# 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 large Latin American bank. 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-quality managers act as an important complement to technology adaptation, lowering adjustment costs and facilitating reallocation toward complex tasks.

**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 (Syverson, 2011), 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 (Doeringer and Piore, 1971)—reallocating tasks, redefining roles, and reshaping worker effort within the existing workforce.

Hence, despite substantial investments in technological changes and automation, firms often confront a "productivity puzzle" where realized gains lag behind technological capacity, contrasting task-based predictions of immediate worker reallocation (Acemoglu and Autor, 2011a; Autor et al., 2003; Acemoglu and Restrepo, 2022). Unlocking these gains requires firms to redesign roles and rebuild coordination structures—complementary organizational investments that accumulate slowly and are poorly measured (Black and Lynch, 2001; Brynjolfsson et al., 2021). Understanding how these organizational complementarities impact incumbent workers behavior, within-firm task reallocation and, in turn, overall 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 when the firm aims to expand output without materially changing headcount. Uniquely, we observe 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 structure allows us to disentangle the direct effects of technology from the organizational complements required to unlock its full potential.

The Tech Intervention takes place in 2018 and introduces a customer-facing mobile app enabling customers to seamlessly open, purchase, and manage selected non-complex 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 visited branches, held meetings with managers and frontline workers, and explicitly communicated that workers' KPIs would be assessed primarily against SME lending and related complex products.

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 11 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: technology creates productive slack but does not direct its deployment. Without changes to performance evaluation, workers continue prioritizing activities that already contributed to their assessments, even as routine work becomes easier. The Task Intervention addresses this friction by reprioritizing performance criteria to emphasize SME lending. Following this explicit reprioritization, workers increase SME production, with upgrading concentrated precisely where evaluation criteria were adjusted. Importantly, neither intervention operates

[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.

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-quality 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.

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

To interpret these patterns, 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 opportunity cost of foregone current revenue, and invests less when training is time-inefficient (Ben-Porath, 1967). The Task Intervention that increases the relative payoff to SME work therefore shifts training 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 training. Managers matter because they can either make training 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 (Autor et al., 2003; Acemoglu and Autor, 2011b; Autor and Handel, 2013; Acemoglu and Restrepo, 2018, 2019, 2020; Ocampo, 2022; Adenbaum, 2023; Autor, 2024). 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 (Garicano, 2000; Caroli and Van Reenen, 2001; Garicano and Hubbard, 2005; Acemoglu et al., 2007; Dessein and Garicano, 2010; Caliendo and Rossi-Hansberg, 2012; Bloom et al., 2014). This body of work shows that communication frictions, learning costs, and information flows shape hierarchical structure and task assignment. Related research on ICT and organizational design highlights that reductions in communication and monitoring costs flatten hierarchies and shift task boundaries. A growing parallel literature demonstrates that managers significantly influence worker productivity, learning, and task allocation (Adhvaryu et al., 2023; Metcalfe et al., 2023; Minni, 2024). 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, managerial quality shapes which workers successfully reallocate tasks: high-quality 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 initiates 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 facilitates over 15 million new trades and becomes 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.

## 2.2. Workers, roles, and the task structure

A typical branch is led by a manager and includes account managers, SME specialists, advisors, and tellers. Account managers (our main focus) are responsible for most trades and have compensation closely tied to performance-based commissions. SME specialists focus on commercial clients, while advisors and tellers handle customer service and transactional activities.

We classify the work performed by account managers into three distinct categories based on product characteristics and digitization potential. Simple trades include routine, non-

[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.

complex 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 small and medium enterprise lending, 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). 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. As a result, reallocating effort toward SME lending reflects genuine reskilling rather than an increase in task intensity within existing activities.

## 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.

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 (Gans and Goldfarb, 2026). This provides a benchmark for understanding the type of adjustment the bank aimed to achieve. Our sequential interventions reveal substantial departures from this frictionless prediction, highlighting 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 technology 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 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 non-complex products are included in the app, while complex, high-value services—like SME loans and other advisory-intensive products—remain exclusively branch-based. Monetary incentives and formal performance criteria are not redesigned at this stage. The rollout of the app is rapid and nearly 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 responsabilities into jobs. Beginning in January 2021, the bank implements a Task Intervention that explicitly redefines the role of account managers around SME loan production. Unlike the Tech Intervention, this reform operates through changes in performance evaluation rather than new technology. Specifically, the bank introduces targeted KPIs tied exclusively to SME loan transactions. While overall monetary incentives remain unchanged, performance evaluation criteria are explicitly re-weighted toward SME lending, while other complex activities are not reprioritized. Account managers are formally reassigned responsibility for SME loans, removing earlier bottlenecks in which such products could only be completed by specialized staff. The reform is rolled out in a staggered fashion and affects approximately 70 percent of branches by March 2023.

To clarify the changes, 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 $w_{\text{SME}}$ 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 $w_{\text{SME}}$ 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 capacity 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 non-complex balances.

*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 technology 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 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, following the completion of the app rollout. Branches are the natural unit of analysis, as both interventions operate at the branch level; worker-level analyses are constructed in parallel 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.

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 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

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

trades and complex trades differ across periods, consistent with changes in task scope and organizational design rather than differences in sample composition.

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.

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 begins in June 2018, when the app becomes 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.

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

$$y_{bt} = \sum_{s \neq -1} \beta_{j,s} D^{j}_{b,t+s} + \alpha_b + \xi_t + \epsilon_{bt}, \tag{1}$$

where $D^{j}_{b,t+s}$ are event-time indicators for intervention $j$, $\alpha_b$ denote branch fixed effects, and $\xi_t$ denote week fixed effects. Coefficients $\beta_{j,s}$ capture the average treatment effect on treated branches $s$ 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. Intervention: 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 technology 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. Individual workers increase the number of trades they perform immediately after the app is introduced, with effects that accumulate gradually 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 quantifies these patterns. The intervention increases worker-level total trades by approximately 11.3 percentage points. When

[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.

excluding SME loans, the effect is 10.7 percentage points, indicating that the productivity gains are especially concentrated in simple and complex non-SME activities.

*Mechanisms: Client base expansion.* Figure 4 sheds light on how workers absorb the productivity gains generated by the technology 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 over-serving 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. Hirings, separations, branch size, and total worker-days remain stable throughout the post-adoption period. Rather than expanding or contracting the workforce, branches absorb the additional productive capacity generated by the app entirely within existing organizational structures and ruling out workforce reallocation or scale adjustments as operative mechanisms.

## 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)),

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

but show no meaningful change in complex trades (Panel (b)) or SME trades (Panel (c)). Despite the substantial increase in processing capacity generated by automation, workers do not reallocate activity toward higher-value complex or SME-related tasks.

This pattern reflects that unchanged performance weights prevent reallocation. The app automated routine transactions and created additional capacity, but workers continued allocating effort according to the original weights because simple volume still contributed meaningfully to performance scores. The technology intervention successfully creates organizational slack but does not direct its deployment, revealing an organizational friction: workers have more time available, yet without explicit direction on how performance is evaluated, they expand simple task volume rather than upgrading into 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. The absence of differential pre-trends and durability of the response indicate sustained behavioral adjustment rather than a short-run reaction. Figure 6 (Panels c-d) shows that hiring and exits remain flat, ruling out employment adjustments as a channel. Unlike the Tech Intervention, however, the Task Intervention operates by restructuring performance evaluation. By explicitly elevating SME lending as the primary criterion for assessment, the intervention changes 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 workers' task portfolios, Figure 8 examines changes in the Herfindahl–Hirschman Index across both interventions. Both interventions increase worker-level task specialization. Figure 9 then uses task composition ratios to clarify the direction of this specialization, 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 or motivation shock, we would expect parallel increases across all complex tasks. Instead, the differential responses—SME increases sharply while non-SME complex trades remain stable—indicate that restructured performance weights, not technology or compensation changes, drive the observed reallocation.

# 5. Organizational frictions

The heterogeneous effects of the technology intervention and the task-based incentive intervention point to two organizational forces that shape adjustment: *tenure-based rigidity* and *managerial quality*. The technology 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 measure managerial quality and assess its role in facilitating upgrading. Third, we study how managerial quality interacts with 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 mean tenure of 8.89 years and median of 8 years.

Table 5 shows how tenure attenuates responses to both interventions using a binary high/low tenure split. Under the Tech Intervention (Panel A), high tenure substantially reduces responses across all trade 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 how responses vary across the tenure distribution. [ADD MORE ON THE TECH INTERVENTION ONCE WE HAVE THE FIGURES]. The Task Intervention (Panels d-f) reveals a different pattern. For simple and complex trades (Panels d-e), responses exhibit a negative tenure gradient: low-tenure workers show positive effects that decline sharply with tenure, while SME lending (Panel f) shows relatively stable effects across the tenure distribution with high-tenure workers increase SME production nearly as much as low-tenure workers. This divergence reveals differential adjustment mechanisms by tenure. High-tenure workers respond to SME reprioritization through within-capacity substitution: they increase SME lending but reduce effort on simple and complex trades. Low-tenure workers, by contrast, exhibit across-the-board expansion. We interpret these patterns as indicating that high-tenure workers face binding capacity constraints from established work routines, requiring them to reallocate fixed capacity across tasks. Low-tenure workers possess greater flexibility, enabling them to expand total output rather than simply reshuffling effort across tasks.

Figure A.5 presents differences-in-differences estimates of total trades by tenure group across heterogeneity dimensions. The negative tenure gradient following the Tech Intervention

[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.

(Panels a-c) is robust to conditioning on worker age, ability, and peer tenure composition. Low-tenure workers exhibit the largest increases while responses attenuate rapidly with tenure within each group. The task intervention (Panels d-f) reveals a similar pattern. Although explicit performance restructuring raises overall activity, the tenure gradient persists conditional on age and ability. The stability of tenure profiles across heterogeneity splits suggests that tenure operates as a main organizational friction rather than proxying for age or ability differences.

Figure A.7 further decomposes these tenure gradients by task type under the task intervention.[7] Panels (a)–(c) show that the strong responsiveness of low-tenure workers is driven almost entirely by simple tasks. For workers with 0–1 and 2–3 years of tenure, simple trades increase sharply, while effects decline monotonically with tenure and become close to zero for the most tenured workers. This pattern is robust across heterogeneity dimensions based on age, pre-period ability, and peer tenure exposure.

Panels (d)–(f) demonstrate that responses for complex non-SME tasks are substantially weaker. Across all heterogeneity splits, estimates are smaller, less precisely estimated, and exhibit a flatter tenure profile. Even among low-tenure workers, the technology intervention generates only modest changes in complex activity, indicating limited upgrading along this margin.

Finally, Panels (g)–(i) show that SME lending responds very little to the technology intervention. Effects are close to zero across the entire tenure distribution and across all heterogeneity dimensions. The absence of systematic responses for SME tasks contrasts sharply with the strong increases observed for simple activities and confirms that the technology shock primarily expands low-value, routine production rather than reallocating effort toward higher-value complex or SME lending.

Heterogeneity by worker age and pre-period ability further sharpens this interpretation. Across simple tasks (Panels (a)–(c)), younger and lower-ability workers exhibit systematically larger responses at low tenure levels, particularly in the 0–1 and 2–3 year cohorts. Older and higher-ability workers respond more weakly at all tenure levels, and their effects attenuate more rapidly with tenure. This pattern suggests that the productivity gains from the technol-

[7] Add also reference to Figure A.6 once we find figures for tech intervention.

ogy intervention for simple activities are concentrated among workers with both low tenure and fewer pre-existing task-specific skills.

For complex non-SME tasks (Panels (d)–(f)), heterogeneity by age and ability is muted. Estimates are small for all groups, and differences between younger vs. older or lower- vs. higher-ability workers are limited and often statistically insignificant. This indicates that accumulated general ability or age-related experience does not substantially relax the constraints on reallocating effort toward complex tasks under the technology intervention.

For SME lending (Panels (g)–(i)), responses remain close to zero regardless of age or ability. Neither younger nor lower-ability workers—despite exhibiting the strongest responses in simple tasks—expand SME activity, underscoring that the absence of SME upgrading reflects binding organizational or informational constraints rather than worker characteristics.

Taken together, 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 fundamental constraint on organizational flexibility rather than a context-specific response to particular shocks.

These tenure gradients can be interpreted through the differential costs of reallocating effort toward SME activities. High-tenure workers have accumulated routines optimized for retail volume, maintain established client portfolios, and possess tacit knowledge tied to the pre-intervention operating model. For these workers, shifting into SME lending entails high fixed and opportunity costs: learning new screening procedures, engaging in time-intensive outreach and relationship-building, disrupting stable routines, and potentially requiring mentoring from colleagues already familiar with SME work. As a result, even when organizational capacity expands or task priorities are clarified, highly tenured workers face strong switching frictions that limit reallocation toward SME activities. By contrast, for low-tenure workers, SME reskilling can be incorporated as part of the onboarding and training process. With fewer entrenched routines and weaker legacy client obligations, these workers are less locked into the old task bundle and more open to adopting new roles. At the same time, the limited SME responses observed even among the lowest-tenure cohorts indicate that informational and organizational constraints remain binding, highlighting that SME upgrading requires not only worker flexibility but also complementary managerial guidance and institutional support.

### 5.2. Manager quality

We next examine whether managerial quality mitigates organizational frictions that constrain task reallocation. Managers play a central role in coordinating production, translating organizational objectives into operational priorities, and reducing the effective adjustment costs faced by workers. Figure A.4 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 in managerial quality translate into differential adjustment to the two interventions. In particular, we examine whether high-quality managers are better able to facilitate task reallocation when organizational change alters either productive capacity or performance priorities.

Table 6 examines heterogeneity by ex-ante managerial quality across both interventions.

Under the **Tech intervention** (Panel A), managerial quality does not materially affect task reallocation. 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 managerial quality is small and statistically insignificant across all outcomes, indicating that high-quality managers do not induce differential task upgrading when technological change expands capacity but leaves task priorities unchanged.

By contrast, under the **Task intervention** (Panel B), managerial quality plays a central role in shaping worker responses. Total trades increase by roughly **9 pp** in the initial post period and **14 pp** thereafter under high-quality managers, and SME lending—the task explicitly prioritized by the redesign—rises by about **5–6 pp**. Effects on non-SME complex trades remain small and statistically insignificant. These patterns indicate that managerial quality mitigates organizational frictions and enables targeted task reallocation only when organizational objectives are clearly aligned through performance evaluation.

*Technology intervention.* Panel A shows that the interaction between the technology intervention and manager quality is small and statistically insignificant across total trades, non-complex trades, and complex trades. These results indicate that managerial quality does not differentially affect worker-level task reallocation in the absence of explicit organizational redesign. Without restructured performance evaluation criteria, workers continue allocating capacity according to the original incentive structures, regardless of manager quality.

*Task intervention.* Panel B shows that managerial quality plays a more pronounced role once performance evaluation is restructured. Workers operating under high-quality managers exhibit substantially stronger reallocation toward complex activities. High-quality managers significantly amplify worker responses along the complex margin: complex trades increase by approximately 16.2 log points for account managers working under high-AKM managers, compared to those under lower-quality managers. In contrast, interactions for total trades and non-SME trades are small and statistically insignificant, underscoring that the task intervention operates primarily through changes in task composition rather than scale.

These findings demonstrate that managerial quality becomes a powerful catalyst for task upgrading once performance weights are explicitly restructured. During the technology intervention, managerial quality does not induce differential task reallocation when evaluation criteria remain stable. Under the task intervention, high-quality managers translate restructured performance weights into substantially stronger worker-level reallocation toward high-value activities explicitly prioritized by the organization.

## 5.3. Manager quality and worker tenure

Finally, we examine whether manager quality—measured by persistent manager effects on branch productivity—amplifies 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 manager quality during the technology intervention. Across total trades, simple trades, and complex trades (Panels (a)-(c)), the dominant pattern is a negative tenure gradient: low-tenure workers respond substantially more than high-tenure workers. Critically, manager quality provides little differential advantage—responses are similar under high and low-quality managers across tenure groups. This shows that during the technology intervention, managerial quality primarily improves coordination and throughput uniformly but does not differentially accelerate reallocation or overcome tenure-related frictions. The organizational friction created by unchanged performance weights constrains adjustment regardless of manager quality.

*Task intervention.* Figure 11 (Panels (e)-(h)) reveals how managerial quality 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 pronounced reallocation that is strongly mediated by managerial quality. Under high-quality 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 managerial quality plays an active role in overcoming adjustment frictions once task priorities are explicitly aligned.

To interpret this heterogeneity, it is useful to view managerial quality as shaping how scarce managerial attention is allocated across workers. High-quality managers allocate managerial effort toward margins with the highest expected returns. Low-tenure workers are typically more malleable: they have fewer entrenched routines and lower switching costs, so managerial guidance translates more quickly into changes in task allocation. Moreover, because these workers have a longer remaining horizon in the labor market, investments in skill acquisition generate higher expected returns, consistent with the Ben-Porath logic embedded in our model in Section 6.

High-quality managers may therefore find it optimal to invest disproportionately in low-tenure employees—through coaching, shadowing, and targeted assignment to complex and SME-related activities—because the payoff from accelerating their transition into complex tasks is larger than for highly tenured workers, whose task bundles and client relationships are harder to reconfigure due to higher opportunity costs of switching. This mechanism provides a microfoundation for why managerial quality amplifies task upgrading primarily among low-tenure workers and helps explain why adjustment remains uneven across the workforce even when task priorities are explicitly aligned.

*Mechanisms and wage effects.* Why are high-quality managers effective in facilitating reallocation 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. Panel (b), which focuses on the Task Intervention, shows 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 managerial quality plays a central complementary role by lowering adjustment costs and translating restructured performance incentives into task-level reallocation toward higher-value activities.

# 6. Conceptual framework

## 6.1. Worker's problem

Workers face an intertemporal tradeoff between current production and future skill accumulation. Investing time in training reduces contemporaneous output but raises future productivity, as in a classic Ben-Porath (1967) human capital framework and in modern organizational extensions (Cavounidis and Lang, 2020). Training converts time into task-specific skill improvements, while production requires the same time resource. Managers shape this tradeoff by altering either the efficiency of training—reducing the time required to generate a unit of skill improvement—or the perceived value of future returns from training.

*Setup.* We consider a worker who faces three types of tasks: *simple*, *SME* (complex with higher returns after the task intervention), and *complex*. Tasks are indexed in that order by $i = 1, 2, 3$. The worker has an initial vector of skills $\boldsymbol{S} = (S_i)_{i=1,2,3}$, while the optimal level of skill for each task is given by the vector $\boldsymbol{T}^{(j)} = (T_i^{(j)})_{i=1,2,3}$, with $j = 0, 1$ representing the first and second period (prior and after the Tech/Task Intervention), respectively.

Thus, in the absence of training, we model the worker's returns in a single period as

$$r_0 := \sum_{i=1}^{3} A_i^{(0)} \pi(S_i - T_i^{(0)}), \tag{2}$$

where $\pi(\cdot)$ is a concave function attaining its maximum at zero, and $A_i^{(0)}$ denotes the task-specific return conversion parameter at period 0. We also assume that $S_i - T_i^{(0)} < 0$, so that there is scope for training. Maximum output in task $i$ is achieved when the worker's skill coincides with the task's optimal level, in which case production equals $A_i^{(0)} \pi(0) := A_i^{(0)}$.

Under these assumptions, the worker's problem is to find the optimal vector of skill investments $\boldsymbol{I} = (I_i)_{i=1,2,3}$ to maximize his returns, provided that he has a unit of time to either train or produce in the first period. Mathematically, he solves the following optimization problem

$$
\begin{aligned}
\max_{\boldsymbol{I}} \quad & r(\boldsymbol{I}) = \max_{\boldsymbol{I}} \left(1 - \sum_{i=1}^{3} t_i I_i\right) r_0 + \beta \sum_{i=1}^{3} A_i^{(1)} \pi(S_i + I_i - T_i^{(1)}) \\
\text{s.t.} \quad & \begin{cases} I_i \geq 0, & \forall i = 1, \ldots, n, \\ \sum_{i=1}^{3} t_i I_i \leq 1. \end{cases}
\end{aligned}
\tag{3}
$$

where $\boldsymbol{t} = (t_i)_{i=1,2,3}$ is the vector of training time conversion factors, and $\beta$ is the time discount factor, assumed homogeneous across tasks. Superscripts index potential changes in the return conversion parameters and target skill levels.

We further suppose the worker does not allocate the entire available time to training. In other words, feasible training allocations satisfy that total training time is at most one period and, in the interior case we focus on, strictly less than one period. Training time is converted into skill improvements according to task-specific conversion factors $t_i$. Training, therefore, entails an opportunity cost because time spent training cannot be used for production.

Intuitively, training reduces first-period returns by the term $\left(\sum_i t_i I_i\right) r_0$ and increases future returns via the second term in (3). Moreover, the discounted marginal gain from investing in skill $i$ is $\beta A_i^{(1)} \pi' \left(S_i - T_i^{(1)}\right)$. From the optimization constraints in (3), it follows that investment in skill $i$ occurs when this marginal future gain exceeds the marginal cost in foregone current returns.

*Interpretation of $\beta$ and $t_i$.* The discount factor $\beta$ captures how much a worker values future returns from investing. Workers with shorter remaining tenure are less patient and thus have lower $\beta$, which reduces their incentive to invest in training. The conversion factor $t_i$ captures how much training time is required to generate a unit of skill improvement in task $i$. Higher $t_i$ means marginal training is more time costly.

## 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 $S$):

$$\beta^J \geq \beta^S, \qquad t_i^J \leq t_i^S, \qquad S_i^J \leq S_i^S, \text{ for tasks } i = 1, 2, 3. \tag{4}$$

Thus, from the set of conditions in (4), it follows that high-tenured workers perceive lower future returns from investing in training, face higher training 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 (4), it follows that workers' single-period returns satisfy

$$r_0^S \geq r_0^J. \tag{5}$$

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

The Tech Intervention operates through an increase in task-specific productivity shifters that scale output directly. Formally, the intervention raises $A_i$ for all tasks, with the increase being largest for Simple Trades:

$$A_1^{(1)} > A_2^{(1)} > A_3^{(1)}, \qquad A_i^{(1)} > A_i^{(0)} \text{ for all } i.$$

Based on these conditions, we derive the following predictions.

*Simple Trades.* For Simple Trades ($i = 1$), the Tech intervention raises productivity directly through a relatively large increase in $A_1^{(1)}$. The worker's optimal training choice satisfies

$$\beta A_1^{(1)} \pi' \left( S_1 + I_1 - T_1^{(1)} \right) = r_0 \, t_1. \tag{6}$$

Because $A_1^{(1)}$ increases by more than in any other task, the marginal return to training rises most strongly in Simple Trades. Despite workers' initial skills being close to the optimal target, this induces the largest training response among all tasks.

Differences in training intensity across worker types are governed by opportunity costs. Since

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

low-tenured workers invest more in training and achieve higher second-period productivity.

Second-period production in Simple Trades for a worker of tenure type $k \in \{J, S\}$ is therefore given by

$$y_{1,k}^{(1)} = A_1^{(1)} \pi\left(S_1^k + I_{1,k}^* - T_1^{(1)}\right), \tag{7}$$

with $y_{1,J}^{(1)} > y_{1,S}^{(1)}$ and the largest productivity gains occurring in this task.

*SME Loans.* For SME Loans ($i = 2$), the Tech intervention raises productivity through a smaller increase in $A_2^{(1)}$. The resulting increase in the marginal return to training induces training by both worker types, though to a lesser extent than in Simple Trades.

As in Simple Trades, higher opportunity costs imply that high-tenured workers invest less in training, so that low-tenured workers are more productive in the second period.

Second-period production in SME Loans for a worker of tenure type $k \in \{J, S\}$ is given by

$$y_{2,k}^{(1)} = A_2^{(1)} \pi\left(S_2^k + I_{2,k}^* - T_2^{(1)}\right), \tag{8}$$

with $y_{2,J}^{(1)} > y_{2,S}^{(1)}$ and productivity gains that are smaller than in Simple Trades.

*Complex Trades.* For Complex Trades ($i = 3$), the Tech Intervention produces the smallest increase in productivity, as $A_3^{(1)}$ rises by less than in the other tasks. Although the higher $A_3^{(1)}$ increases the marginal return to training, high opportunity costs limit training intensity for high-tenured workers.

Training nevertheless occurs for both worker types, but remains quantitatively small.

Second-period production in Complex Trades for a worker of tenure type $k \in \{J, S\}$ is therefore given by

$$y_{3,k}^{(1)} = A_3^{(1)} \pi\left(S_3^k + I_{3,k}^* - T_3^{(1)}\right), \tag{9}$$

with $y_{3,J}^{(1)} > y_{3,S}^{(1)}$ and productivity gains that are smaller than in SME Loans and Simple Trades.

#### 6.2.2. Task Intervention

The primary effect of the Task Intervention is an increase in the returns for doing SME Loans, together with an upward shift in the optimal skill level $T$ across all tasks. Based on this, we have the following predictions.

*Simple Trades.* For Simple Trades ($i = 1$), the worker's optimal training choice is characterized by the first-order condition of problem (3). In an interior solution, optimal investment in skill 1 satisfies

$$\beta A_1^{(1)} \pi' \left( S_1 + I_1 - T_1^{(1)} \right) = r_0 \, t_1, \tag{10}$$

which equates the discounted marginal benefit of training in Simple Trades to the marginal opportunity cost in terms of foregone first-period returns.

Because workers possess their highest initial skill levels in Simple Trades, we can assume that $S_1$ is close to the target skill level $T_1^{(1)}$ for both low-tenured and high-tenured workers. As a result, the marginal productivity of training, $\pi' \left( S_1 + I_1 - T_1^{(1)} \right)$, is positive but quantitatively small. Both worker types, therefore, optimally select training intensities that place them in a local neighborhood of the optimal knowledge frontier, yielding only modest improvements in skill between periods.

Consequently, second-period production in Simple Trades takes the form

$$y_1^{(1)} = A_1^{(1)} \pi \left( S_1 + I_1^* - T_1^{(1)} \right), \tag{11}$$

where $I_1^*$ denotes the optimal training investment. Since $I_1^*$ is small and similar across tenure types, second-period productivity gains in Simple Trades are limited and largely insensitive to managerial quality. Any residual differences in production across worker types arise from heterogeneity in opportunity costs, as captured by differences in $r_0$, $t_1$, and $\beta$.

*SME Loans.* For SME Loans ($i = 2$), the Task intervention operates by increasing their returns, so that

$$A_2^{(1)} > A_2^{(0)}.$$

This change raises the marginal return to training in SME Loans in the worker's optimization problem (3).

In an interior solution, optimal investment in skill 2 satisfies the first-order condition

$$\beta A_2^{(1)} \pi' \left( S_2 + I_2 - T_2^{(1)} \right) = r_0 \, t_2, \tag{12}$$

which equates the discounted marginal benefit of training to the marginal opportunity cost in terms of foregone first-period production.

Since workers' initial skill levels in SME Loans are assumed to be relatively far from the optimal target, the marginal productivity of training, $\pi' \left( S_2 + I_2 - T_2^{(1)} \right)$, is high. The increase in incentives induced by the Task intervention, therefore, leads both low-tenured and high-tenured workers to optimally choose higher training intensities, generating substantial gains in second-period revenues.

Differences in second-period production across worker types are driven by heterogeneity in opportunity costs. In particular, the optimality condition implies that the marginal cost of training is higher for high-tenured workers than for low-tenured workers,

$$\frac{r_0^S t_2^S}{\beta^S} > \frac{r_0^J t_2^J}{\beta^J}. \tag{13}$$

As a consequence, high-tenured workers optimally invest less in training for SME Loans, which leads to lower second-period productivity relative to low-tenured workers. Thus, despite starting with lower initial skill levels, low-tenured workers are more productive in the second period due to their lower opportunity cost of training.

Second-period production in SME Loans for a worker of tenure type $k \in \{J, S\}$ is therefore given by

$$y_{2,k}^{(1)} = A_2^{(1)} \pi \left( S_2^k + I_{2,k}^* - T_2^{(1)} \right). \tag{14}$$

If managerial quality affects workers symmetrically—by shifting $A_2^{(1)}$ or the production function $\pi(\cdot)$ upward by the same amount for both tenure types—then managerial quality induces a proportional increase in output without altering relative training incentives. As a result, managerial quality shifts second-period production upward while preserving the productivity gap associated with workers' tenure.

*Complex Trades.* For Complex Trades ($i = 3$), high-tenured workers optimally choose little to no training. This outcome follows directly from the worker's optimization problem (3). In particular, a no-training corner solution for high-tenured workers is characterized by the condition

$$r_0^S t_3^S \geq \beta^S A_3^{(1)} \pi' \left( S_3^S - T_3^{(1)} \right), \tag{15}$$

under which the marginal opportunity cost of training exceeds its discounted marginal benefit.

Regarding Complex Trades, the Task Intervention does not alter their monetary returns, so that $A_3^{(1)} = A_3^{(0)}$. As a result, the marginal benefit of training remains limited. This reinforces the role of opportunity costs in determining training behavior. Given that high-tenured workers have higher baseline returns, higher training conversion factors, and lower discount factors (conditions (4)–(5)), their opportunity cost of training is strictly higher than that of low-tenured workers:

$$\frac{r_0^S t_3^S}{\beta^S} > \frac{r_0^J t_3^J}{\beta^J}. \tag{16}$$

Consequently, high-tenured workers optimally do not invest in training for Complex Trades, whereas low-tenured workers may still find training profitable.

Second-period production in Complex Trades for a worker of tenure type $k \in \{J, S\}$ is therefore given by

$$y_{3,k}^{(1)} = A_3^{(1)} \pi \left( S_3^k + I_{3,k}^* - T_3^{(1)} \right), \tag{17}$$

with $I_{3,S}^* = 0$ and $I_{3,J}^* > 0$. If managerial quality affects workers symmetrically, it scales output equally across tenure types without altering training incentives. As a result, managerial quality magnifies the productivity gap in Complex Trades: only low-tenured workers experience productivity gains from training, while high-tenured workers' output remains unchanged—or declines if task complexity increases, $T_3^{(1)} > T_3^{(0)}$.

# 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 its 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-quality 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.

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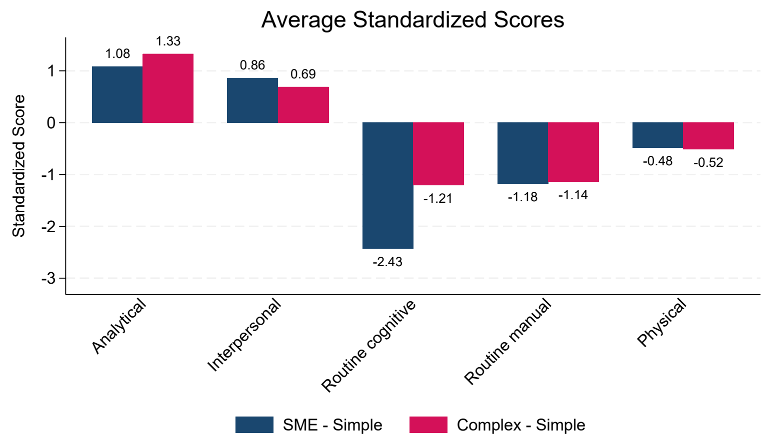
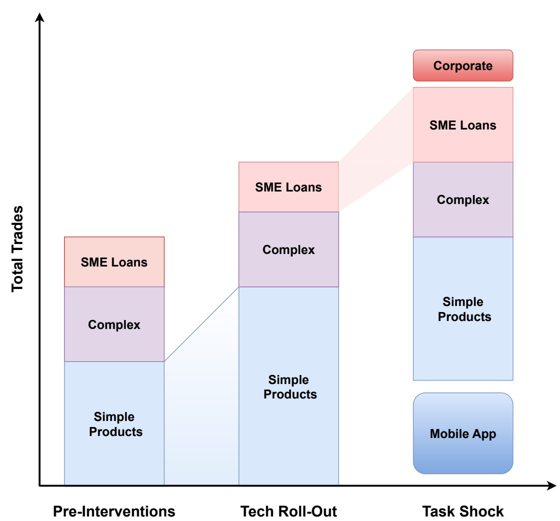
## 8. Figures

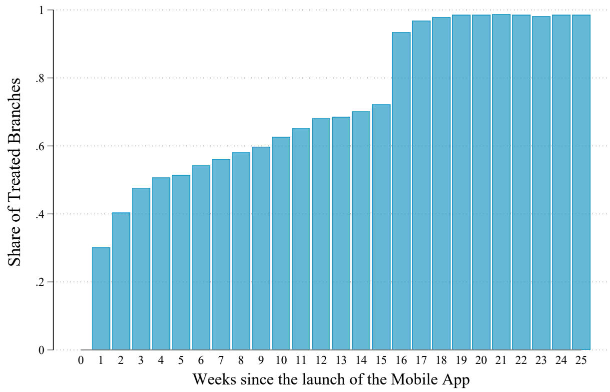



(a) Task complexity by occupation

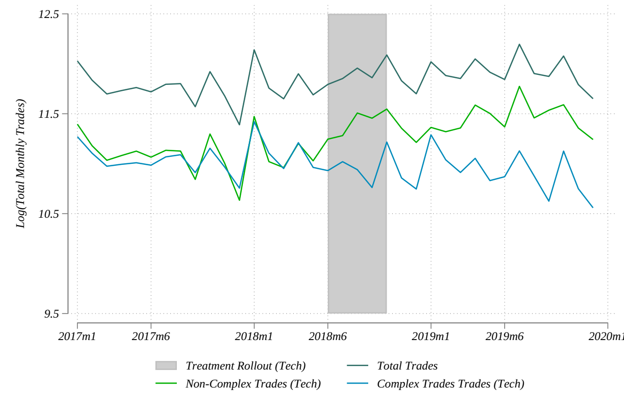



(b) Visual summary of the interventions

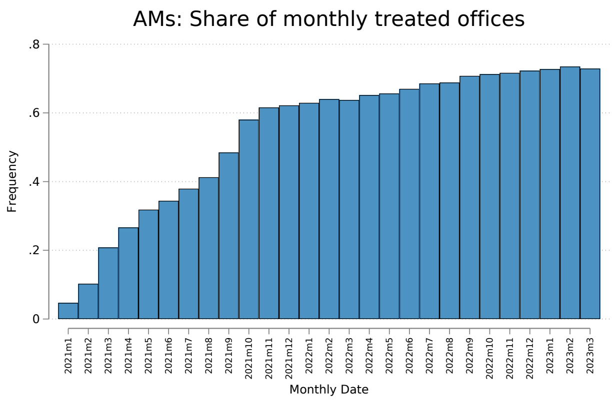
Figure 1: **Interventions and the complexity of tasks.** Panel (a) displays standardized differences in occupational task content relative to simple tasks, based on composite O*NET measures. Blue bars show differences between SME tasks and simple tasks; pink bars show differences between complex tasks and simple tasks. Composite O*NET measures follow Autor et al. (2003). Panel (b) provides a visual summary of the technology and task interventions.



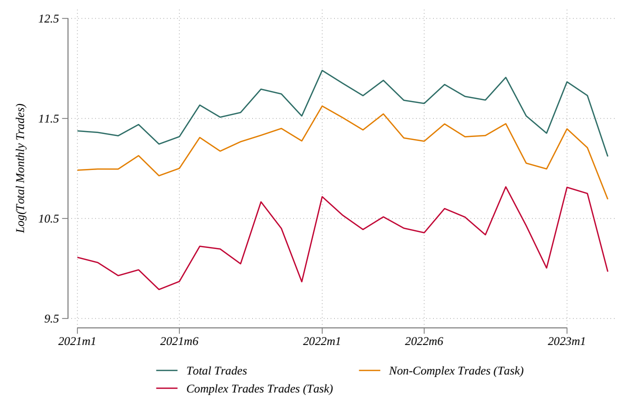

(a) Tech Rollout




(b) Trades under Tech Intervention

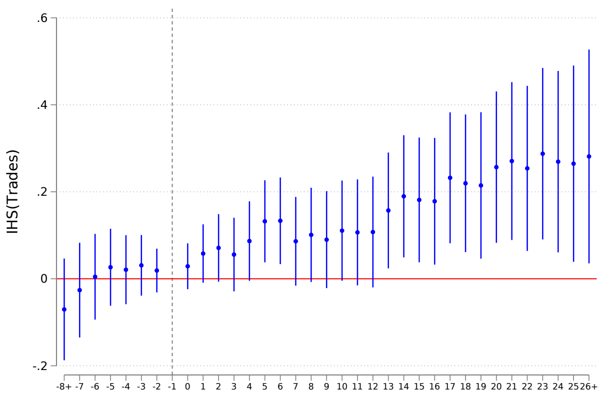



(c) Task InterventionRollout

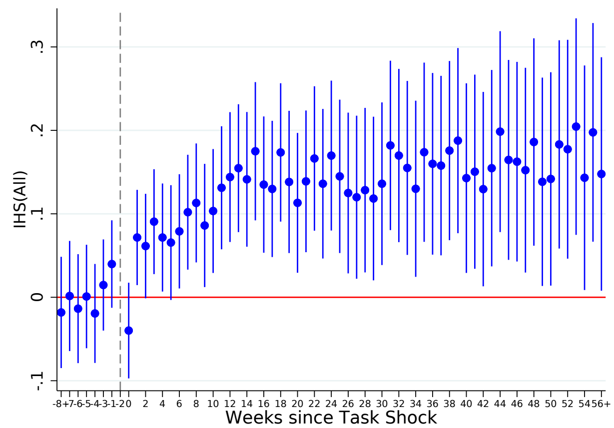



(d) Trades under Task Intervention

Figure 2: **Rollout and aggregate trade dynamics for the technology 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. Total trades increase following the tech intervention, while complex trades remain flat in aggregate.

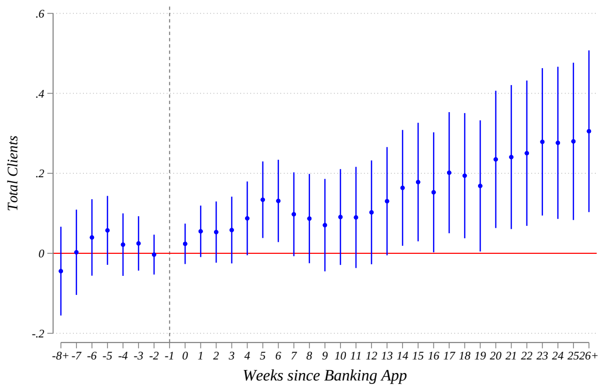



(a) Tech intervention: Worker-level total trades

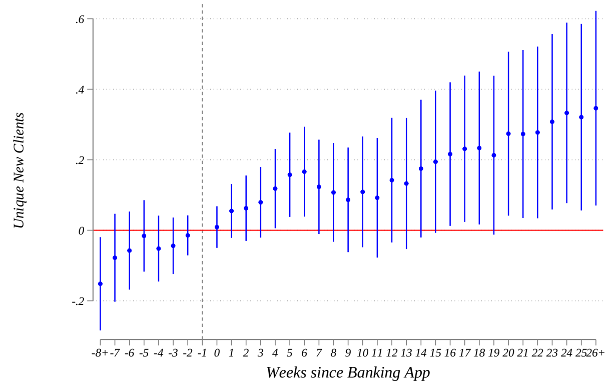



(b) Task intervention: Worker-level total trades

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

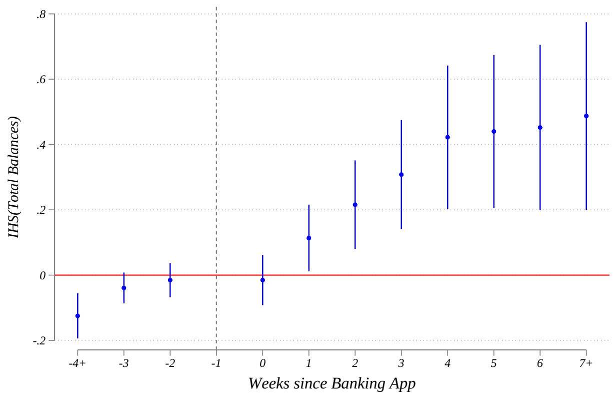



(a) Worker: Total Unique Weekly Clients

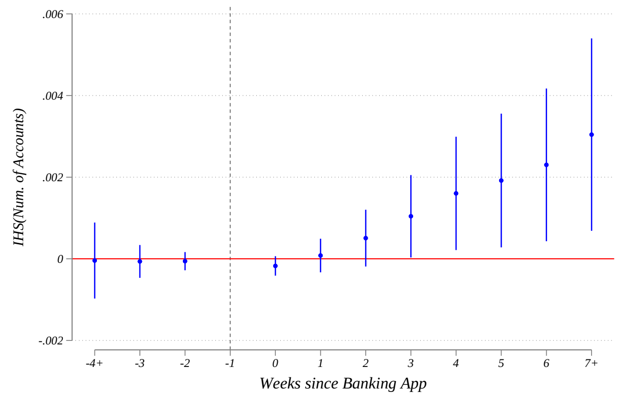



(b) Worker: Unique New Clients (First Time)

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

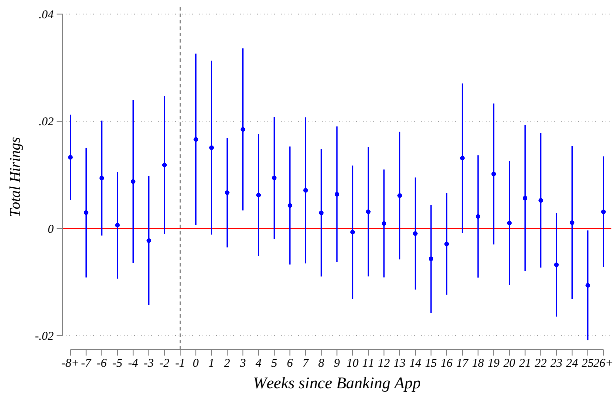



(a) Tech: Total Balances (Branch)

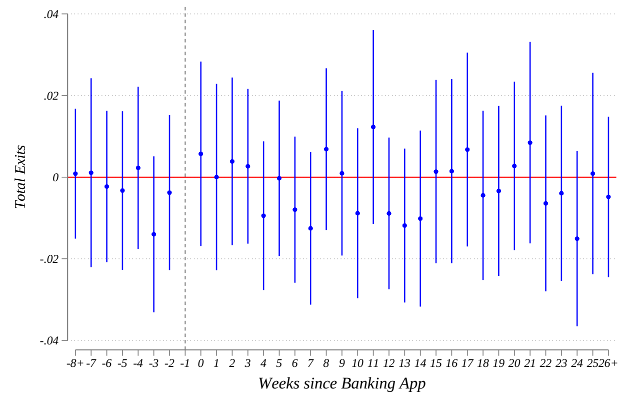



(b) Tech: Number of Accounts (Branch)

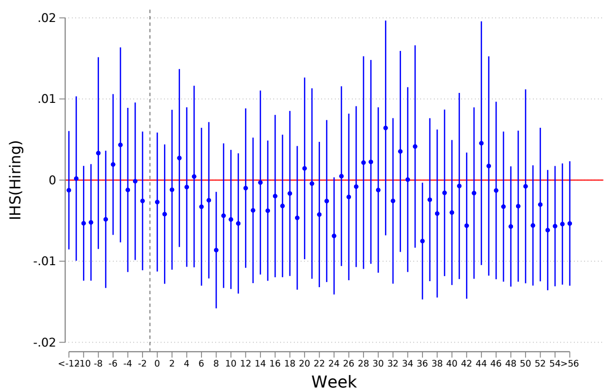
Figure 5: **Effects of Tech Intervention on product quality at the branch level.** Panels (a) shows total balances (measured in millions of COP) and Panel (b) shows the number of active accounts. Both outcomes are expressed in the inverse hyperbolic sine (IHS).



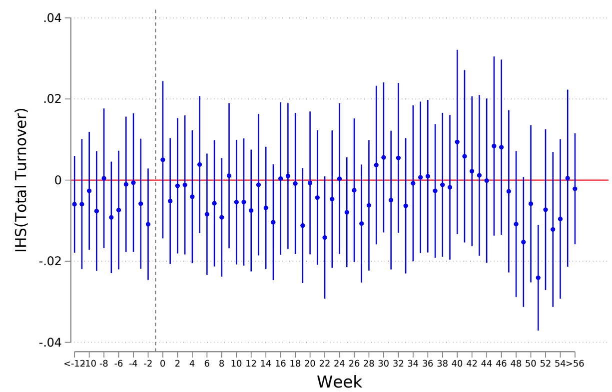

(a) Tech: Total Hiring (Branch)




(b) Tech: Total Exits (Branch)

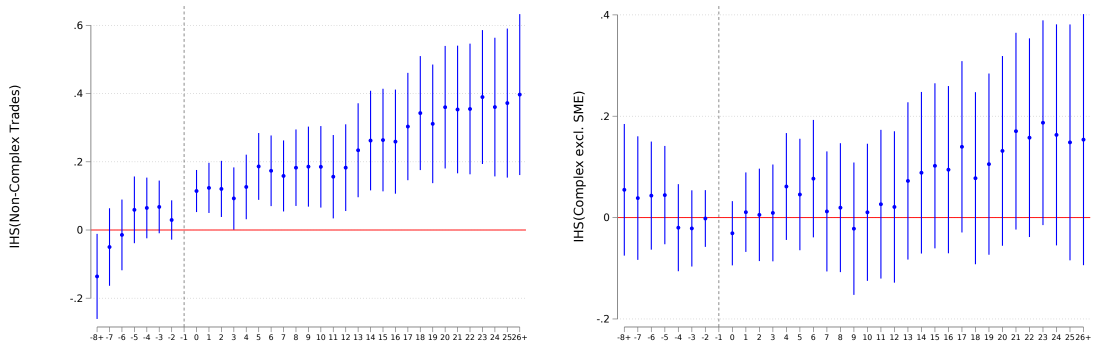



(c) Task: Hiring (Branch)

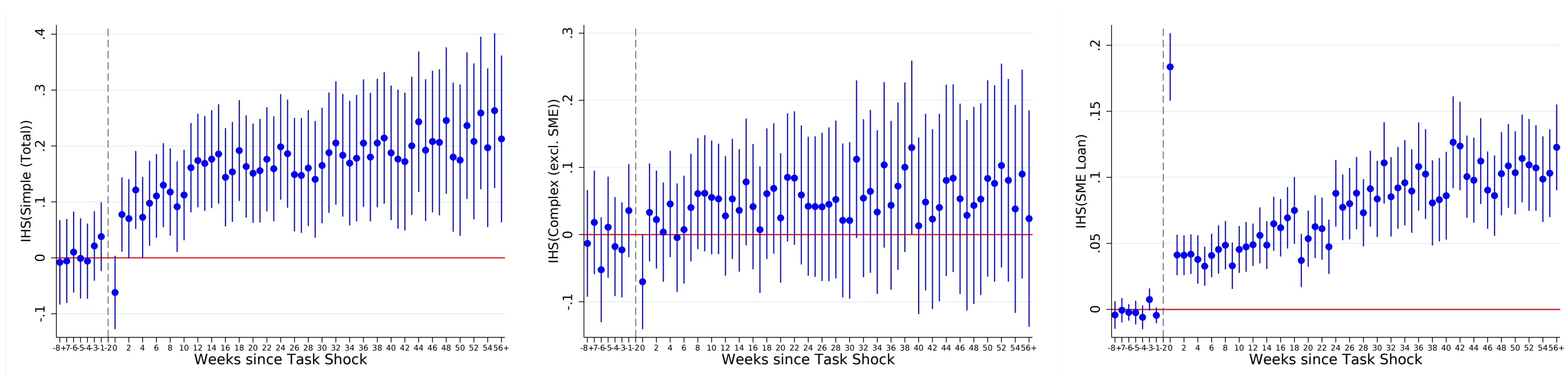



(d) Task: Total Exits (Branch)

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.

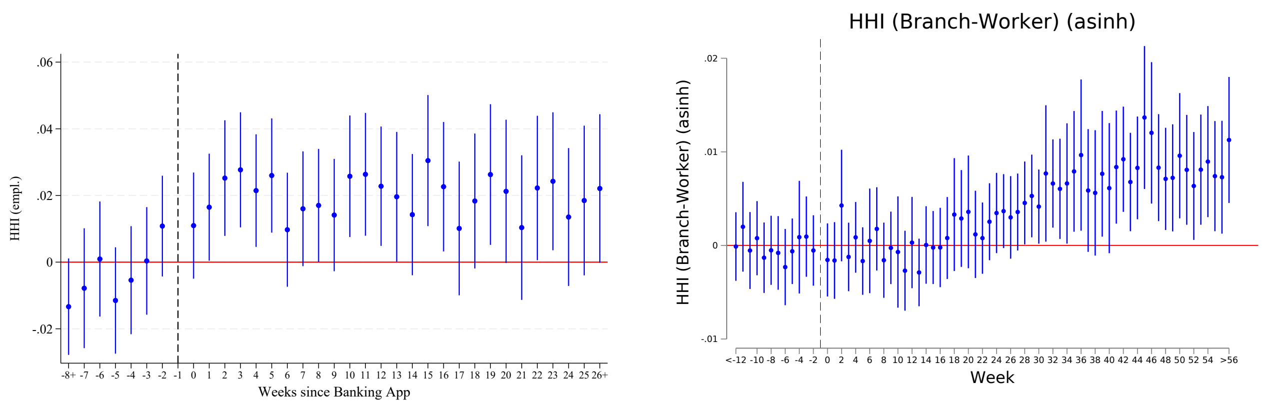



(a) Tech: Simple (Mobile) Trades (b) Tech: Complex Trades (c) Tech: SME Trades




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

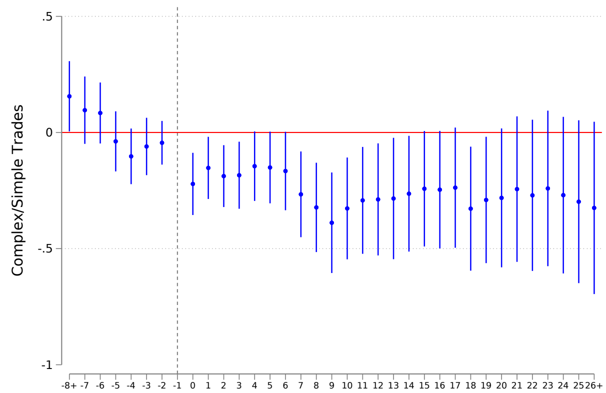
Figure 7: **Effects of Tech and Task interventions on task composition.** Event-study estimates for worker-level task composition by trade type. Row 1 shows the Tech intervention; Row 2 shows the Task intervention. Columns show (a) simple trades, (b) complex trades, and (c) SME trades. All outcomes are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



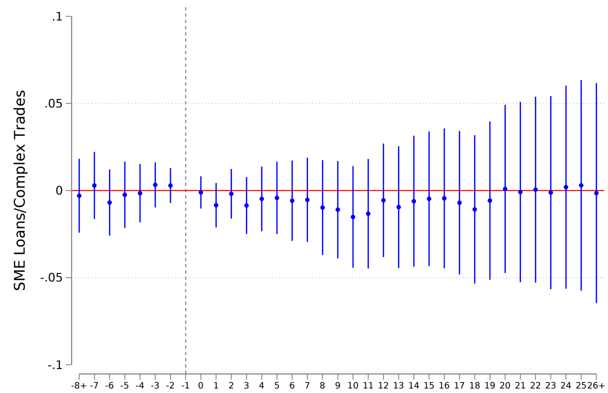

(a) Tech intervention

(b) Task intervention

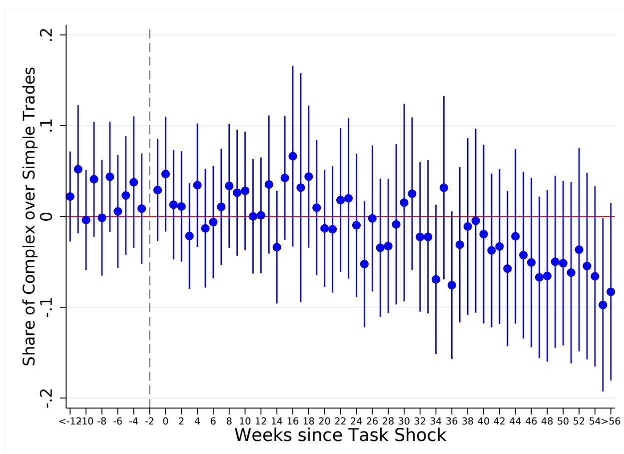
Figure 8: **Task specialization measured by Herfindahl–Hirschman Index (HHI).** Panel (a) shows the Tech intervention; Panel (b) shows the Task intervention. The HHI is computed at the worker-week level based on the distribution of trades across task categories (simple, complex, and SME). Higher values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



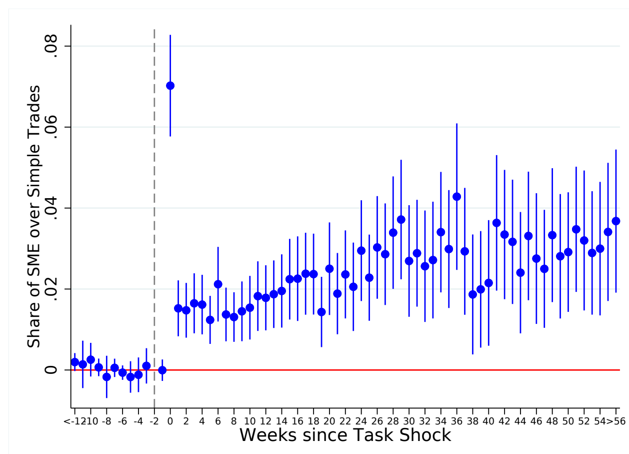

(a) Tech: Complex / Simple




(b) Tech: SME / Complex

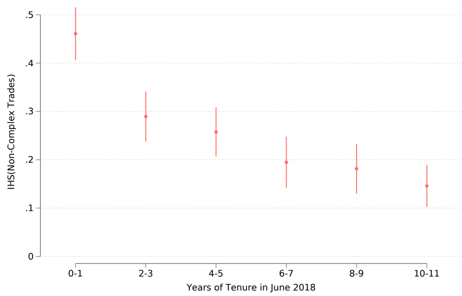



(c) Task: Complex / Simple




(d) Task: SME / Complex

Figure 9: **Worker-level reallocation ratios under Task and Technology interventions.** Row 1 reports the Task intervention; Row 2 reports the Technology intervention. Columns show the ratio of complex to simple trades and SME to non-SME complex trades



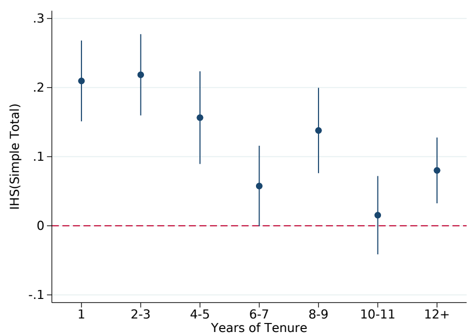

(a) Tech: Simple Trades

Results/placeholder.pdf

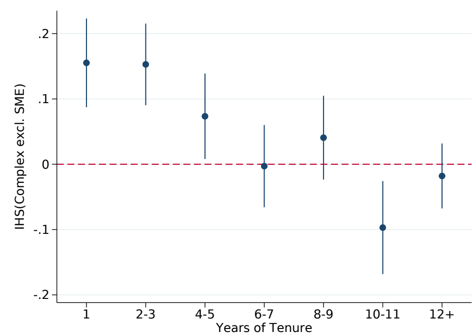
(b) Tech: Complex Trades

placeholder.pdf

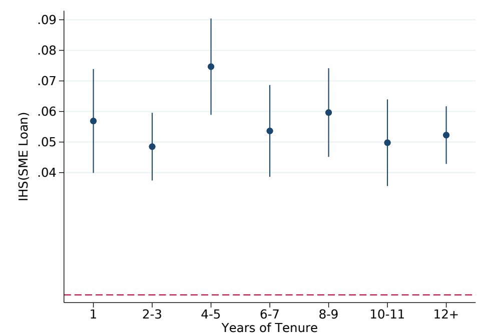
(c) Tech: SME Loans




(d) Task: Simple Trades

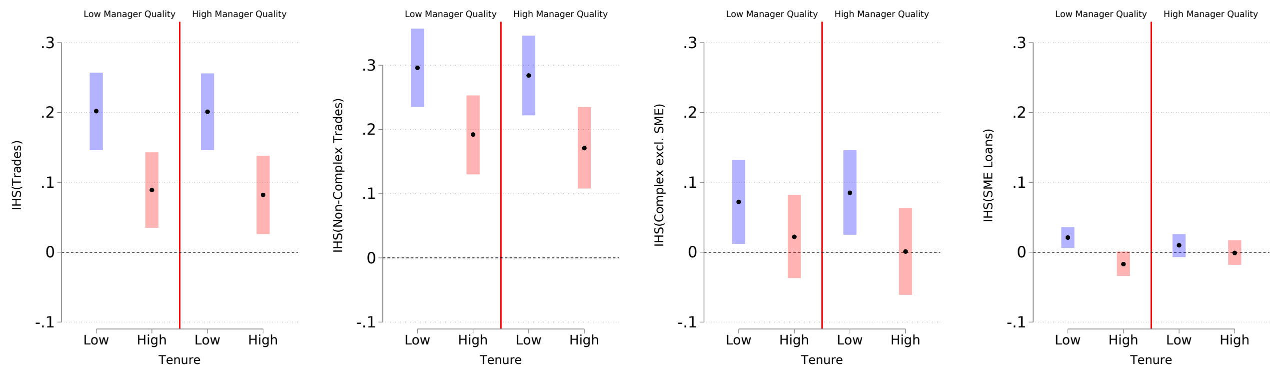



(e) Task: Complex Trades

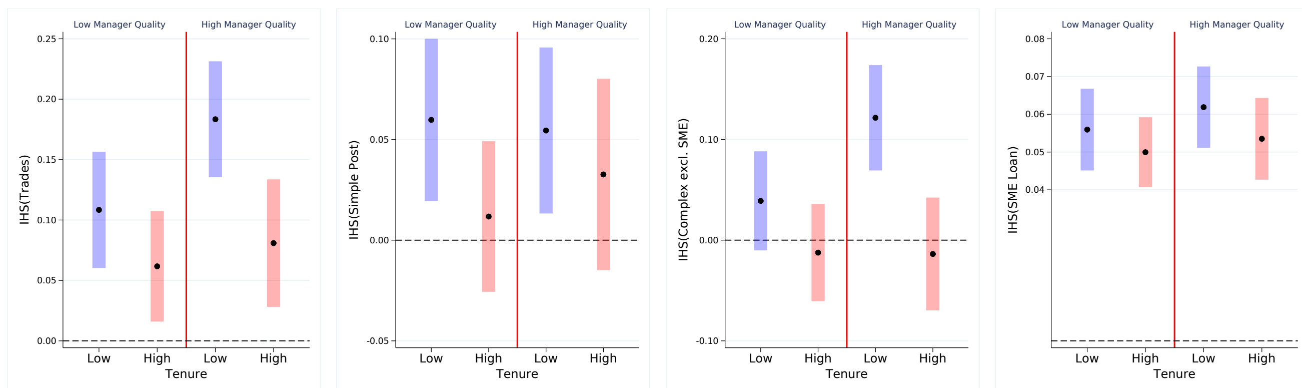



(f) Task: SME Loans

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. 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

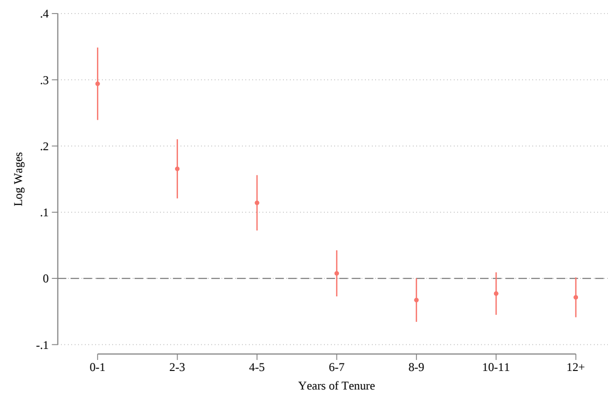



(e) Task: Total Trades (f) Task: Simple Trades (g) Task: Complex Trades (h) Task: SME Loans

Figure 11: **Manager quality X worker tenure heterogeneity under Tech and Task interventions.** Row 1 reports the Tech shock; Row 2 reports the Task shock. Columns show (a) total trades, (b) simple trades, (c) complex trades, and (d) SME loans. All outcomes are expressed in inverse hyperbolic sine (IHS). Low and high manager quality 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.

Results/placeholder.pdf

(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 (placeholder). Panel (b) reports the Task Intervention.

# 9. Tables

| | Tech Intervention | Task Intervention |
|---|---|---|
| Time period | Jan 2017-Dec 2019 | Jan 2019-Mar 2023 |
| Number of branches | 449 | 355 |
| Number of total workers | 6,948 | 8,129 |
| Number of managers | 1,263 | 1,153 |
| Number of account managers | 2,152 | 2,018 |
| Number of bank tellers | 183 | 2,105 |
| Number of Complex products | 4 | 8 |
| Number of Non-Complex 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(Non-Complex 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 non-complex 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(Non-Complex 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 non-complex trades vary across samples, as four financial products were available on the app during the Tech Intervention, while seven products were available by 2021.

Table 4: Balance Between Early and Late Adopters

| | **(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 |

*Notes:* This 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) IHS(Trades) | (2) IHS(Non-Complex Trades) | (3) IHS(Complex Trades) |
|---|---|---|---|
| Tech Shock | 0.248*** | 0.259*** | 0.177*** |
| | (0.0295) | (0.0316) | (0.0321) |
| Tech Shock X Tenure (p50) | -0.135*** | -0.119*** | -0.104*** |
| | (0.0148) | (0.0154) | (0.0133) |
| Observations | 370,163 | 370,163 | 370,163 |
| Mean | 2.576 | 1.865 | 1.749 |
| Std.Dev | 1.098 | 1.224 | 1.156 |

Week and Worker FEs included. SE clustered by Worker

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

**Panel B: Task Intervention**

| | (1) All | (2) Complex | (3) Simple | (4) Simple Pre | (5) Simple Post | (6) All Excl. SME | (7) Complex Excl. SME | (8) SME Loans |
|---|---|---|---|---|---|---|---|---|
| Post | 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) |
| Post × 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**

| VARIABLES | (1) IHS(Trades) | (2) IHS(Non-Complex Trades) | (3) IHS(Complex Trades) |
|---|---|---|---|
| Tech Shock | 0.176*** | 0.208*** | 0.109*** |
| | (0.0292) | (0.0315) | (0.0318) |
| Tech Shock X Manager Quality | -0.00119 | -0.0199 | 0.0123 |
| | (0.0125) | (0.0130) | (0.0116) |
| Constant | 2.568*** | 1.928*** | 1.672*** |
| | (0.0130) | (0.0142) | (0.0143) |
| Observations | 381,532 | 381,532 | 381,532 |
| $R^2$ | 0.623 | 0.659 | 0.501 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Panel B: Task Intervention**

| | (1) All | (2) Complex | (3) Simple | (4) Simple Pre | (5) Simple Post | (6) All Excl. SME | (7) Complex Excl. SME | (8) SME Loans |
|---|---|---|---|---|---|---|---|---|
| Post | 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) |
| Post × 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 |

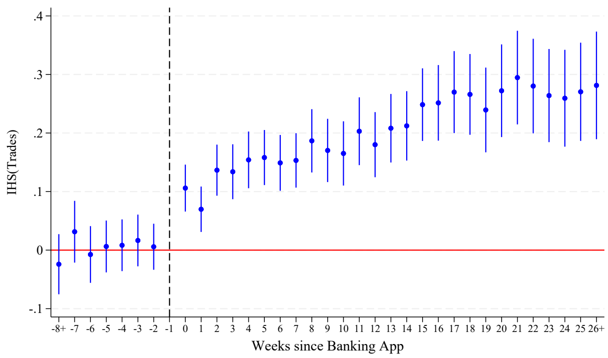
Table 6: **Effect of ex-ante high manager quality on main outcome variables.** The table reports heterogeneous treatment effects by manager quality. Manager quality is measured by manager value added $\theta_m$ estimated from the AKM equation (**??**). The heterogeneity measure is a dummy equal to one if average manager quality at the time of the introductions is above median.

| 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 |

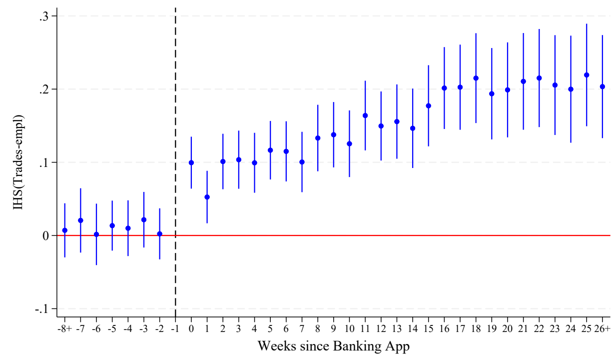
Table 7: **Correlation between manager AKM fixed effects, demographics, and leadership measures.** Leadership, performance, and company values come from the leadership survey, average measures at the bottom of each variable group are the arithmetic averages of the group items. Demographic measures come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

# 10. Appendix

## 10.1. Appendix figures

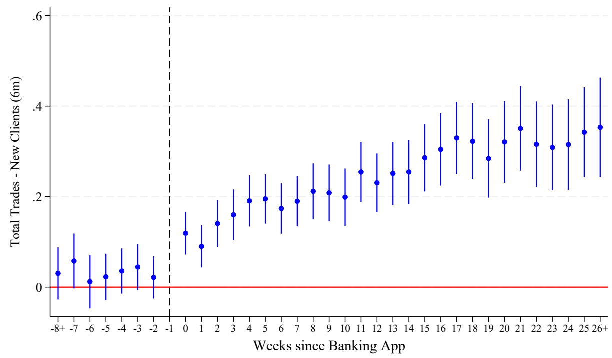



(a) Tech: Total trades

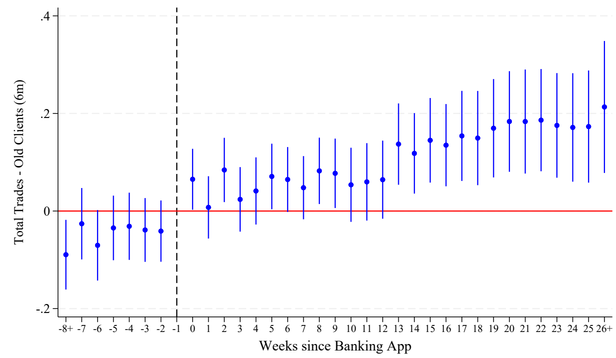



(b) Tech: Productivity

Figure A.1: **Event-study estimates for total trades and productivity at the branch level.** 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 Tech Intervention.** Columns distinguish new clients (left) and old clients (right), defined using a six-month window since the first observed trade.

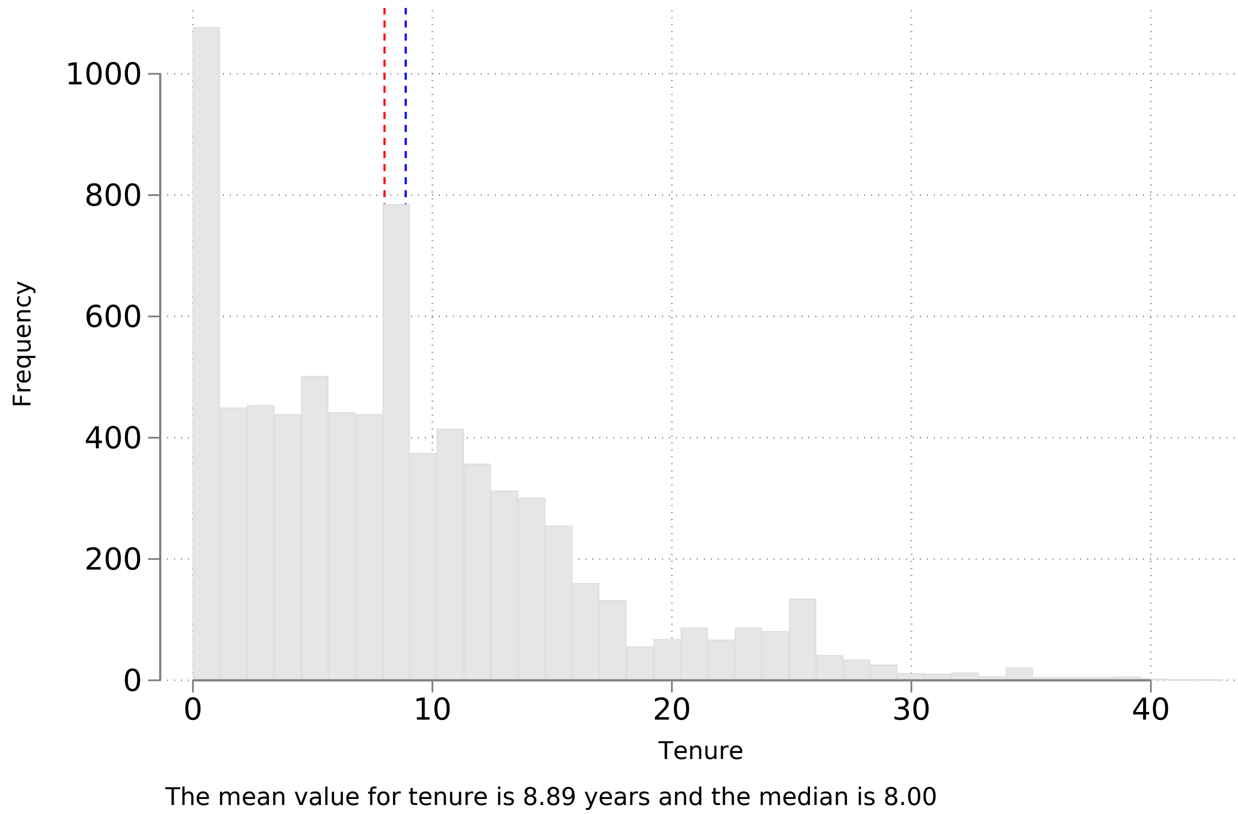



Figure A.3: **Distribution of worker tenure.** The figure displays the frequency distribution of worker tenure (in years). The red dashed line marks the mean (8.89 years) and the blue dashed line marks the median (8 years).

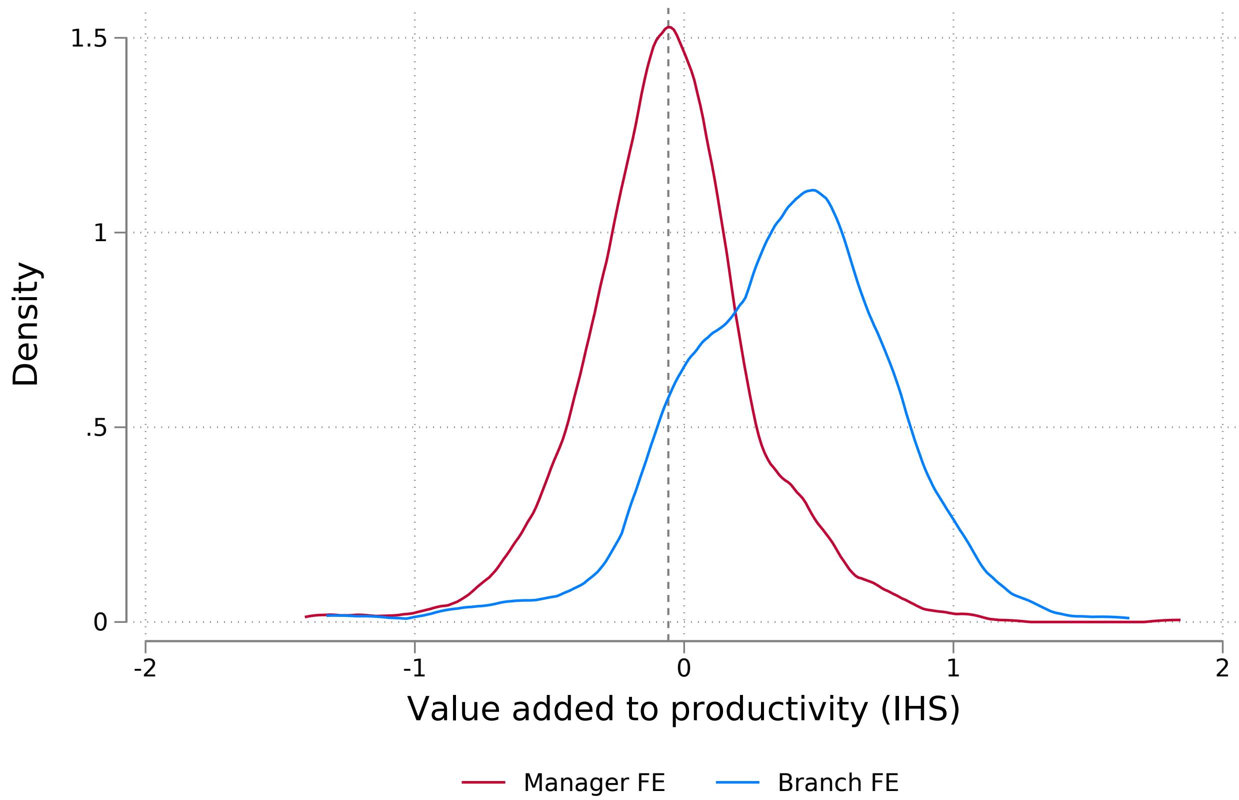
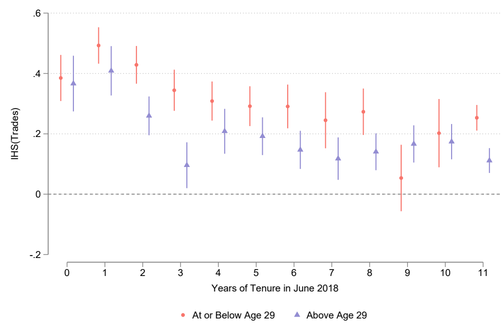
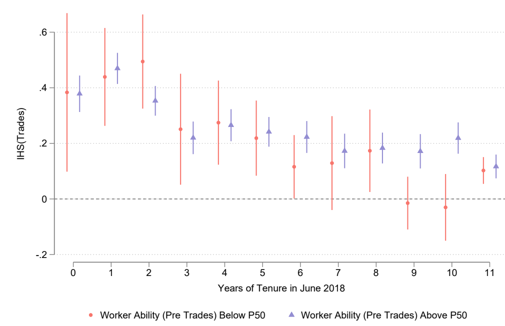


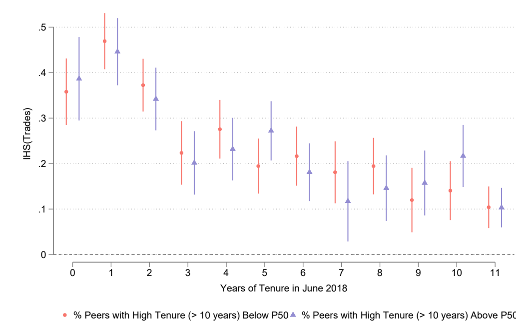

Figure A.4: AKM Variance Decomposition: Worker and manager fixed effects.



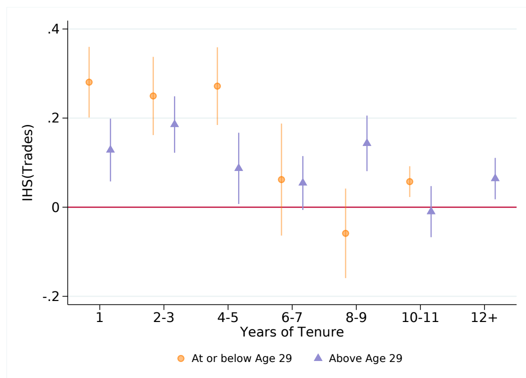

(a) Tech: tenure friction by age



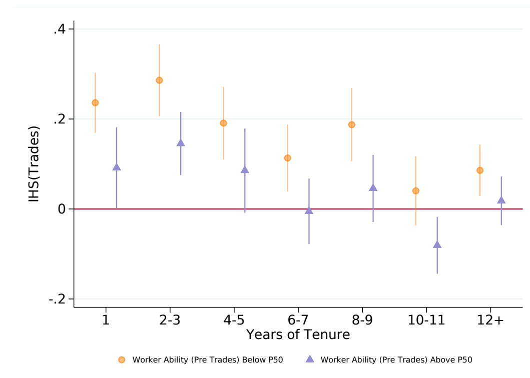

(b) Tech: tenure frictions by worker ability



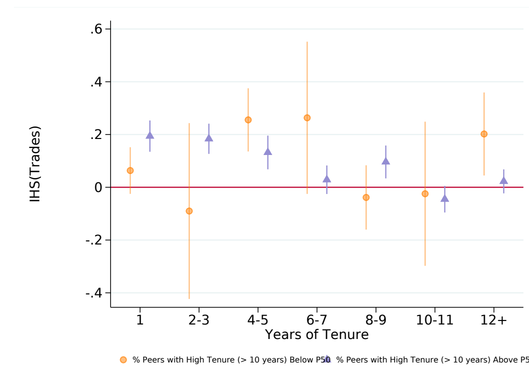

(c) Tech: peer tenure effects




(d) Task: tenure friction by age

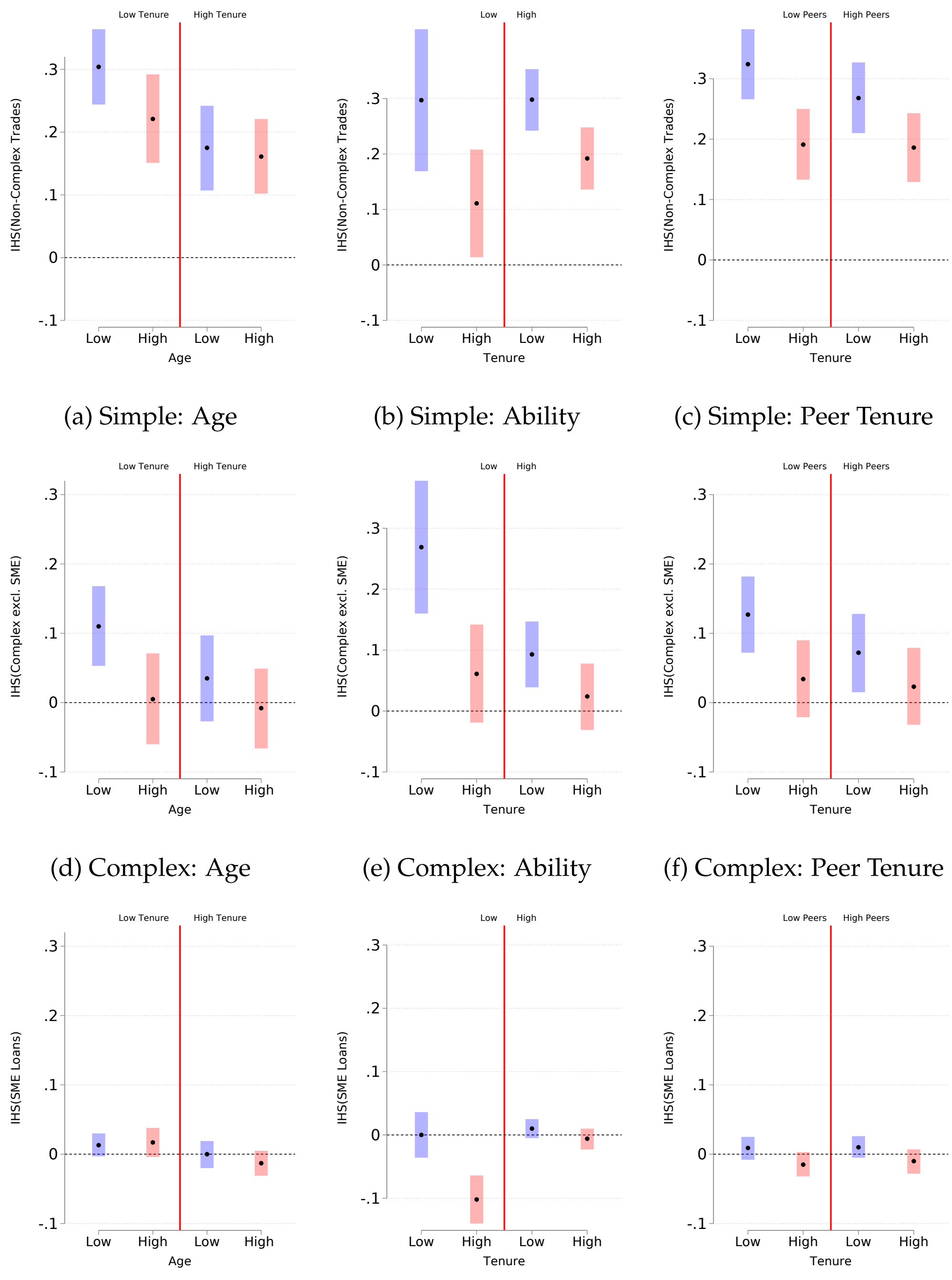



(e) Task: tenure frictions by worker ability




(f) Task: peer tenure effects

Figure A.5: **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 manager quality. 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).

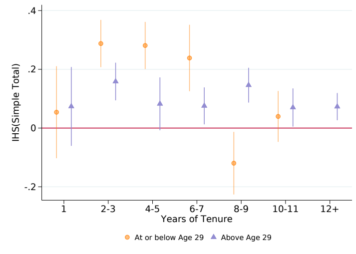



(a) Simple: Age (b) Simple: Ability (c) Simple: Peer Tenure

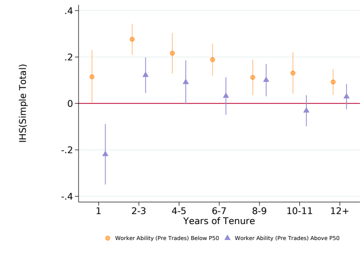
(d) Complex: Age (e) Complex: Ability (f) Complex: Peer Tenure

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

Figure A.6: **Tech intervention: tenure-related frictions by task type.** Rows correspond to task categories (simple, complex tasks, and SME loans). Columns report heterogeneity by worker age, worker ability, and peer tenure exposure. Peers are computed based on whether the branch of the worker at the time of the shock has an above median number of workers with tenure above median, excluding the worker from the computation.



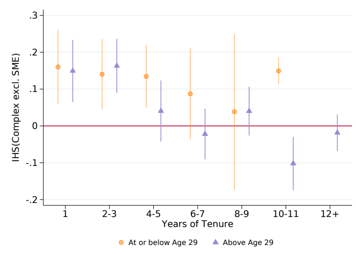

(a) Simple: Age



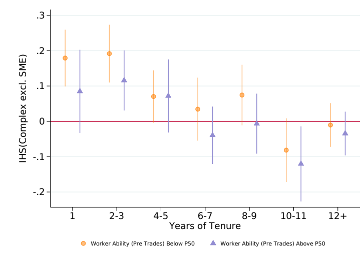

(b) Simple: Ability

Results/Figures/placeholder.pdf

(c) Simple: Peer Tenure



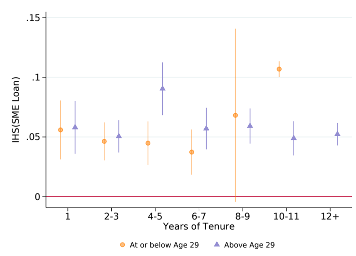

(d) Complex: Age



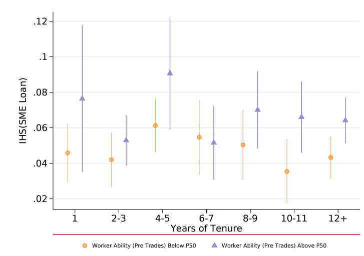

(e) Complex: Ability

Results/Figures/placeholder.pdf

(f) Complex: Peer Tenure




(g) SME: Age




(h) SME: Ability

Results//placeholder.pdf

(i) SME: Peer Tenure

Figure A.7: **Task intervention: tenure-related frictions by task type.** Rows correspond to task categories (simple, complex, and SME loans). Columns report heterogeneity by worker age, worker ability, and peer tenure exposure.

## 10.2. Appendix tables

Table A.1: **Tech intervention: changes in trades and productivity (level effects).**

| | (1)<br>Branch: IHS(Trades) | (2)<br>Branch: IHS(Trades/Empl.) | (3)<br>Worker: IHS(Trades) | (4)<br>Worker: IHS(Trades Excl. SME) |
|---|---|---|---|---|
| Tech Shock | 0.141*** | 0.0967*** | 0.1125*** | 0.1066*** |
| | (0.0204) | (0.0152) | (0.0257) | (0.0258) |
| Observations | 69,465 | 69,244 | 158,697 | 158,697 |
| Dependent Mean | 4.349 | 1.819 | 12.92 | 12.89 |
| Std. Dev. | 1.110 | 0.652 | – | – |

Columns (1)–(2) report branch-level outcomes; columns (3)–(4) report worker-level outcomes.
Week and branch fixed effects are included.
Standard errors are clustered at the branch level.

*p<0.05; **p<0.01; ***p<0.001

Table A.2: **Task intervention: changes in trades and productivity (level effects).**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | IHS(Trades) | Branch: IHS(Trades/Empl.) | IHS(Trades) | IHS(Trades Excl. SME) |
| Task Shock | -0.0237 | -0.0119 | 0.1125*** | 0.1066*** |
| | (0.0149) | (0.0158) | (0.0257) | (0.0258) |
| Observations | 77,830 | 77,774 | 158,697 | 158,697 |
| Dependent Mean | 64.280 | 8.631 | 12.92 | 12.89 |

Columns (1)–(2) report branch-level outcomes and include week and branch fixed effects; columns (3)–(4) report worker-level outcomes and include week and worker fixed effects. Standard errors are clustered at the branch (worker) level.

*$p<0.05$; **$p<0.01$; ***$p<0.001$