heterogeneity extends to compensation. The figure reports non-parametric worker-level TWFE estimates of log wages at the yearly level, separately by tenure group. Both panels show a clear and monotonic decline in wage responses with tenure. Low-tenure workers experience positive and statistically significant wage gains following the intervention, while wage effects attenuate steadily with tenure and become close to zero or negative for long-tenured workers.

This pattern mirrors the tenure gradients observed for task reallocation and production

outcomes. Despite the absence of explicit changes to the compensation scheme, wage adjustments accrue primarily to lower-tenure workers who reallocate effort most strongly toward incentivized tasks. The muted wage response among long-tenured workers is consistent with higher adjustment frictions that limit both behavioral responses and the associated returns. Together, these results indicate that tenure-related rigidity shapes not only how workers adjust tasks but also how the gains from organizational reforms are distributed.

These findings show that task upgrading requires more than technological capacity or incentive redesign alone. Worker tenure constitutes a fundamental friction to reallocation, while high-productivity managers play a complementary role by lowering adjustment costs and translating restructured performance incentives into task-level reallocation toward higher-value activities.

6. Conceptual framework

In this section, we introduce a simple model to help interpret our empirical findings through the lens of the Ben-Porath human capital framework (Ben-Porath, 1967). Workers allocate a fixed time endowment between current production and investment in task-specific skills that raise future productivity (Cavounidis and Lang, 2020). Because learning utilizes the same scarce time input as production, skill accumulation entails an opportunity cost in terms of foregone contemporaneous output. The incentive to invest in a given task depends on the task-specific returns embedded in the firm's performance environment, as well as on the worker's effective horizon.

Managers enter the model as an organizational complement that affects the cost-benefit calculus of learning. In particular, managerial actions can (i) increase the efficiency of learning by reducing the time required to generate a unit of skill, and/or (ii) raise the perceived value of future returns by clarifying objectives, providing guidance, and shaping expectations about the payoff to acquiring new capabilities.

6.1. Model set-up

We consider a worker who faces three task categories: *simple* ($i = 1$), *SME* ($i = 2$), and *complex* ($i = 3$). The worker begins period 0 with task-specific skills $\boldsymbol{S} = (S_i)_{i=1}^3$. The skill level that is optimal for performing task i in period $j \in \{0, 1\}$ is denoted $T_i^{(j)}$, and we collect these in $\boldsymbol{T}^{(j)} = (T_i^{(j)})_{i=1}^3$, where $j = 0$ refers to the pre-intervention period and $j = 1$ to the post-intervention period.

Returns from devoting the full unit time endowment to production in period 0 are

$$r_0 \;:=\; \sum_{i=1}^{3} A_i^{(0)}\, \pi\Big(S_i - T_i^{(0)}\Big)\,, \tag{3}$$

where $\pi(\cdot)$ is concave and maximized at zero; we normalize $\pi(0) = 1$. The parameter $A_i^{(0)}$ is a task-specific payoff (productivity) shifter in period 0. For simplicity, assume $S_i < T_i^{(0)}$ for all i, so there is scope for skill accumulation.

In period 0, the worker chooses task-specific investments $\boldsymbol{I} = (I_i)_{i=1}^3$ that augment next-period skills to $S_i + I_i$. Investing I_i units of skill in task i requires $t_i I_i$ units of time, where $\boldsymbol{t} = (t_i)_{i=1}^3$ are task-specific learning-time conversion factors. Let $\tau(\boldsymbol{I}) = \sum_{i=1}^3 t_i I_i$ denote total learning time, so that $1 - \tau(\boldsymbol{I})$ is the time available for contemporaneous production in period 0. The worker solves

$$\begin{aligned} \max_{\boldsymbol{I}} \quad & \Big(1 - \tau(\boldsymbol{I})\Big)\, r_0 + \beta \sum_{i=1}^{3} A_i^{(1)}\, \pi\Big(S_i + I_i - T_i^{(1)}\Big) \\ \text{s.t.} \quad & I_i \geq 0 \;\; \forall i \in \{1,2,3\}, \qquad \tau(\boldsymbol{I}) \leq 1, \end{aligned} \tag{4}$$

where $\beta \in (0, 1)$ is the discount factor, and superscripts allow the payoff shifters A_i and targets T_i to change between periods.

We focus on interior allocations with $\tau(\boldsymbol{I}) < 1$, so the worker both produces and trains in period 0. The Kuhn–Tucker conditions imply that for each task i,

$$\beta A_i^{(1)}\, \pi'\Big(S_i + I_i^* - T_i^{(1)}\Big) \leq r_0\, t_i, \qquad \text{with equality if } I_i^* > 0. \tag{5}$$

Thus, investment in skill i occurs when the discounted marginal benefit of learning exceeds the marginal opportunity cost in foregone contemporaneous returns.

Interpretation of β and t_i. The discount factor β governs the worker's effective horizon: workers who place less weight on the future invest less in learning. The parameter t_i captures the time cost of acquiring one unit of skill in task i; higher t_i makes learning more expensive in terms of foregone contemporaneous production.

6.2. Predictions

We now incorporate workers' tenure into the model by imposing the following assumptions that distinguish low-tenured workers (denoted by superscript J) from high-tenured workers (denoted by superscript S). We impose the following assumptions:

$$\beta^J \geq \beta^S, \qquad t_i^J \leq t_i^S, \qquad S_i^J \leq S_i^S, \text{ for tasks } i = 1, 2, 3. \tag{6}$$

From (6), it follows that high-tenured workers perceive lower future returns from investing in learning, face higher learning costs, and possess higher skill levels in each task before both interventions, relative to low-tenured workers. Moreover, from the ordering of the skill vectors in (6), it follows that workers' single-period returns satisfy

$$r_0^S \geq r_0^J. \tag{7}$$

Under these assumptions, we derive the following productivity predictions for the Task and Tech Intervention across Simple Trades, SME Loans, and Complex Trades.

6.2.1. Tech Intervention

We model the Tech Intervention as a change in task-specific productivity shifters that scale output directly. To capture that the technology disproportionately improves the efficiency of

simple activities, assume that[7]

$$A_i^{(1)} = A_i^{(0)}(1 + a_i), \qquad a_1 > a_2 \geq a_3 \geq 0.$$

For a worker of type $k \in \{J, S\}$, if $I_{i,k}^* > 0$ the optimality condition is

$$\beta^k A_i^{(1)} \pi' \left(S_i^k + I_{i,k}^* - T_i^{(1)} \right) = r_0^k \, t_i^k. \tag{8}$$

Since π is concave and $\pi'(\cdot)$ is decreasing on the relevant domain, a higher $A_i^{(1)}$ increases optimal learning in task i (under the interior solution), while a higher effective cost term $r_0^k t_i^k / \beta^k$ reduces it.

Simple Trades ($i = 1$). Because a_1 is the largest, the Tech Intervention raises the marginal return to simple-task proficiency the most. Equation (8) therefore implies the strongest incentives to invest in the skills relevant for performing simple trades under the new technology (e.g., learning the new workflow). As a result, the increase in simple-trade output is predicted to be largest.

Moreover, heterogeneity follows directly from the effective cost of learning. Since

$$\frac{r_0^S t_1^S}{\beta^S} > \frac{r_0^J t_1^J}{\beta^J},$$

then monotonicity of π' implies $I_{1,J}^* > I_{1,S}^*$, so low-tenure workers experience larger post-intervention gains in simple-task performance.

SME Loans ($i = 2$). For SME tasks, the productivity shift is weaker ($a_2 < a_1$), so the induced change in optimal learning is smaller. The model therefore predicts more limited gains in SME-related output under the Tech Intervention, especially for workers with higher effective learning costs. In particular, the same comparison of effective costs implies $I_{2,J}^* \geq I_{2,S}^*$ whenever both types invest in SME-related learning.

[7] Throughout, we maintain the interior case $\tau(\boldsymbol{I}) < 1$, so the time constraint does not bind and the worker chooses task-specific investments by equating marginal benefits and marginal costs.

Complex Trades ($i = 3$). Complex tasks receive the smallest productivity improvement ($a_3 \leq a_2 < a_1$), so incentives to invest in complex-task skill rise the least. Consequently, learning and output responses along this margin are predicted to be weak and may be close to zero for high-cost workers (i.e., corner solutions with $I^*_{3,S} = 0$ are possible). This delivers a natural interpretation for why a technology that primarily improves the efficiency of routine tasks generates little upgrading toward complex activities in the absence of an explicit change in performance priorities.

6.2.2. Task Intervention

We model the Task Intervention as a change in the performance environment that increases the return to SME lending. Formally, we assume that the post-intervention payoff shifter for SME tasks rises, $A_2^{(1)} > A_2^{(0)}$, while the payoff shifter for non-SME complex tasks is unchanged, $A_3^{(1)} = A_3^{(0)}$ (allowing the return to simple tasks to weakly fall—$A_1^{(1)} \leq A_1^{(0)}$—would only strengthen the targeted-reallocation predictions below). In addition, we allow target skill requirements to weakly increase, $T_i^{(1)} \geq T_i^{(0)}$ for all i, capturing higher expectations and/or expanded responsibilities after the role redefinition.

For a worker of tenure type $k \in \{J, S\}$, interior optimal investments satisfy the first-order conditions: for each task i,

$$\beta^k A_i^{(1)} \pi' \left(S_i^k + I^*_{i,k} - T_i^{(1)} \right) \leq r_0^k t_i^k, \qquad \text{with equality if } I^*_{i,k} > 0. \tag{9}$$

This condition makes clear that learning increases with the marginal return to post-period proficiency (scaled by $A_i^{(1)}$) and decreases with the effective opportunity cost of learning, $r_0^k t_i^k / \beta^k$.

Simple Trades ($i = 1$). In the simple-task dimension, we assume workers start close to the relevant frontier in the post environment, i.e. S_1^k is near $T_1^{(1)}$ for both $k \in \{J, S\}$. Since $\pi(\cdot)$ is concave and maximized at zero, this implies that the marginal benefit of additional learning, $\pi'(S_1^k + I_{1,k} - T_1^{(1)})$, is small in the relevant neighborhood. Equation (9) therefore predicts limited learning investments in simple-task skills and correspondingly modest changes in

simple-task output relative to SME lending.

Second-period simple-task output for type k is

$$y_{1,k}^{(1)} = A_1^{(1)} \pi\Big(S_1^k + I_{1,k}^* - T_1^{(1)}\Big).$$

Differences across tenure types in this margin are primarily governed by heterogeneity in effective learning costs $r_0^k t_1^k / \beta^k$, but when both types are already close to the frontier these differences are quantitatively muted.

SME Loans ($i = 2$). For SME tasks, the Task Intervention raises the return to proficiency through $A_2^{(1)} > A_2^{(0)}$. Holding fixed r_0^k and t_2^k, equation (9) implies a higher optimal investment in SME-related skills, $I_{2,k}^*$, relative to the counterfactual without the intervention. This increase is amplified when workers are initially far from the SME target, i.e. when S_2^k is well below $T_2^{(1)}$, because $\pi'(\cdot)$ is then relatively high.

Heterogeneity follows from differences in effective opportunity costs. If

$$\frac{r_0^S t_2^S}{\beta^S} > \frac{r_0^J t_2^J}{\beta^J},$$

then the KKT condition implies $I_{2,J}^* \geq I_{2,S}^*$ (with strict inequality under interior solutions), so low-tenure workers exhibit larger increases in SME-related proficiency and output.

Second-period SME output for type k is

$$y_{2,k}^{(1)} = A_2^{(1)} \pi\Big(S_2^k + I_{2,k}^* - T_2^{(1)}\Big).$$

Importantly, the model's clean prediction is about *changes*: the Task Intervention raises SME activity, with larger increases for lower-cost (e.g. low-tenure) workers, while the ranking of output levels across types depends on initial skill gaps.

Complex Trades ($i = 3$). Because the Task Intervention does not increase the return to non-SME complex tasks ($A_3^{(1)} = A_3^{(0)}$), the marginal benefit of learning in this dimension changes

little. A no-learning corner for high-tenure workers arises when

$$r_0^S t_3^S \;\geq\; \beta^S A_3^{(1)} \pi' \Big(S_3^S - T_3^{(1)} \Big), \tag{10}$$

so that the marginal opportunity cost exceeds the discounted marginal benefit at $I_{3,S} = 0$. If at the same time low-tenure workers have lower effective costs (e.g. $r_0^J t_3^J / \beta^J < r_0^S t_3^S / \beta^S$), then $I_{3,J}^*$ may remain positive even when $I_{3,S}^* = 0$.

Second-period non-SME complex output is

$$y_{3,k}^{(1)} = A_3^{(1)} \pi \Big(S_3^k + I_{3,k}^* - T_3^{(1)} \Big), \qquad k \in \{J, S\}.$$

This delivers the key qualitative implication: by raising returns only for SME lending, the Task Intervention generates *targeted* upgrading toward SME activities rather than broad upgrading across all complex tasks.

7. Conclusion

While technological adoption is fundamentally a within-firm process, we know relatively little about how organizations adapt their task structure, managerial practices, and worker roles in response to technological change. Our results highlight that the key margin is not only whether technology creates capacity, but whether organizations can deploy that capacity through their internal labor market.

We also find that adjustment is uneven within the workforce, underscoring heterogeneous switching costs of reskilling. Tenure summarizes a central trade-off: accumulated firm-specific capital can raise capability, but established routines and legacy task bundles can increase inertia in task reallocation.

High-productivity managers translate the redesigned performance function into task assignments and coaching, accelerating task upgrading—but in doing so, they can also widen tenure gaps if they concentrate attention where returns are highest, often among the most redeployable workers. This pattern suggests that effective management may raise average

gains from digital transformation while increasing dispersion in who upgrades.

An organizational implication is that firms may need complementary adaptation policies, such as, for instance, structured training pathways, mentoring capacity, and role designs, that reduce the fixed costs of switching into complex tasks—to ensure that upgrading is broadly accessible rather than concentrated among a subset of workers. In this view, managerial quality and organizational training infrastructure are complements: strong managers help activate task change, but inclusive transformation may require investments that lower adjustment costs for workers who are otherwise slow to reallocate.

References

Acemoglu, Daron and David Autor (2011) "Skills, Tasks and Technologies: Implications for Employment and Earnings," in Ashenfelter, Orley and David Card eds. *Handbook of Labor Economics*, 4, 1043–1171: Elsevier, 10.1016/S0169-7218(11)02410-5.

Acemoglu, Daron and Pascual Restrepo (2020) "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 128 (6), 2188–2244, 10.1086/705716.

——— (2022) "Tasks, Automation, and the Rise in U.S. Wage Inequality," *Econometrica*, 90 (5), 1973–2073, 10.3982/ECTA18738.

Adhvaryu, Achyuta, Anant Nyshadham, and Jorge Tamayo (2023) "Managerial quality and productivity dynamics," *The Review of Economic Studies*, 90 (4), 1569–1607.

Autor, David H. and Michael J. Handel (2013) "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages," *Journal of Labor Economics*, 31, S59–S96, 10.1086/669332.

Autor, David H, Frank Levy, and Richard J Murnane (2002) "Upstairs, downstairs: Computers and skills on two floors of a large bank," *ILR Review*, 55 (3), 432–447.

Autor, David H., Frank Levy, and Richard J. Murnane (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118 (4), 1279–1333, 10.1162/003355303322552801.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2007) "Incentives for Managers and Inequality among Workers: Evidence from a Firm-Level Experiment," *The Quarterly Journal of Economics*, 122 (2), 729–773, 10.1162/qjec.122.2.729.

Ben-Porath, Yoram (1967) "The production of human capital and the life cycle of earnings," *Journal of political economy*, 75 (4, Part 1), 352–365.

Bloom, Nicholas, Luis Garicano, Raffaella Sadun, and John Van Reenen (2014) "The distinct effects of information technology and communication technology on firm organization," *Management Science*, 60 (12), 2859–2885.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt (2002) "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *The Quarterly Journal of Economics*, 117 (1), 339–376, http://www.jstor.org/stable/2696490.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson (2021) "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies," *American Economic Journal: Macroeconomics*, 13 (1), 333–372, 10.1257/mac.20180386.

Cavounidis, Costas and Kevin Lang (2020) "Ben-porath meets lazear: Microfoundations for dynamic skill formation," *Journal of Political Economy*, 128 (4), 1405–1435.

Gans, Joshua S and Avi Goldfarb (2026) "O-Ring Automation," Working Paper 34639, National Bureau of Economic Research, 10.3386/w34639.

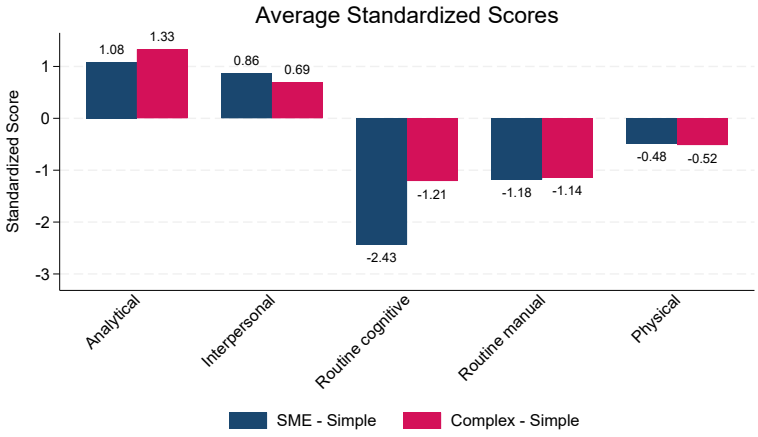
Gibbons, Robert and Rebecca Henderson (2012) "What Do Managers Do?" *Organization Science*, 23 (1), 102–117.

Metcalfe, Robert D, Alexandre B Sollaci, and Chad Syverson (2023) "Managers and productivity in retail,"Technical report, National Bureau of Economic Research.

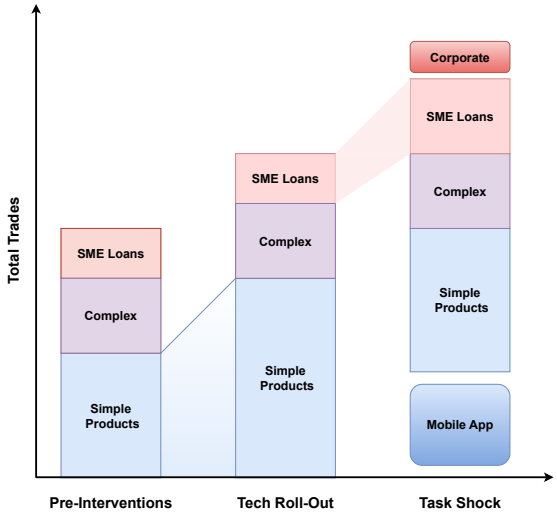
Minni, Virginia (2025) "Making the invisible hand visible: Managers and the allocation of workers to jobs."

Oi, Walter Y (1962) "Labor as a Quasi-Fixed Factor," *Journal of Political Economy*, 70 (6), 538–555.

8. Figures

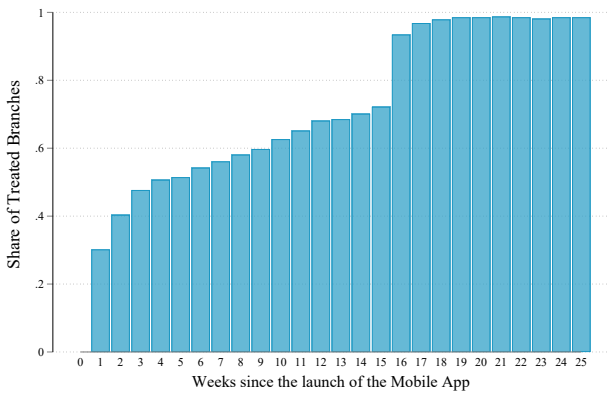


(a) Task complexity by occupation

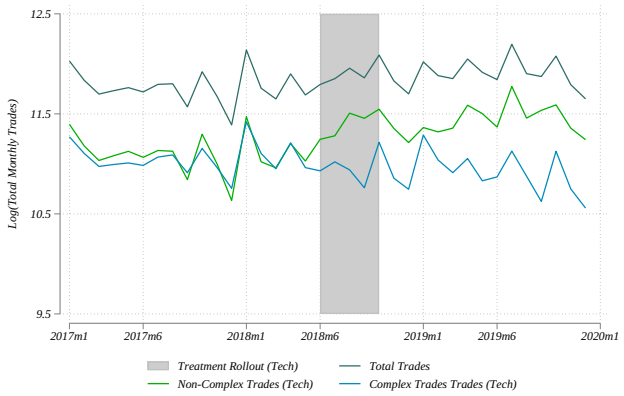


(b) Visual summary of the interventions

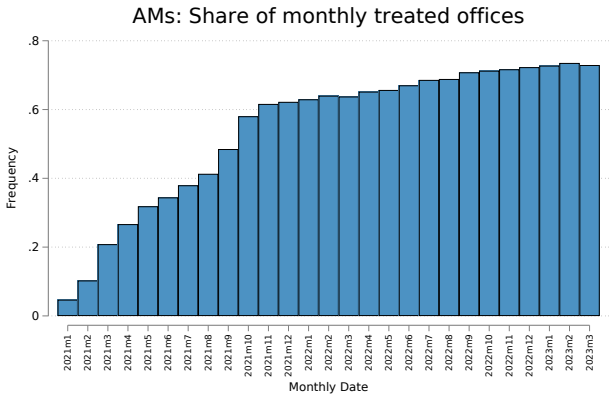
Figure 1: **Interventions and the complexity of tasks.** Panel (a) displays standardized differences in occupational task content relative to simple tasks, based on composite O*NET measures. Blue bars show differences between SME tasks and simple tasks; pink bars show differences between complex tasks and simple tasks. Composite O*NET measures follow Acemoglu and Autor (2011). Panel (b) provides a visual summary of the technology and task interventions.



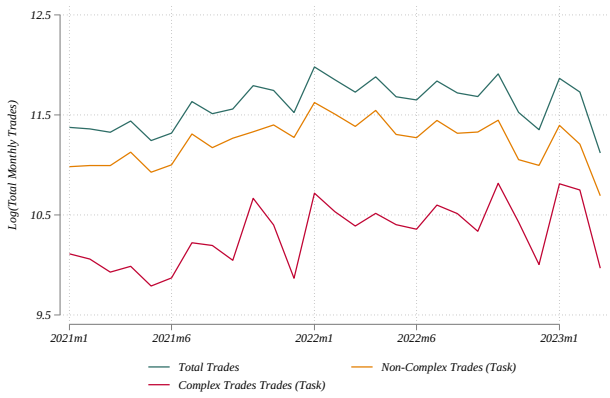
(a) Tech Intervention Rollout



(b) Trades under Tech Intervention

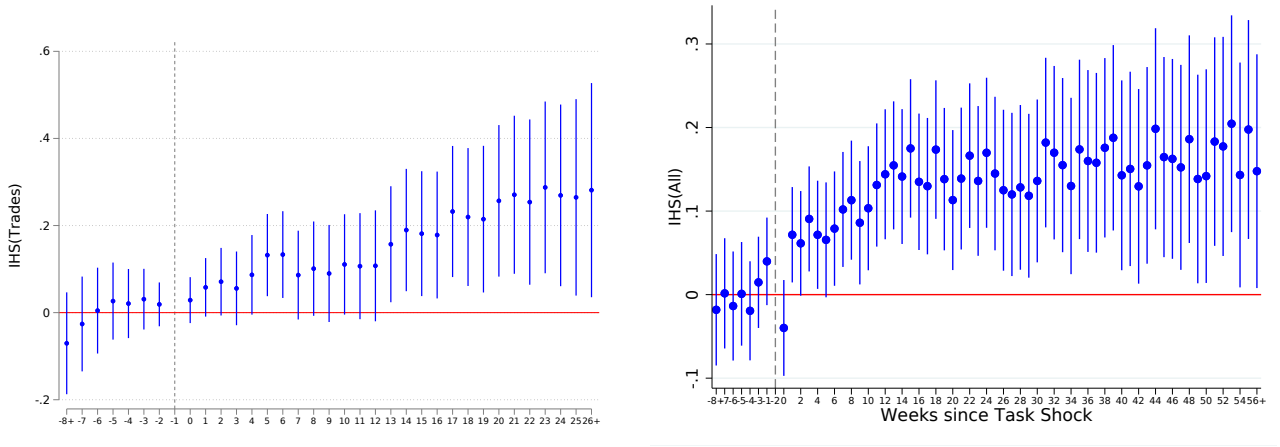


(c) Task Intervention Rollout



(d) Trades under Task Intervention

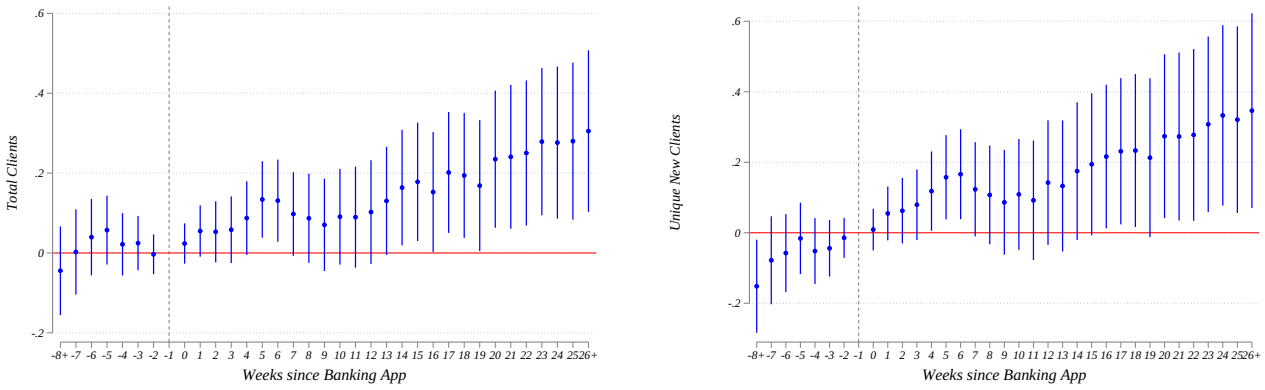
Figure 2: **Rollout and aggregate trade dynamics for the Tech and Task Interventions.** The top row shows the introduction of the mobile app (Tech Intervention) and the corresponding evolution of total trades. The bottom row shows the rollout of the SME task reallocation (Task Intervention) and associated trade patterns.



(a) Tech intervention: Worker-level total trades

(b) Task intervention: Worker-level total trades

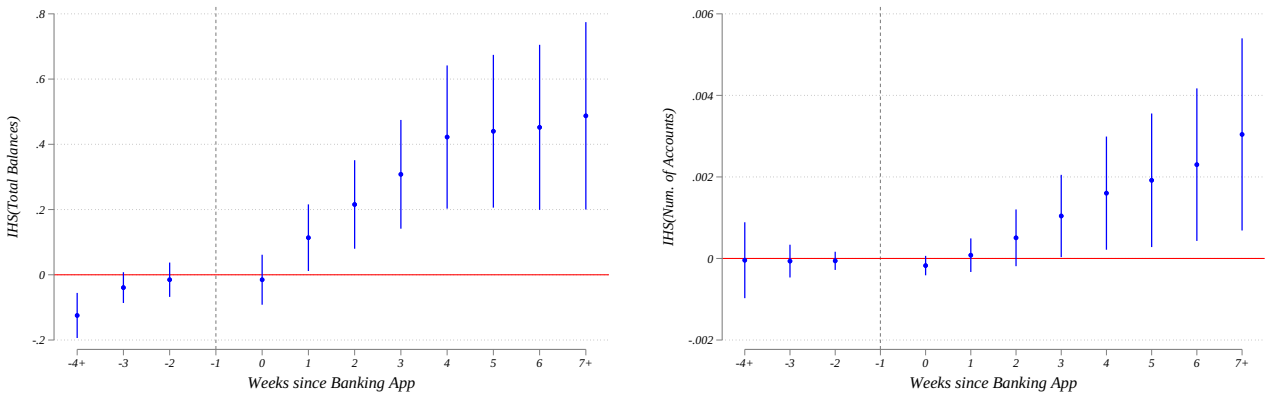
Figure 3: **Event-study estimates for total trades at the worker level.** Panel (a) shows the Tech Intervention; Panel (b) shows the Task Intervention. For both interventions, the sample includes account managers. All outcomes are expressed in inverse hyperbolic sine (IHS). Branch-level event-study estimates are reported in Appendix Figure A.1.



(a) Worker: Total Unique Weekly Clients

(b) Worker: Unique New Clients (First Time)

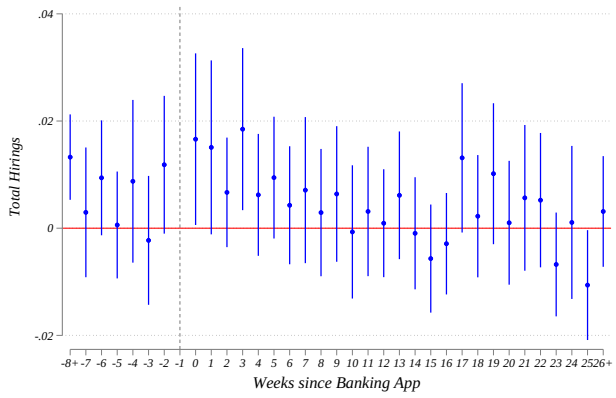
Figure 4: **Tech Intervention: client base expansion.** All outcome variables are expressed in inverse hyperbolic sine (IHS). The analysis sample includes account managers. New clients are defined as individuals who did not perform any trade before 2017.



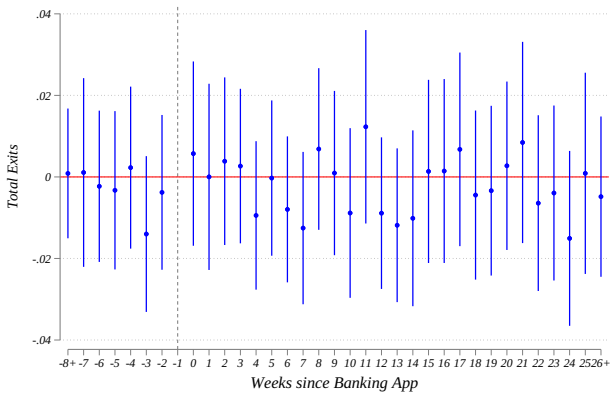
(a) Tech: Total Balances (Branch)

(b) Tech: Number of Accounts (Branch)

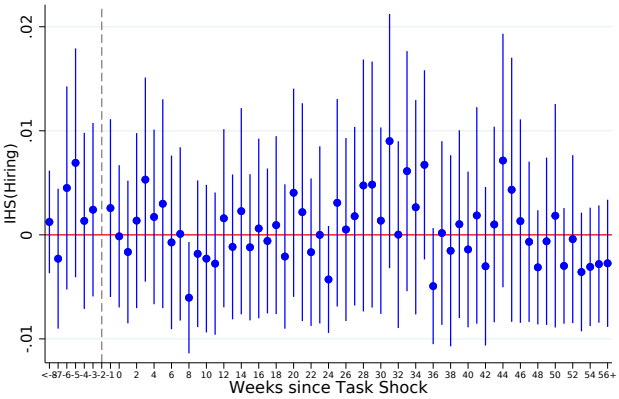
Figure 5: **Effects of Tech Intervention on product quality at the branch level.** Panels (a) shows total balances (measured in millions of COP) and Panel (b) shows the number of active accounts. The analysis sample includes account managers. Both outcomes are expressed in the inverse hyperbolic sine (IHS).



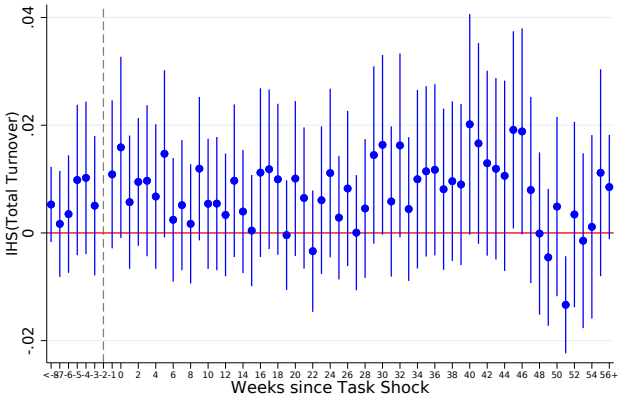
(a) Tech: Total Hiring (Branch)



(b) Tech: Total Exits (Branch)

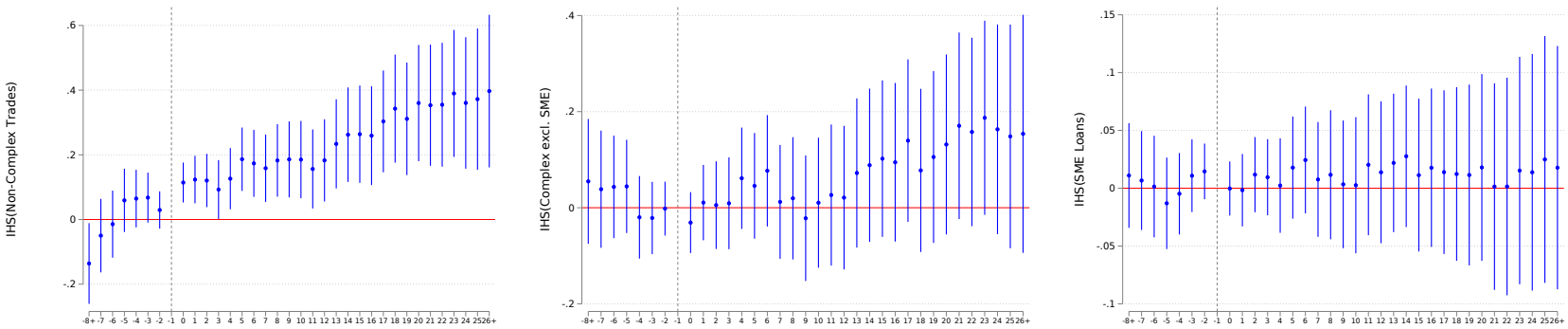


(c) Task: Hiring (Branch)

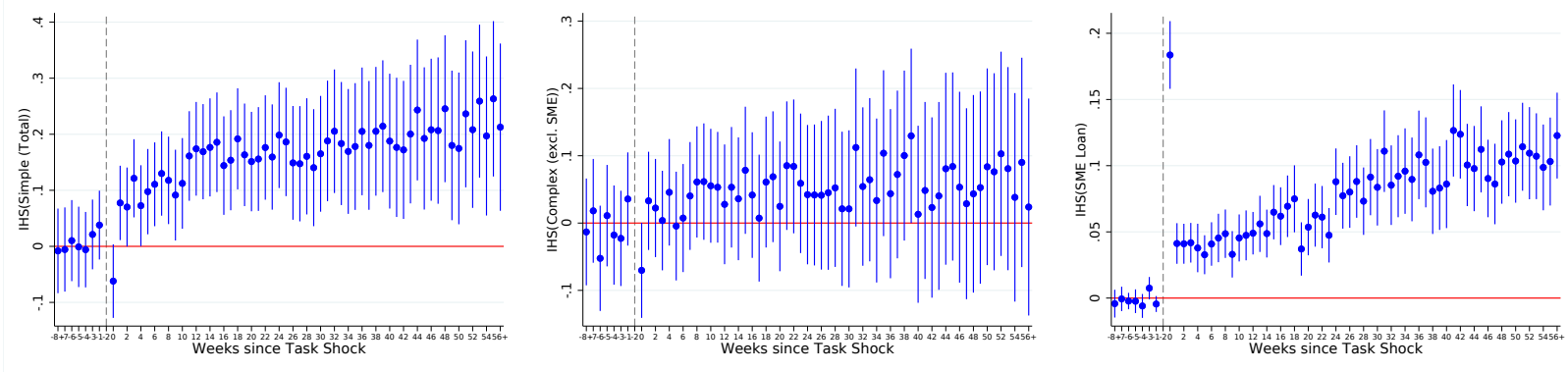


(d) Task: Total Exits (Branch)

Figure 6: **Effects of Tech and Task Interventions on worker turnover at the branch level.** Row 1 shows the Tech Intervention; Row 2 shows the Task Intervention. Panels (a) and (c) report total hirings and Panels (b) and (d) report total exits. All outcome variables are expressed in inverse hyperbolic sine (IHS). Hirings measure the total number of workers who enter the company and are assigned to a given branch in a given week. Exits measure the total number of workers who permanently leave the company in a given week and are assigned to the last branch in which they are observed.

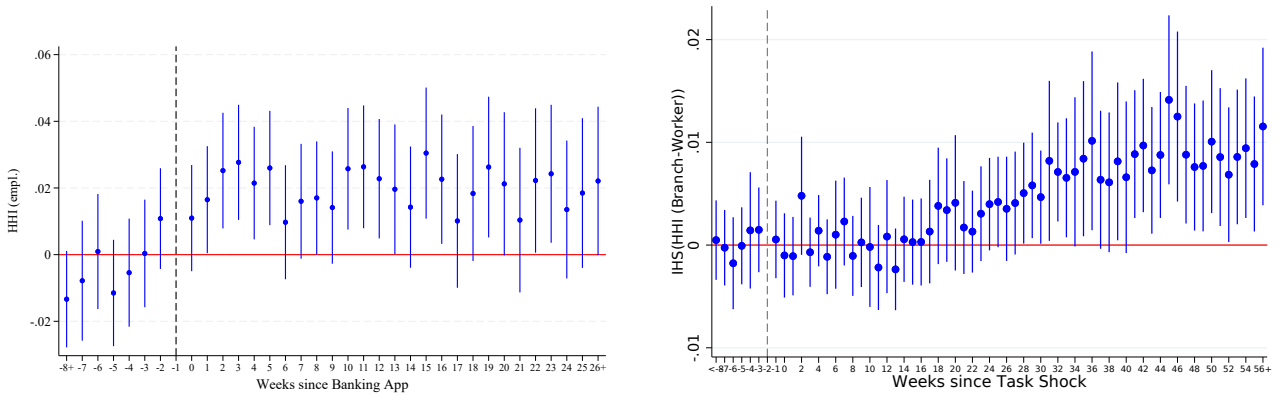


(a) Tech: Simple (Mobile) Trades (b) Tech: Complex Trades (c) Tech: SME Trades



(d) Task: Simple Trades (e) Task: Complex Trades (f) Task: SME Trades

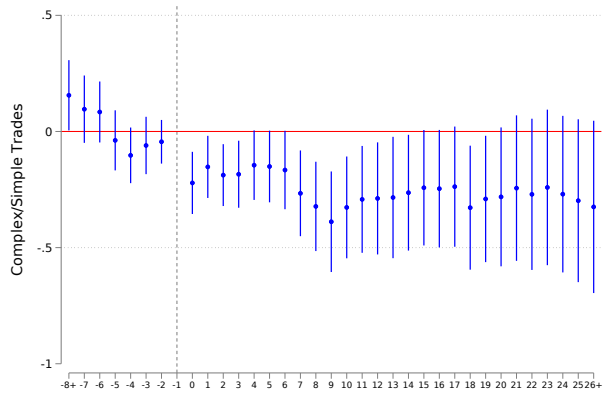
Figure 7: **Effects of Tech and Task Interventions on task composition.** Event-study estimates for worker-level task composition by trade type. Row 1 shows the Tech Intervention; Row 2 shows the Task Intervention. The analysis sample includes account managers. Columns show (a) simple trades, (b) complex trades, and (c) SME trades. All outcomes are expressed in inverse hyperbolic sine (IHS).



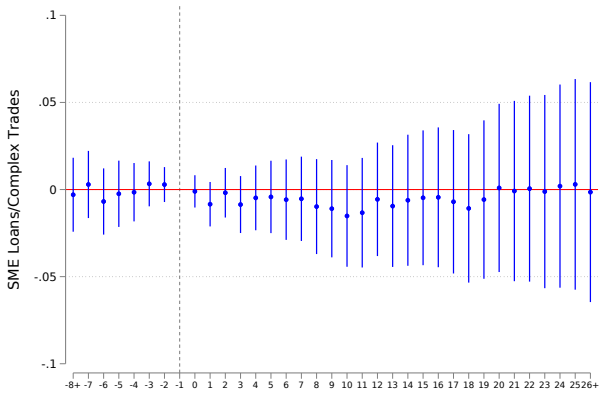
(a) Tech intervention

(b) Task intervention

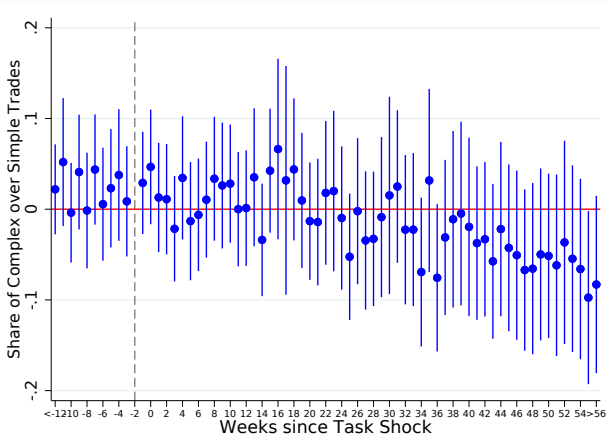
Figure 8: **Task specialization measured by the Herfindahl–Hirschman Index (HHI).** Panel (a) shows the Tech Intervention; Panel (b) shows the Task Interventions. The analysis sample includes account managers. The HHI is computed at the worker-week level based on the distribution of trades across task categories (simple, complex, and SME). Higher values indicate greater specialization.



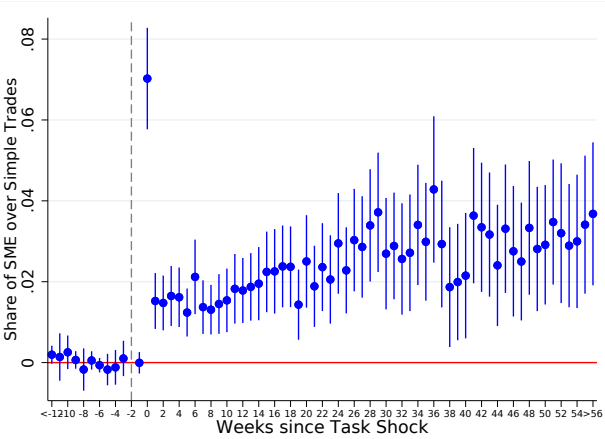
(a) Tech: Complex / Simple



(b) Tech: SME / Complex

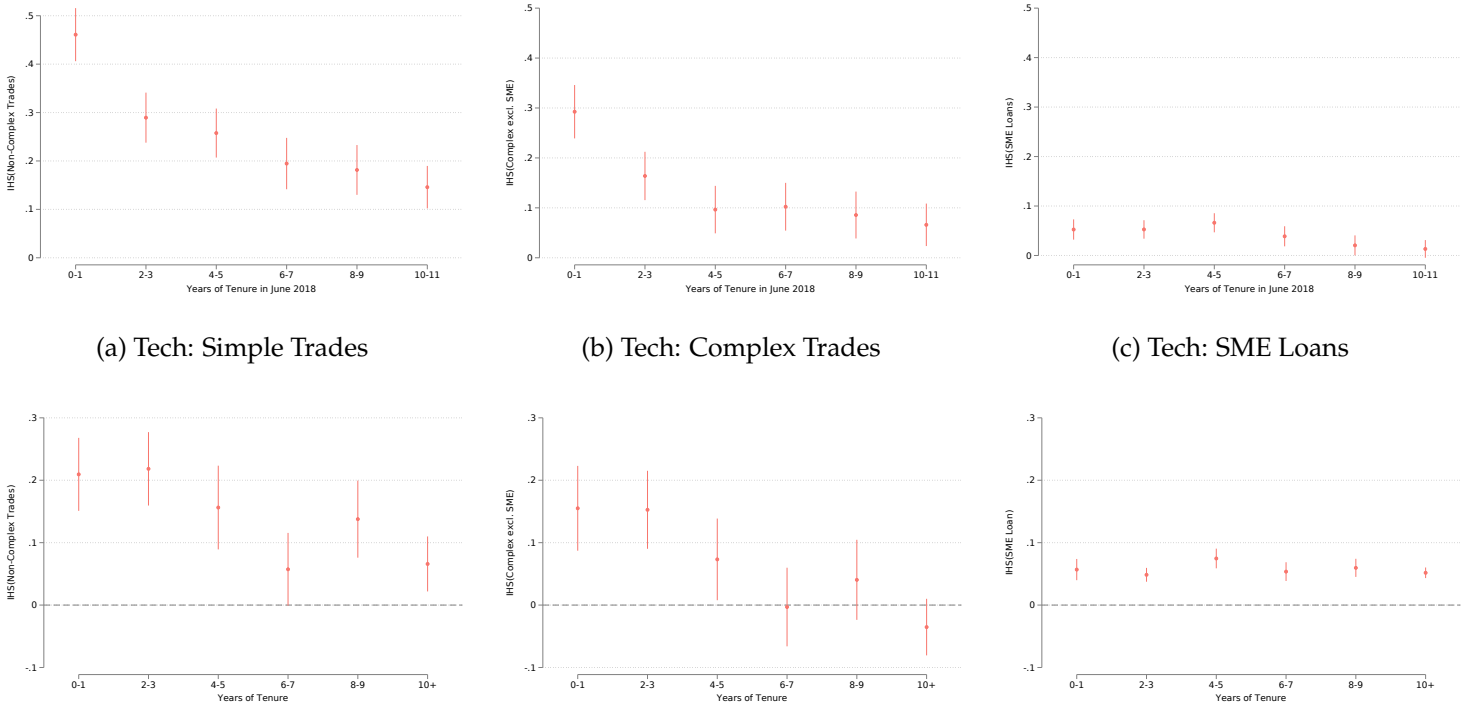


(c) Task: Complex / Simple



(d) Task: SME / Complex

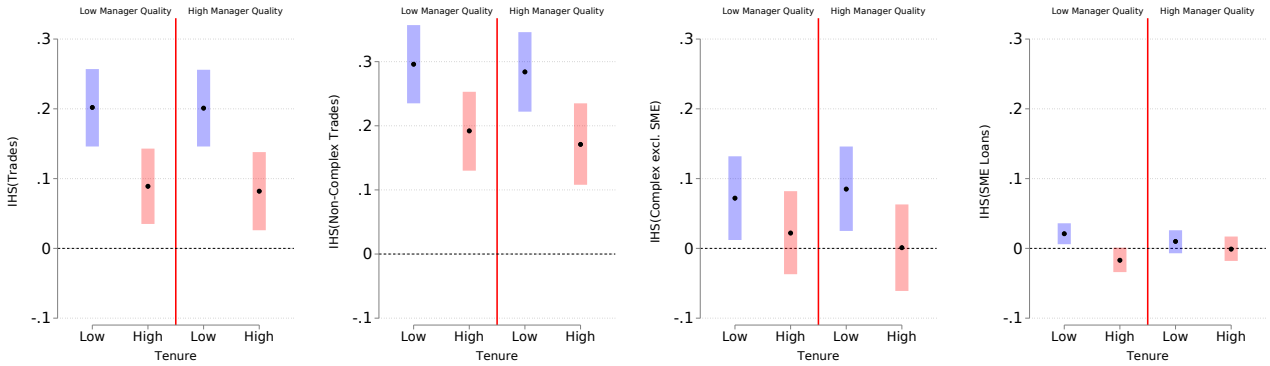
Figure 9: **Worker-level reallocation ratios under Task and Tech Interventions.** Row 1 reports the Tech Intervention; Row 2 reports the Task Intervention. The analysis sample includes account managers. Columns show the ratio of complex to simple trades and SME to non-SME complex trades.



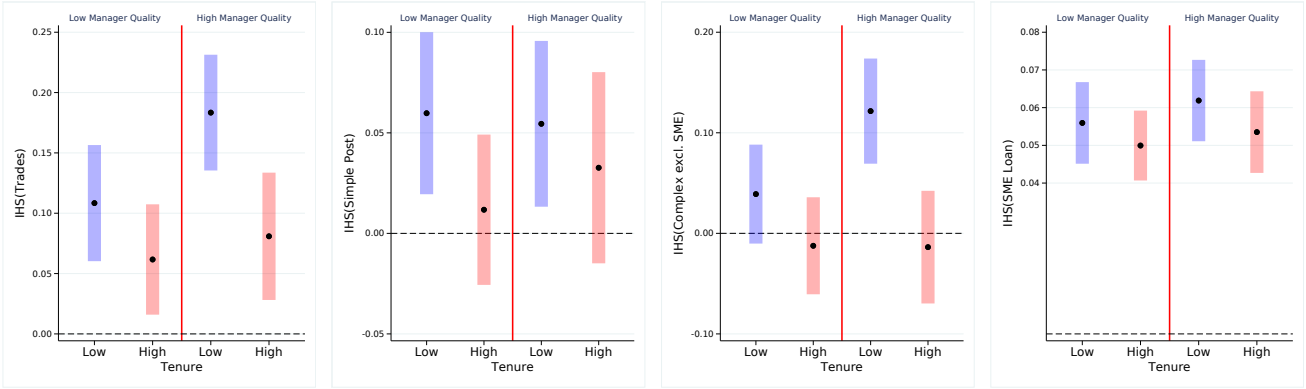
(a) Tech: Simple Trades (b) Tech: Complex Trades (c) Tech: SME Loans

(d) Task: Simple Trades (e) Task: Complex Trades (f) Task: SME Loans

Figure 10: **Worker heterogeneous responses to Tech and Task Interventions by trade type.** Row 1 reports the Tech Intervention; Row 2 reports the Task Intervention.The analysis sample includes account managers. Columns show simple trades, complex trades, and SME loans. All outcomes are expressed in inverse hyperbolic sine (IHS).

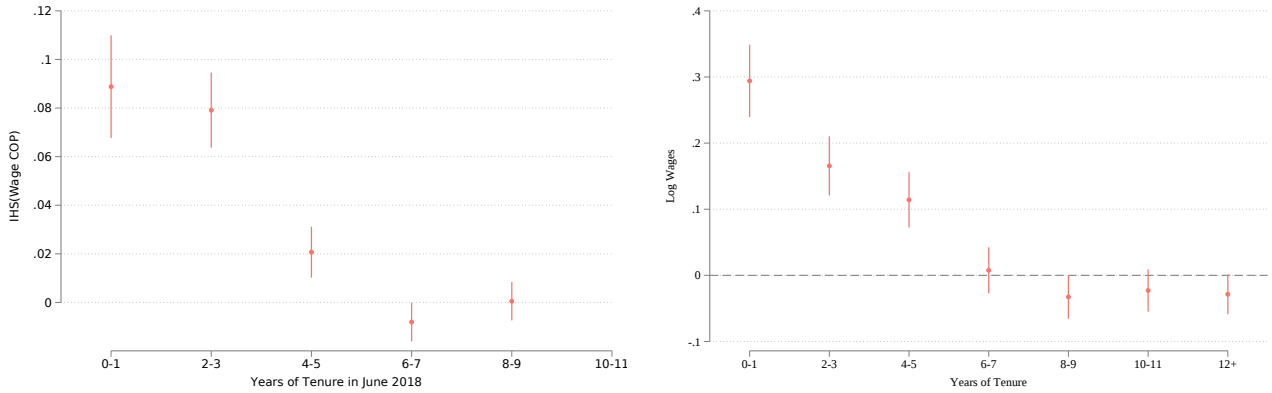


(a) Tech: Total Trades (b) Tech: Simple Trades (c) Tech: Complex Trades (d) Tech: SME Loans



(e) Task: Total Trades (f) Task: Simple Trades (g) Task: Complex Trades (h) Task: SME Loans

Figure 11: **High-productivity managers × worker tenure heterogeneity under Tech and Task Interventions.** Row 1 reports the Tech Intervention; Row 2 reports the Task Intervention. The analysis sample includes account managers. Columns show (a) total trades, (b) simple trades, (c) complex trades, and (d) SME loans. All outcomes are expressed in inverse hyperbolic sine (IHS). High-productivity managers are defined by a median split of the manager fixed effect distribution. Results are robust to using the 75th percentile as the cutoff instead of the median.



(a) Tech: Log wages (yearly)

(b) Task: Log wages (yearly)

Figure 12: **Non-parametric tenure heterogeneity in wages.** Worker-level TWFE estimates of log wages at the yearly level. Panel (a) reports the Tech Intervention; Panel (b) reports the Task Intervention. The analysis sample includes account managers.

9. Tables

	Tech Intervention	Task Intervention
Time period	Jan 2017-Dec 2019	Jan 2019-Mar 2023
Number of branches	449	355
Number of managers	1,263	1,153
Number of account managers	2,152	2,018
Number of Complex products	4	8
Number of Simple products	12	8
Total no. of observations (branch-week)	69,465	77,830

Table 1: **Summary of the data used to assess the Tech and Task Interventions.** SME loans are excluded from this total as they are the focus of the Task Intervention and thus considered separately.

	Tech Intervention		Task Intervention	
	Avg.	Std. Dev.	Avg.	Std. Dev.
No. Workers	5.790	3.323	8.263	4.773
IHS(Trades)	4.575	0.974	4.734	0.717
IHS(Complex Trades)	3.581	1.130	4.180	0.775
IHS(Simple Trades)	4.005	1.006	3.644	0.920
IHS(SME Loans)	1.037	1.029	1.061	0.932
IHS(Trades/empl)	1.846	0.531	2.766	0.502
Observations	69,465		77,830	

Table 2: **Branch-level descriptive statistics.** Definitions of complex and simple trades vary across samples, as four financial products were available on the app during the Tech Intervention, while seven products were available by 2021.

	Tech Intervention		Task Intervention	
	Avg.	Std. Dev.	Avg.	Std. Dev.
IHS(Trades)	2.628	1.098	2.121	1.145
IHS(Complex Trades)	1.707	1.118	0.883	1.026
IHS(Simple Trades)	1.999	1.232	1.747	1.238
IHS(SME Loans)	0.193	0.555	0.148	0.421
Observations	400,901		642,658	

Table 3: **Worker-level descriptive statistics.** Definitions of complex and simple trades vary across samples, as four financial products were available on the app during the Tech Intervention, while seven products were available by 2021.

	(1) Early	(2) Late	(3) Diff.
IHS(Trades)	4.172	4.368	0.195***
	(1.213)	(1.127)	(0.053)
IHS(Complex Trades)	3.192	3.465	0.272***
	(1.413)	(1.296)	(0.058)
IHS(Simple Trades)	3.598	3.732	0.133**
	(1.182)	(1.126)	(0.053)
IHS(Employment)	2.184	2.378	0.194***
	(0.614)	(0.497)	(0.044)
IHS(Trades/Empl.)	**2.722**	**2.711**	**-0.012**
	(0.907)	(0.866)	(0.020)
Observations	12,431	10,544	22,975

Table 4: **Balance Between Early and Late Adopters.** The table compares pre-treatment characteristics of branches that adopt the technology early versus late. Early adopters are smaller on average across multiple measures, but there is no statistically significant difference in pre-treatment productivity (IHS Trades per Employee).

Panel A: Tech Intervention

	(1)	(2)	(3)	(4)
VARIABLES	IHS(Trades)	IHS(Simple Trades)	IHS(Complex excl. SME)	IHS(SME Loans)
Tech Rollout	0.216***	0.298***	0.101**	0.00934
	(0.0358)	(0.0403)	(0.0393)	(0.0111)
Tech Rollout x Tenure	-0.116***	-0.111***	-0.0740***	-0.0215***
	(0.0159)	(0.0176)	(0.0148)	(0.00525)
Observations	250,273	250,273	250,273	250,273
Mean	2.586	1.875	1.548	0.233
Std.Dev	1.095	1.221	1.259	0.626

Week and Worker FEs included. SE clustered by Worker

*p<.05; **p<.01; ***p<.001

Panel B: Task Intervention

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Complex	Simple	Simple Pre	Simple Post	All Excl. SME	Complex Excl. SME	SME Loans
Task Rollout	0.1547***	0.1148***	0.1589***	0.1509***	0.0709***	0.1489***	0.0947***	0.0588***
	(0.0292)	(0.0302)	(0.0295)	(0.0287)	(0.0231)	(0.0295)	(0.0304)	(0.0057)
Task Rollout × Tenure	-0.0832***	-0.1091***	-0.0730***	-0.0675**	-0.0686**	-0.0833***	-0.1081***	-0.0050
	(0.0267)	(0.0295)	(0.0277)	(0.0273)	(0.0269)	(0.0283)	(0.0303)	(0.0073)
Observations	158,697	158,697	158,697	158,697	158,697	158,697	158,697	158,697
Mean	3.0739	1.6738	2.7172	2.5105	0.9624	3.0553	1.6461	0.0564

Table 5: **Effect of ex-ante high tenure on main outcome variables.** The table reports heterogeneous treatment effects by worker tenure. High tenure is defined as above-median average tenure measured in the pre-intervention period. Panel A reports results for the Tech Intervention; Panel B reports results for the Task Intervention. All outcomes are expressed in inverse hyperbolic sine (IHS).

Panel A: Tech Intervention

	(1)	(2)	(3)	(4)
VARIABLES	IHS(Trades)	IHS(Simple Trades)	IHS(Complex excl. SME)	IHS(SME Loans)
Tech Rollout	0.171***	0.209***	0.0839**	0.0268**
	(0.0313)	(0.0339)	(0.0326)	(0.0127)
Tech x Manager Quality	0.00502	-0.00877	0.00434	0.00502
	(0.0132)	(0.0139)	(0.0116)	(0.00489)
Observations	339,290	339,290	339,290	339,290
Mean	2.586	1.875	1.548	0.233
Std.Dev	1.095	1.221	1.259	0.626

Week and Worker FEs included. SE clustered by Worker

*p<.05; **p<.01; ***p<.001

Panel B: Task Intervention

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Complex	Simple	Simple Pre	Simple Post	All Excl. SME	Complex Excl. SME	SME Loans
Task Rollout	0.0930***	0.0387	0.1044***	0.0967***	0.0403*	0.0862***	0.0192	0.0534***
	(0.0288)	(0.0289)	(0.0292)	(0.0287)	(0.0215)	(0.0291)	(0.0290)	(0.0053)
Task Rollout × Manager Quality	0.0512*	0.0475	0.0458*	0.0470*	0.0058	0.0535*	0.0481	0.0051
	(0.0266)	(0.0301)	(0.0273)	(0.0269)	(0.0269)	(0.0278)	(0.0307)	(0.0072)
Observations	157,611	157,611	157,611	157,611	157,611	157,611	157,611	157,611
Mean	3.0739	1.6738	2.7172	2.5105	0.9624	3.0553	1.6461	0.0564

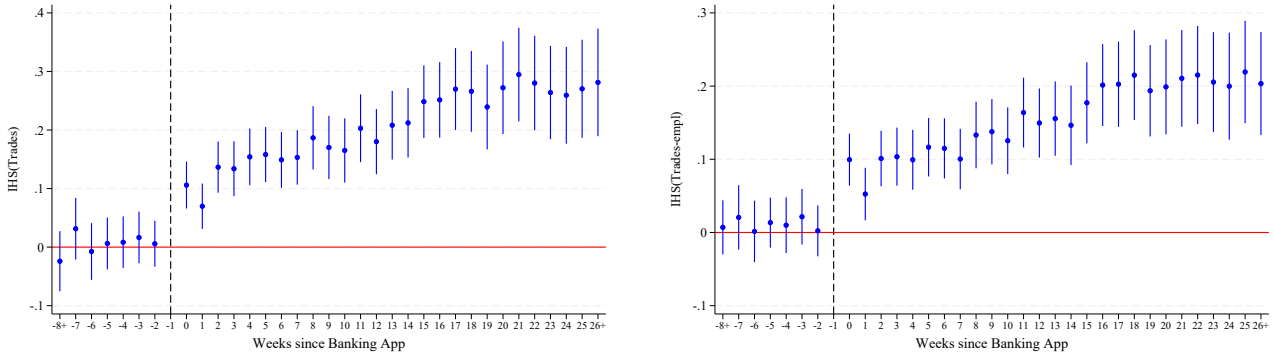
Table 6: **Effect of ex-ante high-productivity managers on main outcome variables.** The table reports heterogeneous treatment effects by high-productivity managers, measured by manager fixed effects (θ_m) estimated from equation (2) using pre-intervention branch productivity data (January 2017–June 2018). High-productivity manager is a binary indicator equal to one if the manager's value-added is above the median. Panel A reports results for the Tech Intervention; Panel B reports results for the Task Intervention.

Prod. Manager FEs	Correlation	p-value
Leadership		
Teamwork	0.255	0.000***
Trust	0.172	0.001***
Embrace Change	0.217	0.000***
Inspire	0.214	0.000***
Avg. Leadership	0.242	0.000***
Performance Measures		
Performance	0.127	0.013**
Objectives	0.138	0.007***
Skills	0.026	0.611
Avg. Performance	0.118	0.020**
Company Values		
Principles	-0.005	0.928
Big Picture	0.032	0.529
Context	0.033	0.520
Client Focus	0.010	0.843
Workforce Development	0.086	0.090*
Co-creation	0.006	0.901
Agility	0.061	0.234
Adventure	-0.002	0.972
Avg. Values	0.036	0.485
Demographics		
Age	0.019	0.717
Tenure	-0.100	0.051*
Inflation Adj. Wage	-0.103	0.045**
Gender	-0.068	0.185

Table 7: **Correlation between manager AKM fixed effects, demographics, and leadership measures.** Leadership, performance, and company values come from the leadership survey, average measures at the bottom of each variable group are the arithmetic averages of the group items. Demographic measures come from the personnel data, wages are adjusted for inflation.

10. Appendix

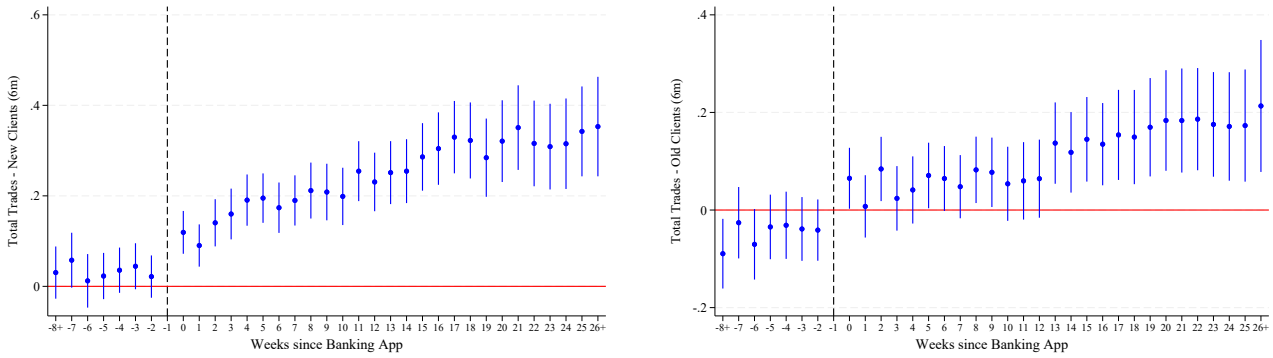
10.1. Appendix figures



(a) Tech: Total trades

(b) Tech: Productivity

Figure A.1: **Event-study estimates for total trades and productivity at the branch level.** Panel (a) reports the Tech Intervention; Panel (b) reports the Task Intervention. The analysis sample includes account managers. All outcomes are expressed in inverse hyperbolic sine (IHS).



(a) Tech: New Clients (6m)

(b) Tech: Old Clients (6m)

Figure A.2: **Consumption by new and old clients at the branch level under the Tech Intervention.** The analysis sample includes account managers. Columns distinguish new clients (left) and old clients (right), defined using a six-month window since the first observed trade.

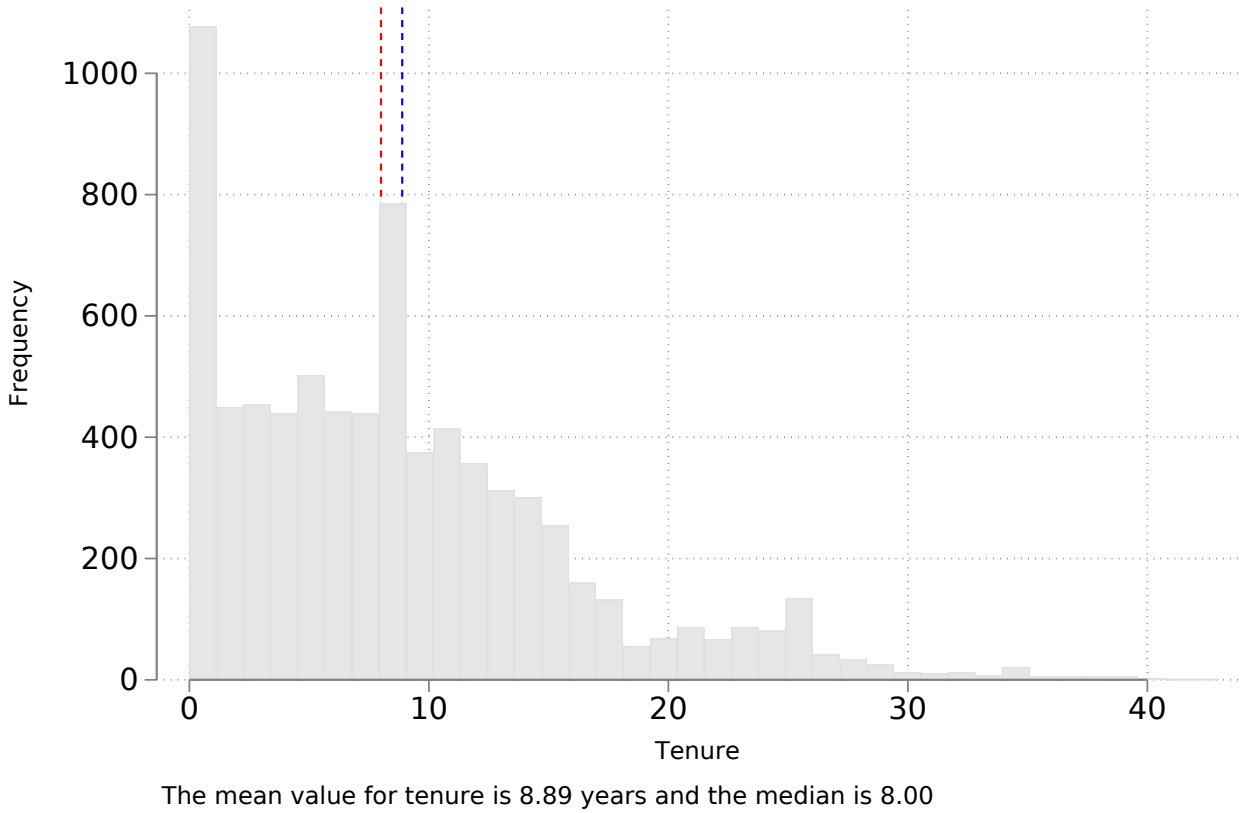
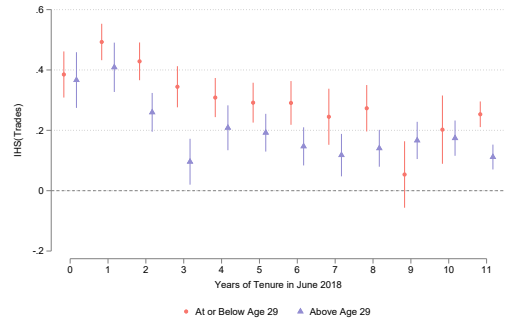
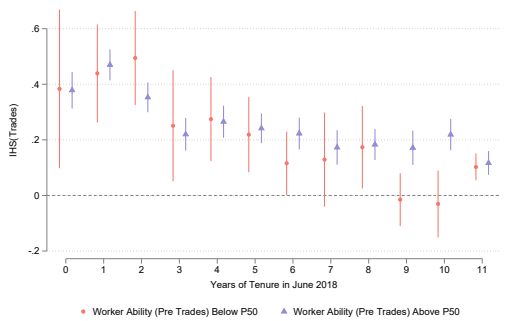


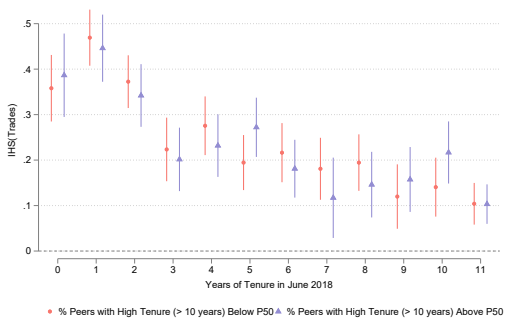
Figure A.3: **Distribution of worker tenure.** The figure displays the frequency distribution of worker tenure (in years). The red dashed line marks the mean (8.89 years) and the blue dashed line marks the median (8 years).



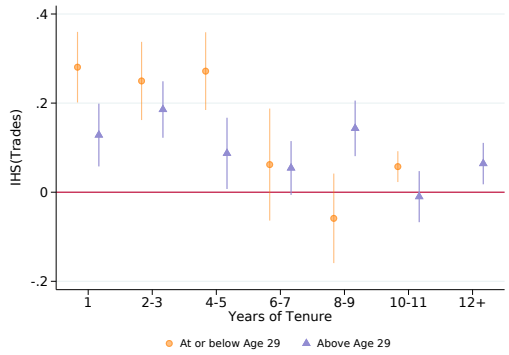
(a) Tech: tenure friction by age



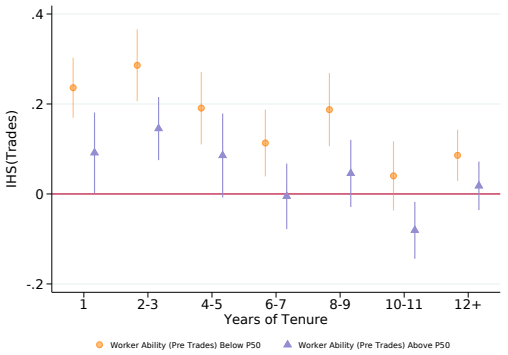
(b) Tech: tenure frictions by worker ability



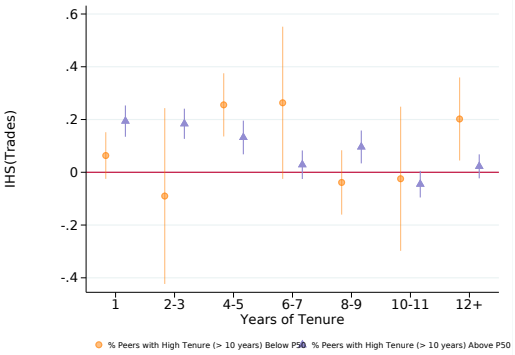
(c) Tech: peer tenure effects



(d) Task: tenure friction by age

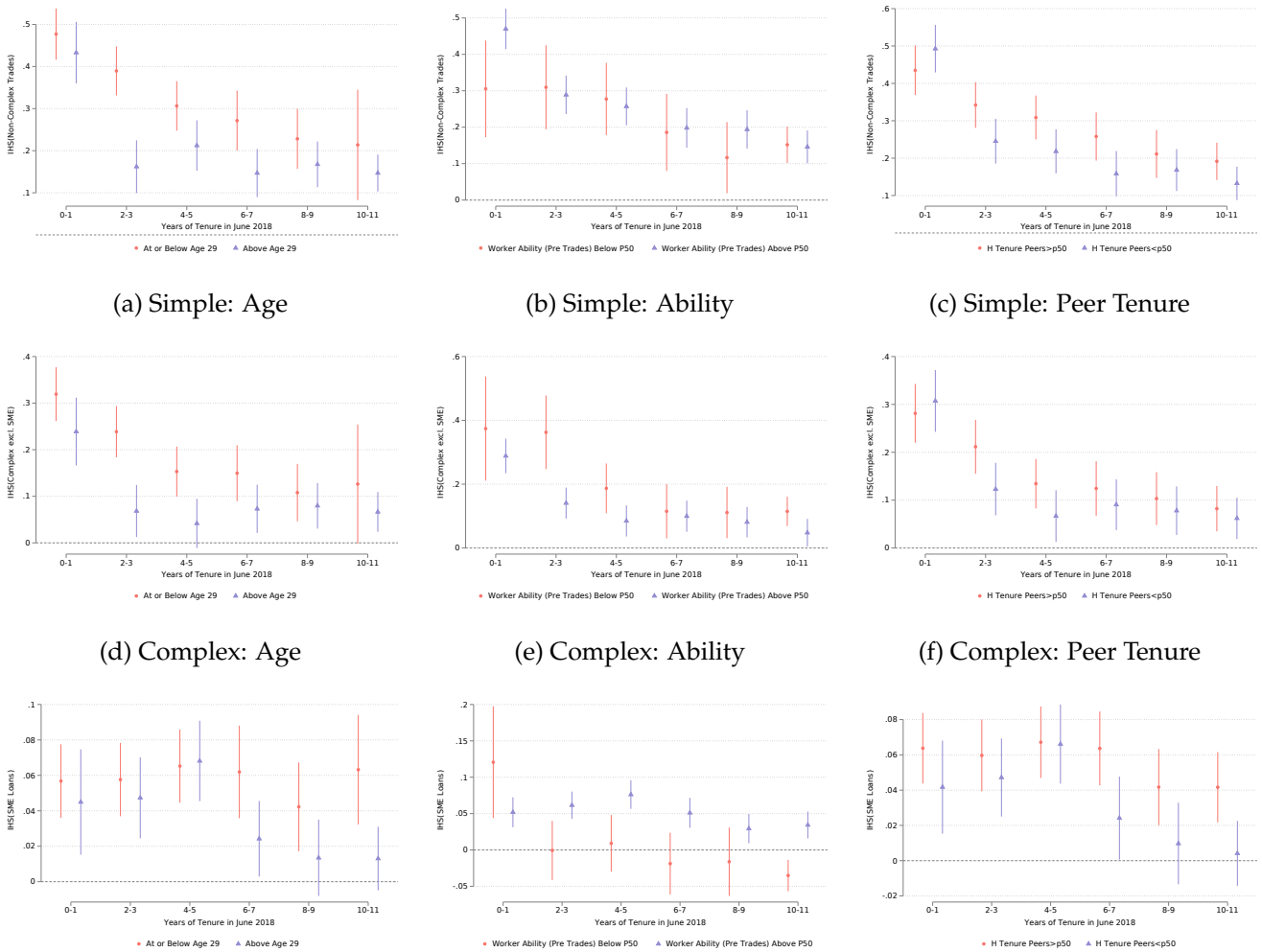


(e) Task: tenure frictions by worker ability



(f) Task: peer tenure effects

Figure A.4: **Tenure-related frictions under Tech and Task Interventions.** Row 1 reports the Tech Intervention; Row 2 reports the Task Intervention. Panels report heterogeneous responses by worker age, worker ability, peer tenure exposure, and high-productivity managers. All outcomes are expressed in inverse hyperbolic sine (IHS). For the worker-age panels, we cannot estimate the coefficient for workers in tenure bin $k = 12+$ who are aged 29 or below because there are no observations in this group (all individuals with tenure bin $k = 12+$ are aged 30 or above).

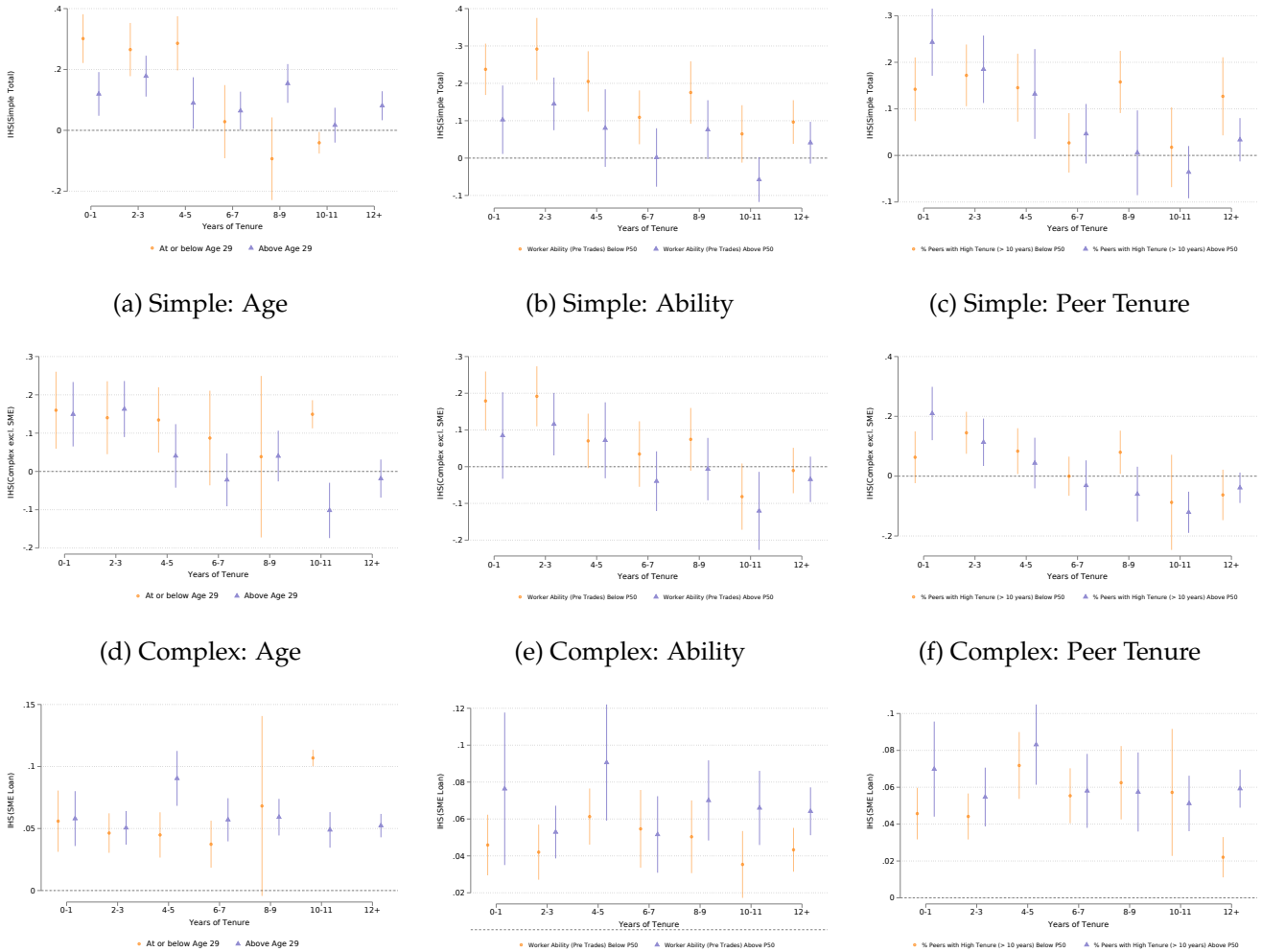


(a) Simple: Age (b) Simple: Ability (c) Simple: Peer Tenure

(d) Complex: Age (e) Complex: Ability (f) Complex: Peer Tenure

(g) SME: Age (h) SME: Ability (i) SME: Peer Tenure

Figure A.5: **Tech Intervention: tenure-related frictions by task type.** The analysis includes all workers. Rows correspond to task categories (simple, complex tasks, and SME loans). Columns report heterogeneity by worker age, worker ability, and peer tenure exposure.



(a) Simple: Age (b) Simple: Ability (c) Simple: Peer Tenure

(d) Complex: Age (e) Complex: Ability (f) Complex: Peer Tenure

(g) SME: Age (h) SME: Ability (i) SME: Peer Tenure

Figure A.6: **Task Intervention: tenure-related frictions by task type.** The analysis focuses only on account managers. Rows correspond to task categories (simple, complex, and SME loans). Columns report heterogeneity by worker age, worker ability, and peer tenure exposure.

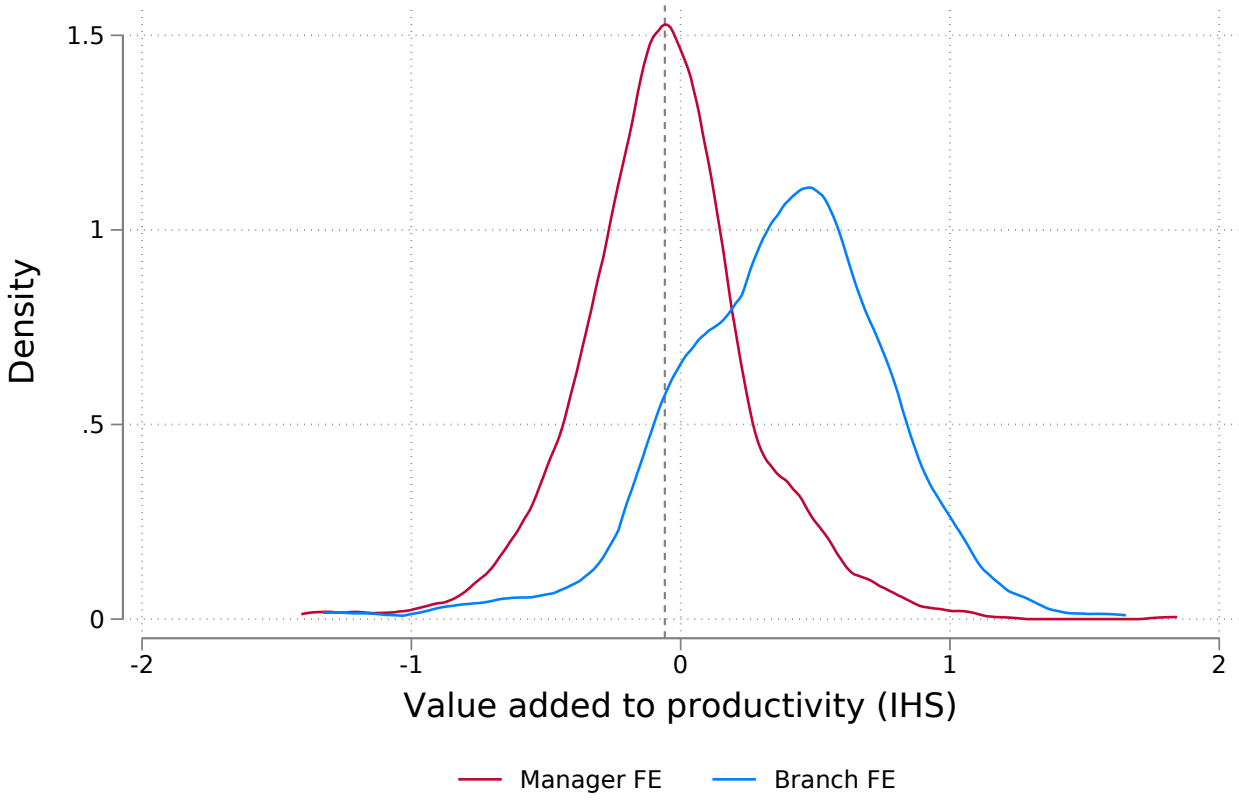


Figure A.7: **AKM Variance Decomposition: Worker and manager fixed effects.** The figure displays kernel density estimates of manager fixed effects (θ_m) and branch fixed effects (η_b) estimated from equation (2) using pre-intervention data (January 2017–June 2018). The outcome variable is inverse hyperbolic sine (IHS) of branch-level productivity.

10.2. Appendix tables

Panel A: Tech Intervention

	(1)	(2)	(3)	(4)
	Branch: IHS(Trades)	Branch: IHS(Trades/Empl.)	Worker: IHS(Trades)	Worker: IHS(Trades Excl. SME)
Tech Shock	0.141***	0.0967***	0.184***	0.163***
	(0.0204)	(0.0152)	(0.0284)	(0.0288)
Observations	69,465	69,244	381,403	382,050
Dependent Mean	4.349	1.819	2.586	2.401

Panel B: Task Intervention

	(1)	(2)	(3)	(4)
	Branch: IHS(Trades)	Branch: IHS(Trades/Empl.)	Worker: IHS(Trades)	Worker: IHS(Trades Excl. SME)
Task Shock	0.1540**	0.1504***	0.1125***	0.1066***
	(0.0683)	(0.0383)	(0.0257)	(0.0258)
Observations	77,830	77,774	158,697	158,697
Dependent Mean	2.726	1.757	12.92	12.89

Table A.1: **Technology and Task Interventions: changes in trades and productivity.** Panel A reports the average effect of the Tech Intervention on trade volume and productivity outcomes at the branch and worker levels. Panel B reports analogous estimates for the Task Intervention and focuses only on account managers. *p<0.05; **p<0.01; ***p<0.001.