Reorganizing Work: Technology Adaptation in a Bank*

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Abstract

This paper examines how organizations adapt to the introduction of new technologies and tasks reassignments exploiting granular, longitudinal data from a large Latin American bank. We examine the organizational responses to two top-down interventions implemented by the bank over the course of five years: the staggered introduction of a mobile banking app, and of a new policy aimed at shifting account managers' activity from retail banking to small and medium enterprises lending (SMEs). We show that, on average, the bank was able to achieve significant productivity gains for newly automated tasks, but failed to shift employees' activity toward complex (non-automated) tasks. We also see considerable heterogeneity in the transition to complex tasks according to the ex-ante productivity of branch managers, and the average tenure of the branch employees. These findings underscore the importance of complementary organizational changes in realizing the benefits of technological adoption and reveal extensive heterogeneity in adaptation to technological change within the same organization.

Keywords: Automation; task allocation; organizational change; worker adaptation; managerial quality

JEL: J24; M53; M54; O33

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1. Introduction

The adoption of new technologies is a fundamental driver of firm productivity (Syverson, 2011), yet this process is often slow and uneven (Andrews et al., 2015). The importance of complementary organizational and managerial innovations and task redesign for technology adoption has been widely documented in the literature (Autor, 2024; Bresnahan et al., 2002; Ichniowski and Shaw, 2003; Bloom et al., 2012; Atkin et al., 2017). However, very little is known about the process or organizational adaptation triggered by technological shifts. Most empirical studies rely on cross-sectional data (e.g., Bloom et al., 2012), which offer limited insight into the micro-level worker-task changes that characterize the adoption process. Bridging this gap in the literature is critical to gain greater clarity on the productivity impact of new technologies, as well as the effectiveness of policies aimed at fostering technology adoption.

This paper leverages detailed administrative data from a large Latin American bank to provide an in depth exploration of the process of organizational adaptation to new technologies and tasks, and the frictions that hinder the implementation of these changes. The bank underwent these shifts in the context of a major digital transformation towards a mobile first banking approach, which required tailoring products and services to attract new customers, enhance engagement, and streamline banking operations.

As part of this strategy, the bank introduced a customer-facing mobile app in 2018, enabling customers to seamlessly open, purchase, and manage selected non-complex financial products, such as consumer loans and debit cards. The transition also automated critical processes like ID verification and compliance checks, making transactions faster and more efficient. To drive adoption and address resistance from branch employees, the bank integrated the app rollout within its branch network, positioning branches as key facilitators in onboarding customers. Branch employees assisted with initial setup and app usage, ensuring a smoother transition to digital banking. To further incentivize adoption, the bank introduced a monetary rewards system tied to in-app transactions. Specifically, the app included a field where account managers could enter their employee ID, allowing them to receive credit for customer enrollments and usage.

In January 2021, the bank implemented a top-down organizational change restructuring roles across and within branches to further align its operations with its digital transformation strategy and shift the activity of account managers (AMs) towards higher value added products (loans for small and medium enterprises (SME loans) requiring in-depth financial expertise. This transition required personal AMs to move beyond retail tasks and develop new capabilities, including assessing creditworthiness, conducting due diligence, offering tailored financial solutions, and managing client relationships. [1]

We study the impact of these top-down interventions on the organization of work and workers inside bank branches. We show that, while the bank was able to increase the productivity of some tasks, branches characterized by high-tenure workers struggled to transition to more complex, non-automated tasks. This finding highlights the presence of significant frictions in the process of adaptation to new technologies and tasks. We show that high-productivity managers play a crucial role in mitigating the costs of missing complementary organizational changes by facilitating adaptation, even in branches with a high share of tenured workers.

This study contributes to three strands of the literature. First, it adds to research on how technological change reshapes jobs and tasks (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Handel, 2013; Acemoglu and Restrepo, 2018b, 2019, 2020; Ocampo, 2022; Adenbaum, 2023; Autor, 2024). While prior work has primarily focused on economy-wide effects, this paper provides a firm-level perspective, highlighting the heterogeneity in adaptation across workers within the same organization. While our study is focused on a single firm, it is worth noting that the banking sector has undergone significant transformations due to digital technologies, fundamentally altering how financial services are delivered (Autor et al., 2002; Bessen, 2016). The digital strategy undertaken by the bank studied in this paper is typical in the banking sector. As such, this study provides evidence of how the introduction of mobile banking reshapes job design, task allocation, and employment, which is likely to generalize beyond specific organizations. Our findings reveal the complexities of technological adaptation within organizations and underscore the critical role of managerial and organizational responses in realizing the productivity gains from technological change.

[1] The bank introduced explicit key performance indicators (KPIs) to guide and evaluate personal AMs' transition into their expanded roles.

Second, the paper contributes to the literature on the organization of production and knowledge hierarchies (Garicano and Rossi-Hansberg, 2006; Caliendo and Rossi-Hansberg, 2012) by showing that firm-level shifts in response to technological change interact with the organization of the firm and the allocation of employees to different tasks.

Finally, the paper advances understanding on the role of managers in facilitating change (Adhvaryu et al., 2023; Metcalfe et al., 2023; Minni, 2024). Our findings suggest that productive managers critically contribute to easing the transition to new technologies by reallocating workers, even in the absence of explicit incentives.

2. Context: The Bank

We partner with one of the largest and most established banks in a Latin American country. With a presence of over 50 years in the local economy, the bank serves individuals, businesses, and the rural sector, employing over 10,000 people and catering to approximately 3 million customers.

In 2017, the bank launched a comprehensive digital transformation strategy aimed at evolving into a fully digital bank with a mobile-first approach. Although customers already had access to home banking and a mobile app, the services on the platforms were limited to transactions such as payments and money transfers. With the change in strategy, the bank decided to create a banking app that would allow clients to open accounts and purchase selected financial products through the app, bypassing physical branches altogether. This initiative sought to enhance accessibility to banking services, attracting new customers by offering user-friendly digital experiences. A key pillar of the strategy was the introduction of a new value proposition centered on personalized, always-on financial services tailored to mobile platforms. Gathering retail client information would further allow the use of data analytics to improve customer insights and enhance risk management capabilities. The banking app was launched in June 2018. The transition was also instrumental in changing work within branches, allowing workers to focus on more complex, higher value-added products. Operational efficiencies were another central objective, with digitization expected to reduce the

need for physical branches while optimizing overall service delivery. As part of this transformation, the bank also redefined the in-branch experience, integrating digital tools and streamlining processes to align with its broader strategic vision.

Although the digital transformation deeply affected workers, there was no change in the workforce. The bank was committed to avoid layoffs, and the expansion that followed the digital transformation did not make them necessary, our empirical analysis corroborates this claim. During our study period (2017–2023), the bank facilitated over 15 million new trades and became one of the largest banks in the country, as measured by financial assets.[2]

The adoption of the technology was successful: workers quickly learned to assist customers with using the app, and adopted the new processes associated with the financial products that are now digital. However, adaptation in the aftermath of the technological change was less straightforward, as workers struggled to shift their focus to higher value-added and complex trades. For this reason, the bank implemented a top-down reorganization of work across and within branches to facilitate this objective. Workers received monetary incentives to move from retail tasks to loans for small and medium firms (SMEs), with the objective of facilitating the shift to high value-added tasks. Both interventions——the integration of the banking app into branch processes (*tech shock*) and the reallocation of account manager tasks (*task shock*)——are centrally coordinated by HR and rolled out in a staggered, quasi-random fashion.

The first intervention, launched in June 2018, is implemented across all branches within four months. This technology shock requires branches to assist customers in onboarding onto the app and is aimed to shift branch activity toward higher-value-added products. Panel (a) of Figure 1 summarizes the rollout of the tech intervention across branches.

However, instead of enabling task expansion, the adoption of the mobile app does not lead to a transition to more complex trades within branches. In response, the second intervention begins in 2021, affecting 70% of branches by March 2023 and reassigning 976 account managers from retailed-focused tasks towards non-digitalized products, particularly SME lending. These employees are directly incentivized, through explicit KPIs, to sell SME loans. This adjustment, informed by the app experience, leads to structural changes in job roles, with

[2]Throughout this paper, we use the term *trade* to denote a major event in the management of a financial product, such as opening a credit line or checking account.

SME loan sales integrated into account managers' KPIs. Panel (b) of Figure 1 summarizes the rollout of the task intervention across branches.

3. Tech and Task Interventions

Tech Intervention: Introduction of the mobile app. The bank launches a banking app in June 2018, allowing customers to open accounts, apply for loans, and manage credit cards directly from their smartphones.

While the bank offers a broad range of products through its physical branches——including bonds, checking accounts, pension services, insurance, mortgages, and SME loans——the mobile app's product selection is deliberately limited. Only products that can be easily automated, such as savings accounts, small loans, and credit cards, are included. More complex products requiring technical knowledge, intricate processes, or higher compliance burdens remain available exclusively through in-person branch visits. Throughout the paper, we define tasks that can be completed via the app as *non-complex* and those that require in-branch interactions as *complex*, and the completion of a task coincides with the completion of a trade.

The app's introduction reshapes both customer access to banking services and worker processes. Our focus is on workers' ability to adapt to new processes and adopt new technologies, rather than customers' engagement with the banking app outside of their interaction with workers. Within four months of its launch, branches phase out older, time-consuming procedures for newly automated products. Rather than manually processing these trades, branch employees assist customers in downloading the app and completing transactions digitally, significantly reducing task completion times. On the other hand, processes for products not available on the app remain unchanged. Workers operate under monthly goals and piecewise trade incentives, which do not differentiate between complex and non-complex trades.

Task Intervention: Introduction of the SME loans task change. Starting January 2021, the bank introduces a major organizational change in response to the productivity gains from the mobile app. Specifically, the role of account managers evolves from serving individual customers to focusing on SME loans. As retail banking products become increasingly digitalized, the bank

was expecting that account managers would shift their attention to complex, non-digitized products. However, the sale of complex products remained remarkably stable after the introduction of the app (these results are discussed in section 6). The organizational change directed at account managers is designed to incentivize them to increase their production of complex trades, by offering piecewise incentives for the sale of SME loans, on top of pre-existing targets.

A typical branch is led by a manager and includes several account managers, SME specialists, advisors, and bank tellers. Our primary focus is on account managers, who are responsible for opening accounts and selling new products. Although these tasks are not exclusive to them, their monetary incentives and productivity targets are the most dependent on the completion of such tasks. Other workers who also complete trades are SME specialists, who, however, mostly focus on commercial clients. Advisors and bank tellers handle secondary tasks, such as customer service and facilitating financial transactions (withdrawals, deposits).

After the introduction of the banking app, more products are added to the mobile catalog. By 2021, the number of products available on the banking app has risen from the initial four to eight, while the total number of available financial products remains stable at sixteen. A substantial amount of tasks primarily done by account managers are now automatized or substantially facilitated. For this reason, the bank decides to add the sale of SME loans, a complex, high value added product, to the explicit responsibilities of account managers. Previously, this product was exclusively managed by SME specialists, who are now shifting to larger, corporate client portfolios. The task change removes an organizational barrier—the delegation of SME loans to SME specialists—and introduces incentives for account managers to close these deals.

Figure 2 summarizes the main features of the interventions. The amount of trades done in a branch is represented by the vertical bars, while the bubbles represent trades done outside of branches, such as directly through the banking app or in the corporate headquarters. The tech intervention increases the productivity of non-complex trades by digitizing the relevant processes (yellow bar). While in principle clients can download the app and complete trades independently, most of them still access physical branches in the immediate aftermath of

its introduction. The task intervention incentivizes the production of SME loans, by allowing more workers–account managers–to perform them (blue bar). Over time, customers also start acquiring financial products directly on the app ("Banking App" orange bubble, these products are non-complex), while some SME specialists start managing corporate client portfolios and migrate to the corporate office ("Corporate" red bubble, these products are complex).

Each intervention only affects one type of product respectively, whereby the tech shock changes the productivity of less complex, more easily automated products, while the task shock changes the incentives for very complex ones. The rest of the paper investigates how workers adopt the new technology, how they adapt their efforts in the aftermath of its introduction, and how they respond to incentives.

4. Data

We obtain access to granular branch- and worker-level data from our partner. The data can be broadly grouped into three different groups: productivity, personnel, and manager characteristics. Additionally, we leverage an ancillary survey to further examine the role of manager characteristics. All data is confidential and subject to restricted access.

Trades data. Our primary source of data is the detailed record of all financial trades carried out by the bank between 2015 and 2023. A trade is defined as any major event regarding the purchase or opening of a financial product, such as opening an account, acquiring a loan, or obtaining a credit card. Routine transactions such as transferring money or repaying a loan are excluded from our dataset. For each trade, we observe the product type, date, branch, and the employee who executed it. This includes mobile trades that occur in a branch, as the app allows employees to input their ID when assisting customers. Since the total number of trades is the bank's main KPI, we will use this information as our preferred measure of productivity. In fact, all monetary incentives and goals pertaining to worker and manager productivity are set in terms of trades completed rather than sales volume at the time of the trade. Although our data includes sales values at the time of the trade, we do not rely on this metric extensively. Revenue from financial products is typically generated over time

through accrued interest rather than at the point of sale, making trade volume a more relevant measure of performance. To assess the broader financial impact of our interventions, we also incorporate monthly branch-level balance data available from 2018 to 2022. However, this information is aggregated at the branch level across products and does not allow for the separate identification of balances accrued through complex and non-complex products.

Personnel records. We have access to yearly HR records for all workers from 2017 to 2022. We know each worker's job title, tenure, wage, gender, and location. We use this information to understand how workers with different characteristics are impacted by the technological shock. This information is also crucial to identify the workers impacted by the task intervention (account managers), and branch managers who can facilitate adaptation.

Leadership surveys. In 2020, the company started collecting yearly survey information on workers' perceptions of their managers. The survey includes questions on leadership, objectives, and values. The leadership questions evaluate management styles along four dimensions: teamwork, adaptation to change, and their ability to inspire workers and build a trusting environment. The questions on the objectives include managers' ability to meet objectives, their performance, and skill level. The value portion of the survey focused on how aligned the managers are with the company's core values, such as client focus, employee development, and agility.

Final branch-week panel datasets. We combine this information to create two branch-weekly level panels to assess the interventions separately. The first dataset, which covers the tech intervention, leverages information available between January 2017 and December 2019. We disregard information prior to January 2017 as the digital-first strategy had not been announced yet, and we do not have access to HR records prior to that time.

The second dataset is used to assess the impact of the task intervention and runs from January 2019 (after the rollout of the tech intervention) to March 2023, the most recent available data. Table 1 summarizes the information available for the treated branches in each intervention. The lower number of branches in the task intervention is due to the lower number of

treated branches (Figure 1). The variation in products available on the banking app between the two interventions is due to the ongoing digitization of products and addition to the app by 2021.

We set our main unit of observation as the branch because this is the level at which the interventions and any organizational responses occur. To further understand how the interventions impact workers, we also perform relevant analyses at the worker level, described in Table 3.

5. Empirical Strategy

We investigate how the two interventions affect production, productivity, the types of tasks completed, and employment.

A branch is considered treated by the tech intervention the first time we observe a product being sold through the app in a branch, indicating a change in processes. In line with knowledge gathered from the bank, the process started in June 2018, as soon as the app became available to consumers on smartphone app stores. Similarly, a branch is considered treated by the task intervention once we observe an account manager selling a SME loan, indicating a change in the tasks assigned to these workers. The change in worker tasks began in January 2021. Figure 1 summarizes the rollout of the treatments.

Outcome variables. Overall branch output is measured by the total trade volume in a given branch-week, while productivity is defined as trade volume per worker within the same period.[3] Throughout both periods, there are 16 financial products available through online and physical channels.[4] The opening or sale of each of these products is a trade and is counted in the overall trade volume. Finally, we leverage the unique client identifiers associated with each trade to compute the number of number of clients.

[3]To account for workers moving across branches, we count each worker only once per week, assigning them to the branch where they conducted the most trades (their "home branch").

[4]One new financial product was added directly in the app in March 2023. Given the low overall volume of trades associated with it (fewer than 800), and its inclusion only in the last period of the available data, we disregard it.

Task changes are measured through the completion of complex (non-mobile) and non-complex (mobile) tasks, and additionally SME loans in the context of the task intervention. A task is classified as non-complex if the corresponding financial product was available on the banking app during the relevant period—2017-2019 for the tech shock and 2021-2023 for the task shock. In the first period, only four products are available on the app: a saving account, credit card, and two small loans. In the second period, three additional products are digitized and added to the app and thus considered non-complex: term deposit certificates, a type of mortgage, and car loans. All the remaining products are considered complex and include any other types of accounts (e.g., checking, saving), any other types of loans or mortgages (e.g., revolving, business), and various financial products (e.g., investment funds, pension funds, life insurances). The difference in the definition of complex products between the first and second intervention is that all the above-mentioned products, as well as the late additions to the app, are considered complex when investigating the tech shock, hence there are 12 complex products and 4 non-complex products. In the second intervention, small business (SME) loans are examined separately even though they are complex, as they are the focus of the task shock. Non-complex products consist of the seven digitized ones, while the remaining eight are classified as complex. All outcomes built on trade volumes are presented in the inverse hyperbolic sine transformation (IHS) to account for possible zeros.

Changes in employment are captured by HR data on exits and hirings, as well as worker reallocation across branches and tasks. Hirings are given by the HR hiring date, which is also used to compute tenure. We then compute the number of newly hired workers in any branch/week. We consider a worker exiting the company the last time we observe a worker doing a trade in the full dataset, which includes never treated branches to avoid measurement error in exits. We identify three relevant measures of reallocation: across tasks (back- to front-office), across branches, and across business units. We consider workers to be reallocated in tasks when we observe them perform a trade in a branch for the first time, where any trade is considered a front-office task, in contrast with back-office tasks which are all the other unobserved tasks done in a branch. We make sure to capture reallocation from back office to front-office tasks–and not onboarding–by only considering workers who had been employed

for at least three months. Similarly, we compute the number of workers in a week who are reallocated across branches, i.e., who move from one branch to another. Reallocation across business units is the movement of workers from the retail branches, which we observe in the productivity data, to the corporate office. As we only observe workers in the corporate office in the yearly personnel data, we must build an ad hoc yearly panel for this analysis.

Event-study set-up. We use two complementary approaches to estimate the causal effects of introducing the new technology across branches: a staggered event-study design and a generalized difference-in-difference model, including week and branch fixed effects.

The staggered event study allows us to identify the average dynamic treatment effects of the introduction of the banking app. We are interested in the effect of the app D_{bt} on one of the outcomes y_{bt} described in Section 4 in a panel of branches $b \in \{1, ..., B\}$ observed over time periods $t \in \{1, ..., T\}$. We estimate the following equation:

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

where D^{j}_{b} denote the event study indicators $j \in \{\Delta_{\text{banking app}}\}$, α_b and ξ_t denote branch and week fixed effects, respectively. Throughout the analysis of the tech intervention, one period will be one week long, and we will consider dynamic effects from 8 or more weeks before the introduction of the app, up to 26 or more weeks after. Weeks -8 and 26 will absorb all lags and leads outside of the window of interest, respectively. The study of the task intervention will consider dynamic effects from 12 weeks before the shock to 56 weeks after, given the longer rollout throughout the period of interest.[5] We restrict our analysis to treated branches such that our control group comprises branches that are yet to be treated. This facilitates the interpretation of coefficients $\beta_{j,s}$ which represent the average treatment effect on the treated (ATT) s periods after the introduction of banking app j.

We retrieve the causal effect of the introduction of the new technology across branches using a generalized difference-in-difference model (Neumark and Wascher, 1992) that includes

[5]Cohort-robust heterogeneous dynamic treatment effects using the Sun and Abraham (2021) estimator are available upon request. Results are consistent across event study specifications.

week and branch fixed effects. In the main specification, we estimate the regression

$$y_{bt} = \beta_{\text{post}} \times \text{post}_{bt} + \alpha_b + \xi_t + \epsilon_{bt} \tag{2}$$

where post_{bt} is a treatment indicator equal to one if a branch b has been treated at time t and for all subsequent periods, and the coefficient of interest β_{post} is the effect averaged over time of treatment. While this approach does not investigate the dynamic adaptation to the new technology, it allows us to investigate which characteristics of the branch, workers, and managers affect such adaptation by introducing features of branch heterogeneity.

Heterogeneity Analysis. We augment equation (2) to include heterogeneity along a given dimension h:

$$y_{bt} = \beta_{\text{post}} \times \text{post}_{bt} + \beta_h \times \text{post}_{bt} \times h_b + \alpha_b + \xi_t + \epsilon_{bt} \tag{3}$$

The heterogeneity dimension h is time-invariant and typically splits branches along a dimension using the median of the continuous heterogeneity variable, such as average tenure in a branch or manager value added to productivity.[6] For example, when investigating the role of tenure in technology adaptation, we compute the average tenure within a branch until the time of the introduction of the app, and h_b is an indicator equal to 1 if the average age in branch b is above the median age and 0 otherwise. We are interested in the coefficient β_h that compares branches with different characteristics.

We further disentangle the impact of the intervention along two time-invariant dimensions of heterogeneity, such as manager quality and worker tenure, by estimating the fully interacted equation (4):

$$\begin{aligned} y_{bt} =& \beta_{\text{post}} \times \text{post}_{bt} + \beta_a \times \text{post}_{bt} \times a_b + \beta_n \times \text{post}_{bt} \times n_b + \\ & \beta_{an} \times \text{post}_{bt} \times a_b \times n_b + \alpha_b + \xi_t + \epsilon_{bt} \end{aligned} \tag{4}$$

[6] As h is time invariant, we cannot estimate the main effect of h when including time fixed effects.

where a denotes the first measure of heterogeneity, n the second, and α_b, ξ_t, and ϵ_{bt} capture idiosyncratic time and branch heterogeneity. In the analysis that follows, the measures of heterogeneity are always split along the median of the continuous variable prior to the intervention for ease of interpretation.

Manager value added to branch productivity. Our main heterogeneity measure of interest is manager quality. We compute manager value added to branch productivity using a two-way fixed effects model where we have branch and manager fixed effects, and the data is constructed at the week-branch-manager level, where branch productivity is the main outcome. This is analogous to the worker-firm sorting model studied by Abowd et al. (1999), and previously applied in the context of manager value added by Adhvaryu et al. (2023) and Fenizia (2022).

To obtain the manager fixed effects θ_m, we estimate equation

$$asinh(\textbf{productivity}_{bmt}) = \theta_m + \eta_b + \tau_t + \iota_{mt} + \epsilon_{bt} + \varepsilon_{bmt} \tag{5}$$

where the inverse hyperbolic sine transformation of productivity ($asinh$) is on the left hand side and varies at the branch b manager m and week t level, and θ_m are manager FEs, η_b are branch FEs, τ_t are time components, and ι_{mt}, ϵ_{bt}, ε_{bmt} are idiosyncratic unobserved heterogeneity.

We estimate manager value added separately for both projects, using observations from the beginning of the data until the intervention to avoid any confoundedness of the intervention with manager productivity. For the tech intervention, this is the period from January 2017 until the introduction of the banking app in each branch after June 2018, and for the task intervention it is the period from January 2021 until the change in account manager tasks. The validity of the AKM approach to retrieve manager FEs that are informative of the manager's value added to branch productivity relies on managers switching across branches. Furthermore, the model relies on the assumption that manager mobility does not correlate with unobservables. We believe this is the case because the company adopts a leadership model where managers are encouraged to move frequently to observe and learn from other

branches. This manager rotation is managed centrally by HR and is independent of the rotation of other workers, which are mostly driven by worker absences. Finally, identification relies on the branches producing a similar set of outputs, such that the outcome variable of the manager AKM is comparable across branches. Indeed, all branches perform both complex and non-complex trades throughout our period of interest.

6. Tech Intervention: Impact of the Banking App

This Section investigates the impact of the banking app on productivity, worker reallocation, and tasks. Then, it assesses how worker and manager characteristics affect adaptation. All results refer to the period between January 2017 and December 2019. The introduction of the banking app has an immediate and sizable effect on worker productivity, whereby productivity increases by up to 20pp. However, the intervention alone is not sufficient to shift workers towards more complex tasks. Higher tenured workers especially suffered, reducing their production of complex trades. Branches with productive managers increased their productivity along all outcomes, driven by a strategic reallocation of workers from back office to front office jobs.

6.1. Main Results

Productivity. We investigate how introducing the new technology affects the bank's financial performance by estimating equation (1) for two key outcomes: trades and productivity. The results are presented in Figure 3, all outcomes are expressed in inverse hyperbolic sine units to reduce the skewness of these variables and account for any zeros (Friedline et al., 2015). The introduction of the app led to immediate and significant gains in both trades and productivity. Total trades 3a show a statistically significant increase of 8 percentage points by week 3, rising steadily to about 30 percentage points by week 15, remaining high thereafter. A similar trend is observed in productivity, which increased immediately by 8pp from week 0, plateauing at around 20 percentage points from week 16 onward (Figure 3b). Table 4 showcases consistent estimates of the average effect of the introduction of the app on trades and productivity from

equation (2), whereby trades increase by 14.1pp on average, and productivity by 9.7pp.

The results presented in Figure 3 depict a positive impact of the banking app on branch operations, reflected in increased trades and productivity. While these outcomes align with both an increase in worker effort and the productivity gains enabled by the app, the sustained long-term improvements across all indicators suggest that the app fundamentally transformed how trades are conducted, rather than relying solely on temporary increases in worker effort. Notably, the bank explicitly chose not to alter its incentive scheme, recognizing the risk that workers might resist the technological change if they perceived it as a threat. Although we cannot entirely rule out that workers adjusted their effort in response to the app's introduction, any such adjustments are likely transitory and minimal compared to the significant overall gains in productivity driven by the app. These results are consistent when we investigate the impact of the app at the worker level. Column 1 of table 10 estimates the impact of the banking app on workers and finds a similar increase in production (+18.4pp).[7]

The increase in productivity can also be rationalized by an increase in the client base of the bank. While the introduction of the banking app attracted new clients to the bank, it also increased the interaction of old clients, increasing the total trades performed both on the request of new and old clients. Panel 4a documents that the overall foot traffic of clients increased after the introduction of the app by approximately 40pp 18 weeks after the introduction of the app, where the total number of clients is given by the unique number of clients who appear in a branch in any given week. Panel 4b indicates a stark increase in the unique number of clients, up to 60pp 26 weeks after the introduction of the app. We ensure that new customers are uniquely counted by only considering the first trade that they perform in a branch, also including trades information dating back to 2015 to exclude returning ones. Panels 5a and 5b showcase the change in total trades done by new and old clients respectively after the technological shock. Here, we measure the intensity of the engagement with the bank. To do so, we restrict clients to be considered new only in the first six months since they joined the bank and compute the total number of trades in this time window. Similarly, total trades for old clients are computed for anyone who has been a client for more than six months. These results in-

[7] Production and productivity coincide at the worker level as we cannot, by definition, divide by the number of workers.

dicate that the banking app was an effective consumer-facing technology, as it increased both the client base and engagement, consistent with recent evidence that customer-facing technologies improve the client experience as well as that of workers (Brynjolfsson et al., 2025).

Tasks and Specialization. We investigate how the banking app impacts workers along two dimensions: the complexity of the tasks that workers complete and the specialization of branches and workers in the products they trade. Figure 6 summarizes these findings. We measure tasks by the number of trades completed by workers, defining tasks (or trades) as complex if they are not available on the app, and non-complex if they are. Non-complex tasks include four straightforward products like basic accounts, small loans, and credit cards, while complex tasks encompass products such as mortgages, SME offerings, insurance, and more intricate accounts and loans.

Non-complex trades (Figure 6a) rose significantly shortly after the introduction of the app, increasing by over 40 percentage points six months after the technological change. In contrast, complex trades (Figure 6b) do not increase during our period of interest. These results suggest that the technology successfully enhanced labor output, but frictions that prevented workers from easily transitioning between non-complex and complex trades prevailed.

Difference-in-difference estimates both at the branch and worker level showcase a similar increase in non-complex trades, by 22.7pp at the branch level (table 5), and 20.4pp at the worker level (table 10). While complex trades did not increase at the branch level, they increase at the worker level, suggesting that reallocation of workers across tasks might mask within worker reallocation to complex tasks.

We investigate changes in specialization by computing the Hirschmann-Herfindahl Index (HHI) of task concentration (Herfindahl, 1950). We compute the index at the branch level, both unweighted—concentration of tasks in a branch—and weighted by worker productivity, i.e. concentration of tasks by worker, averaged over the branch and weighted by worker productivity.

For each branch, the branch-level HHI (branch-level specialization) is given by:

$$HHI_b = \sum_{j=1}^{J} \left(\frac{t_{jb}}{\sum_j t_{jb}} \right)^2 \qquad \forall\ b \in B \tag{6}$$

Where t denotes the total number of tasks of type $j \in J$ in branch $b \in B$. For simplicity, weekly subscripts have been omitted. For each branch, we compute the worker-weighted HHI (worker-level specialization) as:

$$HHI_w = \frac{\sum_{i=1}^{I} HHI_{ib} \cdot t_{ib}}{\sum_i t_{ib}} \qquad \forall b \in B \tag{7}$$

where $HHI_i = \sum_j \left(\frac{t_{ji}}{t_i} \right)^2$ and $t_i = \sum_j t_j$, $i \in I$ denotes individuals working in a branch b. This index is the average HHI of the workers in a branch, weighted by how many trades they do, where the weighting reduces the impact of low-performing workers on the measure of concentration.

Panels 6c and 6d present the impact of the technological change on task specialization at the branch and worker level, respectively. Not surprisingly, branch specialization increased following a pattern similar to the increase in non-complex trades. This is partially mechanically due to the differential increase in non-complex trades which drives concentration. The effects of the banking app on worker specialization are more nuanced: while specialization marginally increased for all workers, the estimates are more noisy, suggesting heterogeneity in specialization at the worker level. Furthermore, the estimates tend to decrease in time. This is consistent with specialization driven by learning in the first weeks following the introduction of the app.

Together, these results point to frictions in the adaptation to more complex trades, as predicted by standard task models such as Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018a), whereby technologies are skill-biased in the sense that they augment the labor of high-skilled workers. Investigating these frictions and the heterogeneity in adaptation that stems from them will be the focus of Section 6.2.

Turnover and Worker Reallocation. Here, we investigate the impact of the banking app on worker turnover and reallocation, both in tasks (trades) and in space (across branches). While labor input in the production of trades increased after the introduction of the banking app, this was not driven by hiring, but rather by the reallocation of workers from back office (non-trade producing) to front office (trade producing) tasks.

First, we document that worker hirings and exits do not change after the introduction of the banking app. These results are summarized in Figures 7a and 7b. We do not observe any inflow of workers in terms of new hires, where hirings are measured with hire dates available in the company's HR records, nor do we observe an increase in worker exits. To measure worker exits, we use an extended version of the HR data set ranging from 2017 to 2023 to observe workers who exit the company, focusing on workers who have a permanent contract and excluding apprentices and fixed-term workers. We then add precision to this measure of exits by using the extended trades data (i.e., 2017-2023) to set the exit date as the last one where a worker is observed making a trade. Hence, a worker is considered leaving the company if she no longer performs trades and she is no longer included in the HR roster of the company.

Even though the stock of workers does not change, we observe extensive reallocation of workers towards tasks that result in completing trades, effectively moving from back office to front office jobs. Panel 7c showcases the number of workers each week who are observed completing trades in a branch after the introduction of the app, leading to an increase of about 5pp. Panel 7d corroborates this finding by showing that labor input—as measured by worker-days—increases by up to 10pp. This suggests that more workers are making trades, both on a regular and occasional basis.

Second, we investigate how workers are reallocated, both in trades (tasks)—from back-office and support tasks to front office trade-producing tasks—and in space—across branches. The results are collected in Table 6 and indicate that the increase in labor input for trade-producing tasks is driven by the reallocation of workers towards these functions (column 1), and the workers who were already engaged in front office duties are more likely to move across branches (column 2). Reallocation to trades is the number of workers who are reallo-

cated toward trade-producing tasks in a given branch each week. To obtain this outcome, we compute the number of workers who are observed doing a trade for the first time. We ensure that we are capturing the reallocation of workers towards tasks that require the production of trades—and not hiring or onboarding—by imposing that a worker must be employed by the bank for at least three months before doing a trade for the first time. Our results imply that after the introduction of the banking app, 0.03 more workers are reallocated towards the production of trades, an 18.9% increase. Column (2) presents the number of workers who change branch in any given week. Importantly, this outcome captures workers who are already involved in front office jobs. The results suggest that the banking app led to an increase in the number of workers who moved across branches by 26pp, equivalent to a 40% increase.

The results in Table 6 point to extensive reorganization after the technological change: workers who had not previously performed trades are now more likely to do so, and all workers are more likely to move across branches. These results can be rationalized in the context of task complexity and learning. The app effectively makes mobile tasks easier and more accessible, as they can in principle also be conducted independently by customers. Consistent with Acemoglu and Restrepo (2018b), less skilled workers are able to perform automated tasks, as they serve as human signposts to assist customers in these specific instances. The reallocation in space is consistent with a reduction in layers and the transmission of knowledge across the organization through informal channels (Ocampo, 2022).

6.2. Heterogeneity: Worker and Manager Characteristics

Worker Tenure. We investigate how experience matters for adaptation to technological change: on one hand, higher exposure to the organization's processes might facilitate the shift towards more complex trades, on the other hand, frictions may arise due to unwillingness to move away from older processes. Our results show that the negative effects of experience prevail, whereby more tenured workers increase non-complex trades to a lesser extent, and reduce complex trades.

We investigate the role of tenure by performing the heterogeneity analysis outlined in equation (3) for branches with workers who are above median in average tenure, using the meth-

ods outlined in Section 5. Figure 10 documents substantial cross-sectional variation in average tenure.

Table 7 presents the differential impact of tenure on tasks performed after the tech intervention. While the banking app resulted in a global increase in total trades——driven by non-complex trades——branches with these demographics significantly reduced their production of complex trades by 7.9pp. At the worker level (table 11), workers with above median tenure showcase a similar pattern, underperforming less tenured workers by over 10pp.

These findings suggest that frictions related to tenure—reflecting process "stickiness" and resistance to change—significantly halt technological adoption and adaptation. This highlights the importance of within-organizational norms and dynamics in shaping technological adaptation. As we will see in the next paragraph, high-quality managers can mitigate these adverse effects.

Manager value added to productivity. Using the AKM model outlined in Section 5, we investigate how manager value added to productivity facilitates the adaptation to the banking app. The heterogeneity analysis results are presented in Table 8. Branches managed by a high productivity manager are more likely to shift to complex trades, even absent formal incentives, suggesting that managerial practices affect adaptation to technological change. Exposure to a high value-added manager leads to a higher overall production of trades by 6.8pp. This is driven by the fact that branches with high quality managers produce 7pp more complex trades than branches with low-quality managers, and 5.3pp more non-complex trades. This is informative of the impact of managerial practices on technological adaptation: as expected, managerial practices do not impact the newly-automated tasks where human input is low, but they facilitate the transition to complex tasks where knowledge transmission is crucial. The comparison of the negative coefficient in column 3 for low-value added managers (-0.0405*) with the positive coefficient for high-value added managers (0.0695***) might also be suggestive of a difference in time management between high- and low-types, whereby low-types substitute between complex and non-complex trades which are easier, while high-types do not and are able to exceed pre-technological shock performances. Figure 8 further

decomposes the effect of manager quality on workers of different tenures. Even though good managers help all branches, high productivity managers are particularly effective when interacting with less experienced branches, while low productivity managers decrease the productivity in branches with more experienced workers. Table 12 suggest that the gains of high quality managers in branches are not reflected at the worker level, where manager quality does not increase performance. This is indicative of managers' crucial role in appropriately matching workers and tasks, rather than affecting individual performance.

Table 9 further suggests that high value added managers are able to increase the productivity of their workers because they actively reallocate workers to front office jobs. In fact, column (1) indicates that worker reallocation to trade-producing tasks is higher by 2.4pp when a high value added manager is involved. This sheds light on the active role of managers in the reallocation of resources and provides evidence on effective bottom up initiatives to facilitate adaptation.

We complement this analysis with internal surveys to understand what the manager AKM fixed effects capture. An external consultant began delivering yearly surveys on manager capabilities in 2020. The survey measures leadership, performance, and alignment with company values and is delivered to workers who must rank their manager along these dimensions. It includes four leadership dimensions (teamwork, trust, ability to embrace change, and ability to inspire), three performance items (overall performance, skill level, and ability to meet objectives), and seven company value items, such as agility and client focus.[8] While this information is only available after the intervention, exploring the relationship between these soft skill measures, demographic information, and value added to productivity is informative of high quality manager detection.

Table 13 presents the pairwise correlations between manager AKM fixed effects and various groups of variables, including leadership, performance, values, and demographics. We find that high-productivity managers are positively and significantly correlated with leadership values, performance, and the ability to meet objectives. This suggests that workers perceive high-productivity managers as stronger leaders and more effective performers. In contrast,

[8]The seven value items are alignment with company principles, understanding the big picture, context, client focus, co-creation, workforce development, agility, and adventure.

alignment with company values and demographic characteristics show no significant correlation with productivity value added. While these correlations do not explain why higher-order skills such as leadership contribute to productivity, they underscore the challenge of identifying high-quality managers based on observable traits alone. We believe the leadership measures capture time-invariant and intrinsic manager characteristics, i.e. unaffected by external conditions. The presence of within-manager serial correlation of each leadership dimension using observations between 2020-2023 corroborates the presence of time-invariant components. We interpret the leadership measures as capturing intrinsic, time-invariant managerial characteristics, unaffected by external conditions. Supporting this interpretation, we find strong within-manager serial correlation in each leadership dimension using data from 2020 to 2023. The Wooldridge test of serial correlation rejects the null hypothesis of no serial correlation (p-value$<$ 0.000 for all leadership dimensions), and the first-order serial correlation is above 35% across all years for every leadership dimension (Wooldridge, 2010; Drukker, 2003).

7. Task Intervention: SMEs Loans for Account Managers

The adoption of the banking app leads to a significant productivity increase within branches, allowing for the expansion of tasks completed without layoffs. All branches experience an immediate and substantial rise in non-complex trades (processed via the banking app), yet there is no corresponding shift toward more complex, non-digitalized tasks. Furthermore, the adjustment is highly heterogeneous across tasks and workers. Branches with more tenured employees face greater difficulties adapting, while high-productivity managers play a crucial role in facilitating the transition to new tasks. Additionally, the shift prompts greater reallocation of workers from back-office roles to front-office tasks. As a second policy, drawing from the app adoption experience, the bank implements explicit organizational changes both across and within branches to further support task adaptation.

This Section investigates the impact of the task intervention introduced in January 2021, a strategic shift in the role of account managers (AM) from retail banking tasks to services for

small and medium enterprises, particularly loans. This transition, aimed at expanding engagement with higher-value-added products, is reinforced by explicit KPIs on SME loans. Simultaneously, the bank creates a new cadre of managers dedicated to high-value SME clients, operating outside traditional branch structures.[9]

This new strategy effectively introduces a top-down mandate for account managers to move toward more sophisticated financial products, requiring a new set of tasks. These include assessing creditworthiness, offering tailored financial solutions, conducting due diligence, and managing long-term client relationships. At the same time, account managers continue to oversee the broader transition from non-complex, app-based transactions to more complex financial products, balancing digital adoption with the need for in-person expertise.

We examine how this intervention impacts account managers' activity across three categories of financial products over time: 1) SME loans, sophisticated products not available on the app and target of the intervention, 2) complex products not on the banking app and focus of the tech intervention, 3) non-complex (mobile) products which are the object of the app's automatization process. Importantly, new products were automated between 2019 and 2021, such that the non-complex products now also include mortgages, more types of loans, and fixed-term bonds. This Section uses information from January 2021 to March 2023, the most recent data we can access.

7.1. Main Results

Tasks and Specialization. First, we document how trades change over time in response to the task intervention, focusing on complex, non-complex trades, and SME loans. Branches increase their SME loans by over 20pp in the long run (Figure 11a). However, all other trades decline over the same period (11b) by over 5pp. The decline is driven by a reduction in non-complex trades (11c), due to the increase in customer independence in opening non-complex trades directly on the banking app and bypassing branches altogether, which accelerated during the Covid-19 pandemic. Contrary to the bank's expectations, complex trades remain stable (11d). These results suggest little spillover effects across complex tasks: even though

[9] Throughout, the analysis we conduct only considers workers in the branches.

workers appear to have sufficient skills to perform the complex SME loans, this does not extend to other complex trades. Incentives crucially drive the reallocation of tasks, whereby workers quickly reorganize their effort towards the incentivized task (i.e. the SME loans). As with the tech intervention, the reorganization leads to a permanent increase in worker specialization (Figure a.12). However, unlike the previous intervention, at the branch level there is no global shift in the types of trades performed (Figure b.12).

We additionally document how the task shock affected the productivity of account managers, the workers targeted by the intervention (Figure 13). As expected, SME loans increase immediately. Overall trades also increase slightly, but neither non-complex and complex trades do not seem to explain the increase alone. We interpret these findings to suggest that the change in incentives increased the productivity of the affected workers, driven by either an increase in skill due to the exposure to more complex tasks, a change in effort facilitated by the new incentives, or both.

Worker reallocation. The organizational change introduced by the bank affects all workers involved with enterprise clients, both the restricted group of enterprise account managers who were dealing with them before the intervention, and the newly involved retail account managers, who are now required to sell SME loans. The former did not see a change in their jobs, as they were previously tasked with completing all types of trades. However, given their higher experience, they were encouraged to interact with larger, high value-added corporate clients. We investigate whether the upskilling of retail account managers led to a subsequent upskilling of enterprise account managers by computing the number of enterprise account managers who are reallocated to the corporate headquarters (Table 14). As we do not observe production outside of retail branches, we leverage the yearly HR information which contains complete information on all of the bank's employees' location to identify workers who are reallocated outside of retail branches. The lower number of observations is due to the yearly frequency of the data. Table 14 documents that workers only moved from retail branches to the corporate headquarters (column 1), and not the other way around (column 2). Furthermore, this is the only reallocation of workers at this time, as we do not observe any

change in hiring or exits after the intervention for account managers, and limited turnover for other job profiles (Table 15). These results are consistent with the bank's success in upskilling both the retail account managers affected by the intervention as well as enterprise account managers.

7.2. Heterogeneity: Worker and Manager Characteristics

As with the tech intervention, we investigate how worker tenure and manager value added to productivity affect adaptation to the new tasks. The heterogeneity variables are computed as before, except they now use the relevant time period from January 2019 until the task intervention in each branch to compute the time-invariant, median value that determines the branch split.

Table 16 presents the results on heterogeneity in tenure on tasks at the branch level. Branches with higher average tenure see no changes in non-complex trades, while complex trades decline significantly (-8.9pp). Interestingly, tenured workers do not adapt differently to SME loans (the point estimate is positive), suggesting that experience alone is not a barrier to adaptation to complex trades. Incentives might be at play here, and the lack of such might explain worker reluctance to perform complex trades. Similarly, at the worker level, more tenured workers underperform along trade outcomes (table 18).

Using the AKM model outlined in Section 5, we investigate how manager value added to productivity facilitates the adaptation to the task shock. Table 17 presents the results on heterogeneity on manager value added at the branch level. Branches exposed to high productivity managers are able to shift to complex trades, at the expense of a reduction in non-complex trades. In these branches, workers handle more SME loans at the expense of non-complex trades rather than complex ones. Furthermore, there is a faster transition from non-complex to complex trades. This increases the branch's output, as complex trades are typically higher value than non-complex ones. As with the branch level results, exposure to high productivity managers increases the completion of complex trades substantially by 16.2pp (table 19), suggesting that productive managers successfully help workers transition to complex tasks.

Similar to the tech intervention, exposure to a high-quality manager benefits branches with

low tenure the most, and low productivity managers are especially ill suited in contexts with more experienced workers (figure 14).

8. Conclusion

We examine the effects of a top-down reorganization of tasks aimed at accelerating the shift toward high-value-added bank products on branch operations. Although the transition to digital technologies increases the productivity in routine tasks, it does not fully sustain the expected shift toward other complex trades that remained outside the app.

The introduction of SME loans as a strategic priority leads to a substantial increase in lending to small and medium enterprises at the expense of other complex products, while branch activity continues the shift away from routine, non-complex trades that are now automated through the banking app. The adjustment is particularly challenging for high-tenure branches and for those led by low-productivity managers, highlighting the heterogeneity in adaptation across the organization. The success of the top-down task reallocation underscores the necessity of organizational cohesion to enable transformation, as simply freeing up capacity through automation does not lead to reallocation unless firms actively redesign roles and workflows.

These findings underscore that technological change alone does not drive transformation; rather, complementary organizational adjustments are necessary to fully realize its benefits. Historical examples from electricity, ICT, and digital technologies suggest that productivity gains depend not only on the introduction of new technologies but also on how firms internally restructure work processes and realign incentives. The case of mobile banking adoption highlights that whether technology enhances productivity and job enrichment ultimately depends on managerial decisions and the ability of organizations to adapt their structures to new technological realities. Good managers are crucial to the success of adaptation to technological and organizational changes, where effective managerial practices center primarily around the reallocation of workers to appropriate tasks and job profiles.

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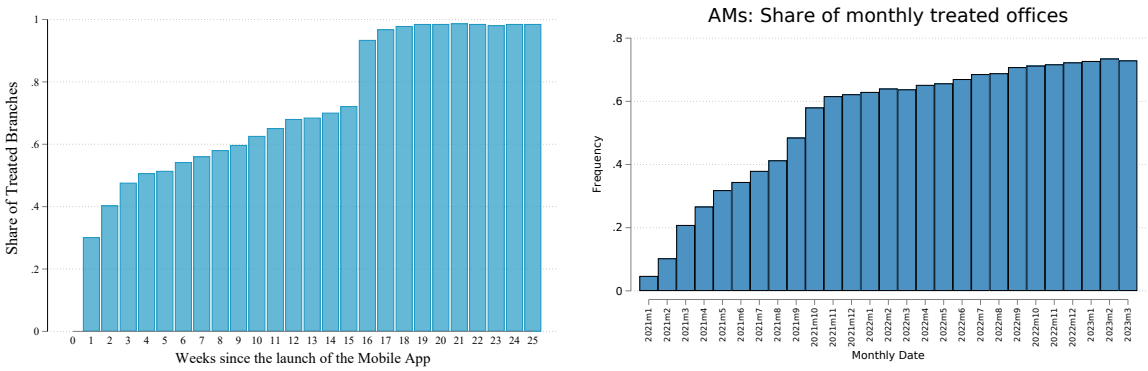
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9. Figures



(a) Tech Intervention

(b) Task Intervention

Figure 1: Treatment rollout for tech and task interventions

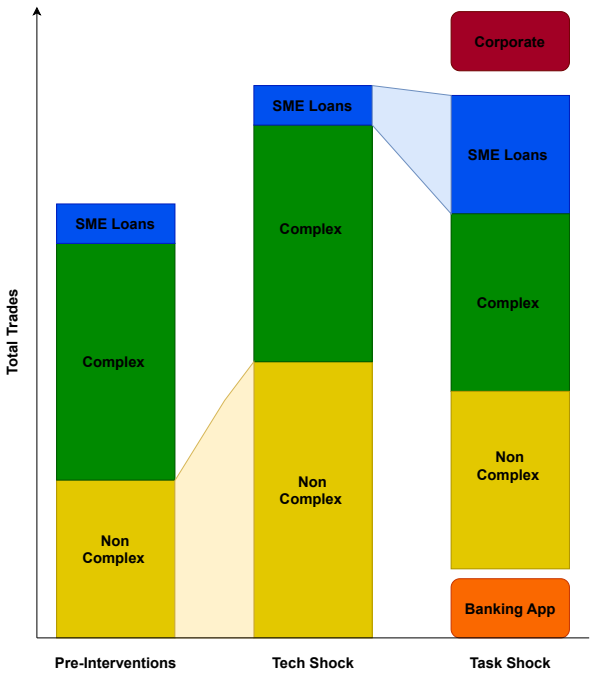
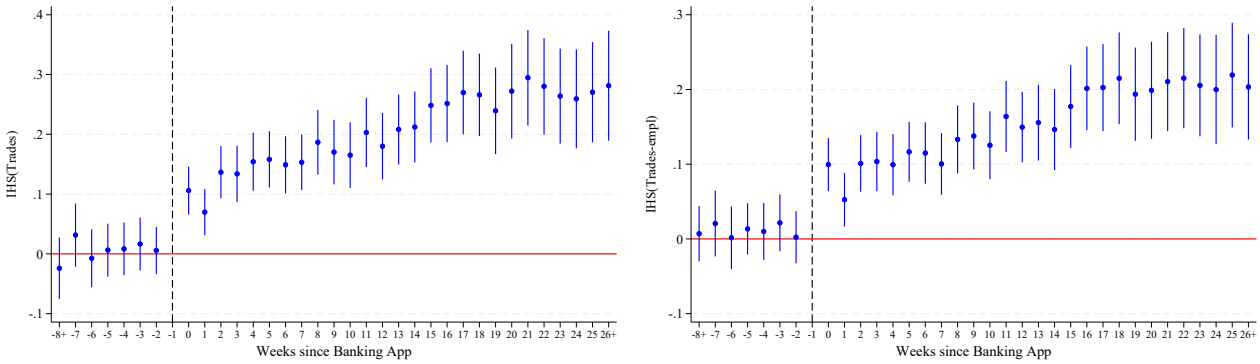


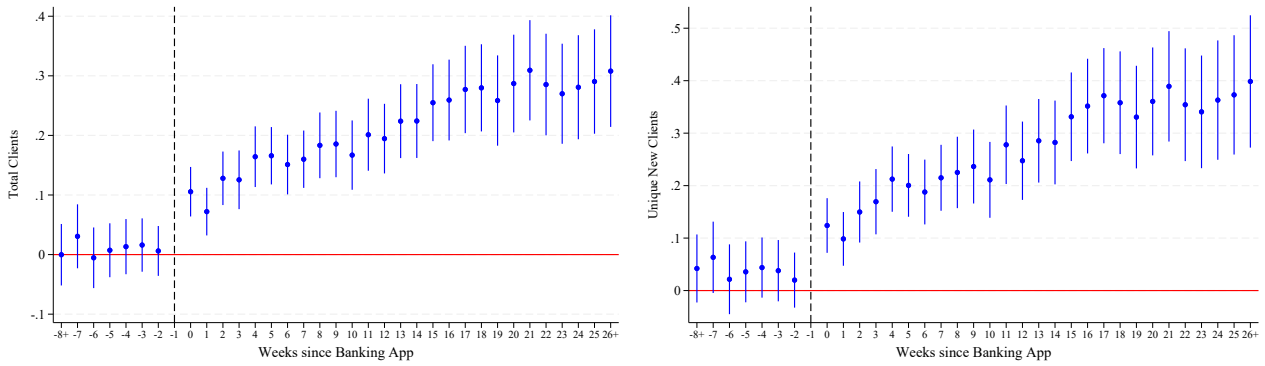
Figure 2: **Summary diagram of interventions**



(a) Total Trades

(b) Productivity

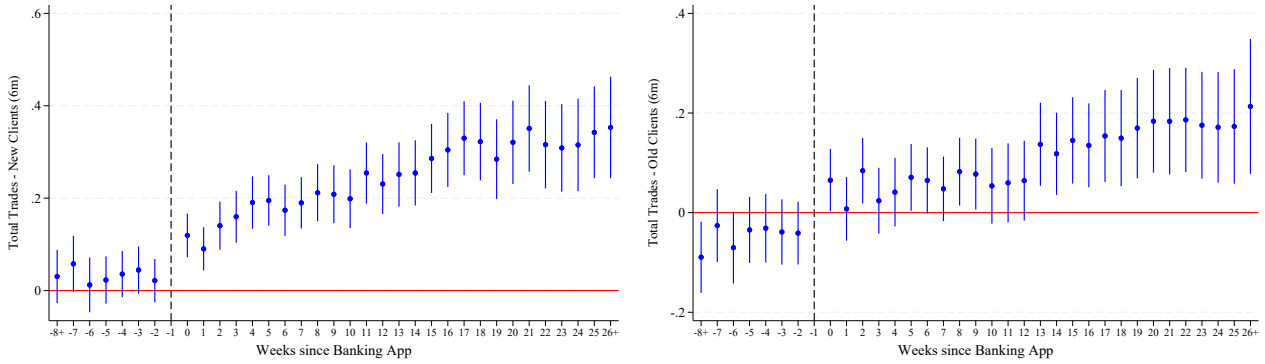
Figure 3: **Tech Intervention: Trades and Productivity.** All outcome variables (vertical axes) are in IHS. These panels plot the results from coefficient D_b^j in equation (1) for each of the outcome variables. Panel 3a shows the total number of trades performed in a branch/week. Panel 3b shows productivity in a branch/week, defined as the number of total trades divided by the total number of workers ever branch/week.



(a) Total Clients

(b) Unique New Clients

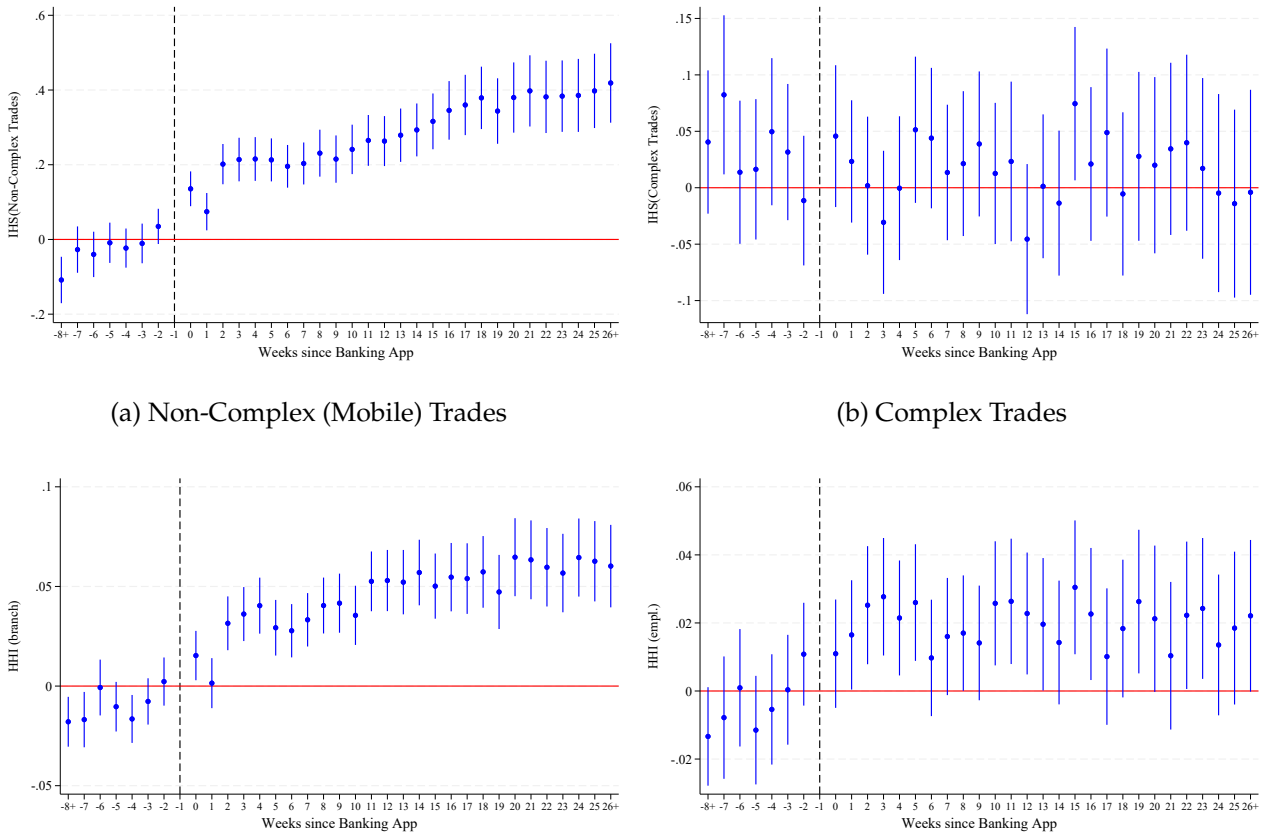
Figure 4: **Tech Intervention: Client base expansion.** All outcome variables (vertical axes) are in IHS. Panel (a) shows the total unique number of clients who perform a trade in a branch in a week. Panel (b) shows the number of unique clients who are a performing their first trade in a branch/week, where new clients are defined as such if they did not perform any trade before 2017.



(a) New Clients (6m) - Total Trades

(b) Old Clients (6m) - Total Trades

Figure 5: **Tech Intervention: Consumption by old and new clients.** All outcome variables (vertical axes) are in IHS. Panel (a) shows the number total trades in a branch/week performed by new clients, where new clients are defined as such only for six months after they perform their first trade. Panel (b) shows the number total trades in a branch/week performed by old clients, which are clients that did trades before 2017 and clients for which there has been more than six months after they performed their first trade after 2017.



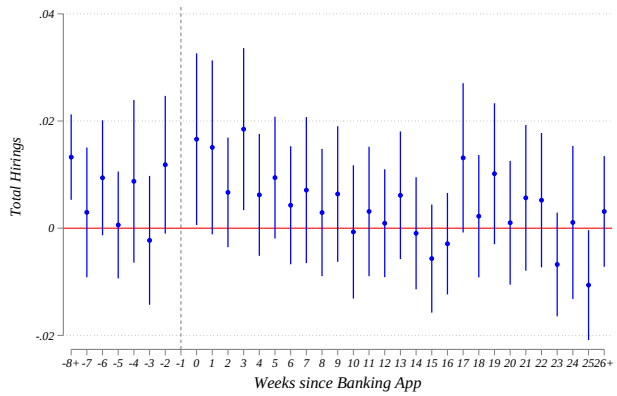
(a) Non-Complex (Mobile) Trades

(b) Complex Trades

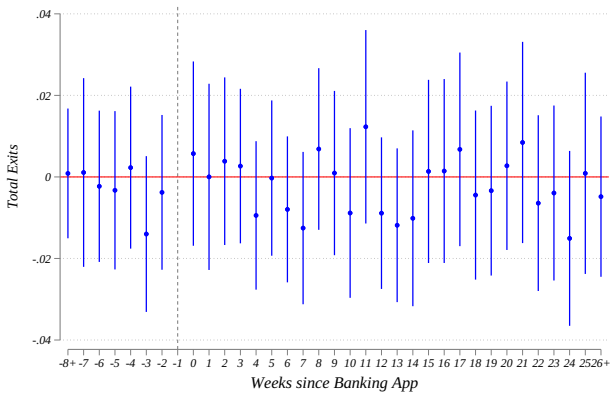
(c) Branch-level HHI

(d) Worker-level HHI

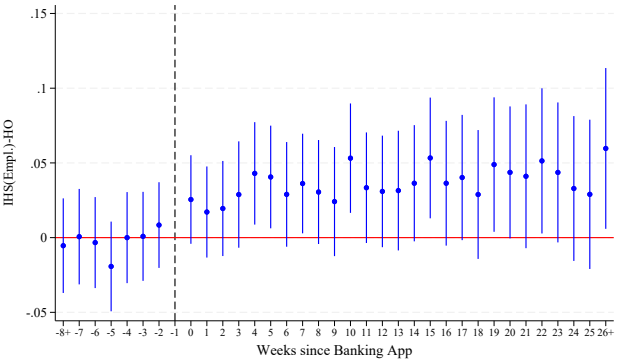
Figure 6: **Tech Intervention: workers' task composition.** All outcome variables (vertical axes) are in IHS. These panels plot the results from coefficient D_b^j in equation 1 for each of the outcome variables. Panel (a) shows the total number of Non-Complex (Mobile) trades performed in a branch/week. Panel (b) shows the total number of Complex (Non Mobile) trades performed in a branch/week. Panel (c) shows Branch Specialization HHI_b, defined in equation 6, each branch/week. Lastly, Panel (d) shows Worker Specialization HHI_w, defined in equation 7, each branch/week



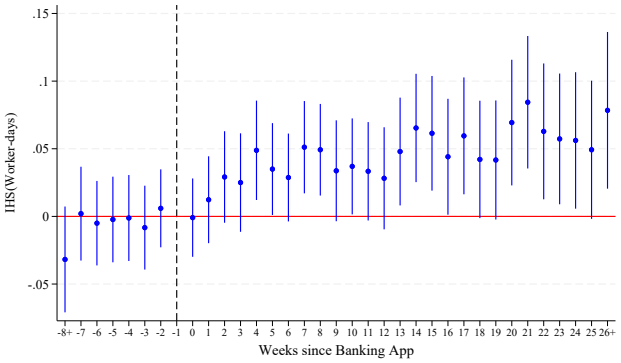
(a) Total Hiring



(b) Total Exits

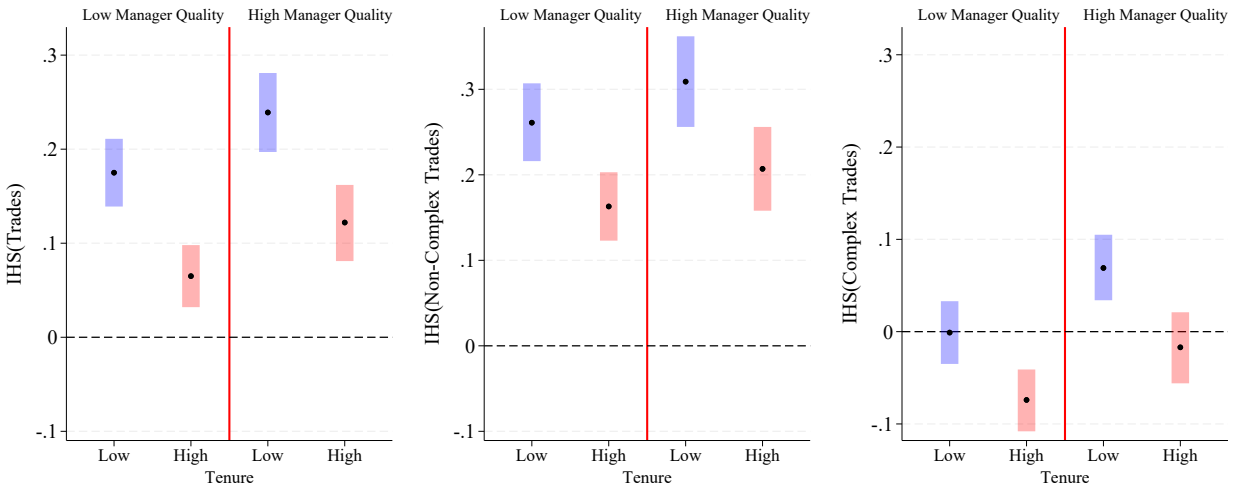


(c) Number of Employees



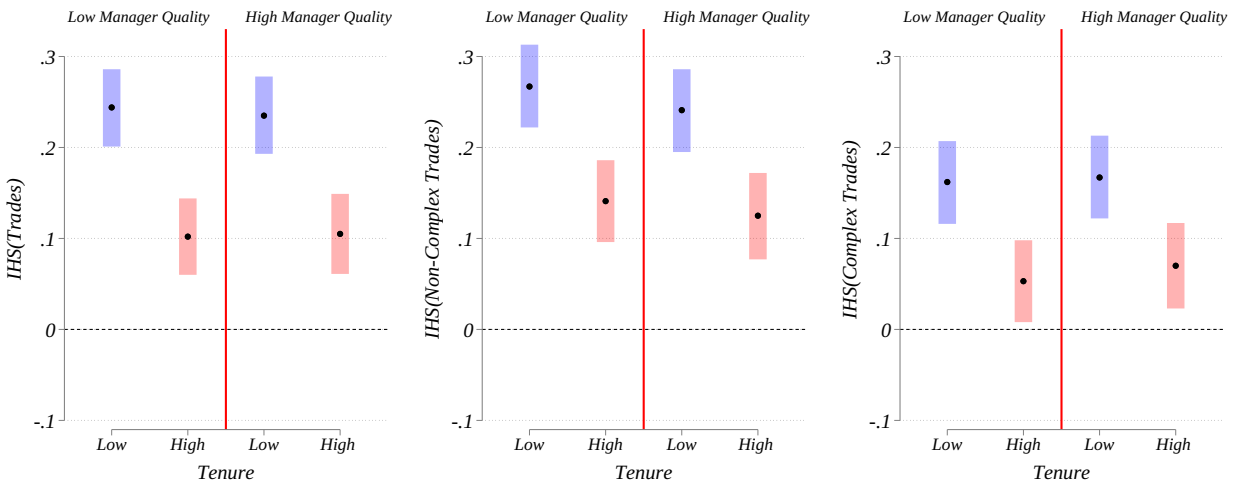
(d) Worker-days

Figure 7: **Tech Intervention: Turnover and branch size**. All outcome variables (vertical axes) are in IHS. Hirings are the total number of workers who enter the company and branch in a week. Exits are the total number of workers who permanently leave the company in a week, assigned to the last branch where they are observed. The number of employees is calculated by computing the unique number of workers in a branch and week. Finally, worker-days is the weekly sum of unique workers in an branch in a given day.



(a) Total Trades (b) Non-Complex Trades (c) Complex Trades

Figure 8: **Tech Intervention: Joint effect between managerial productivity and tenure on main outcome variables. Branch level analysis.** Display of the linear combinations of coefficients from an equation with the triple interaction of the tech shock, worker (tenure), and manager characteristics. 83% C.I.s. are displayed. Outcome variables are in inverse hyperbolic sine transformation.



(a) Total Trades (b) Non-Complex Trades (c) Complex Trades

Figure 9: **Tech Intervention: Joint effect between managerial productivity and tenure on main outcome variables. Worker level analysis.** Display of the linear combinations of coefficients from an equation with the triple interaction of the tech shock, worker (tenure), and manager characteristics. 83% C.I.s. are displayed. Outcome variables are in inverse hyperbolic sine transformation.

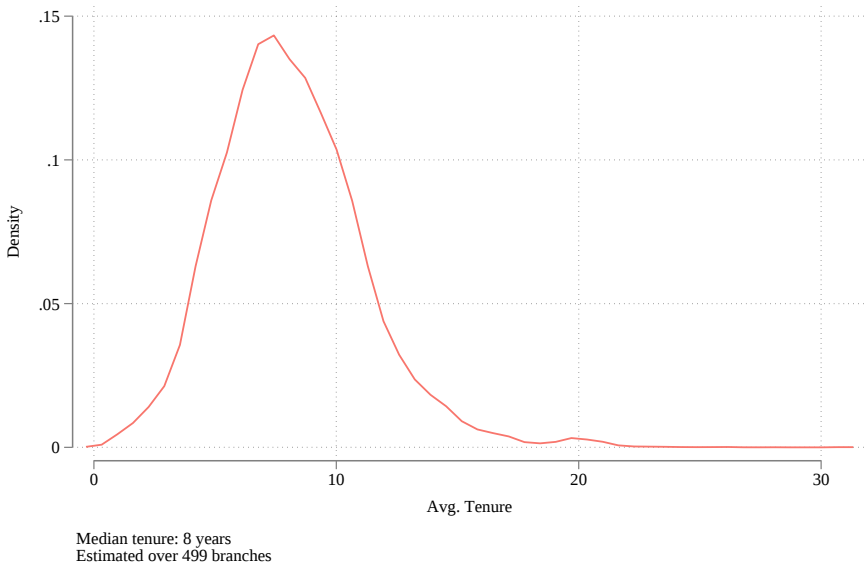
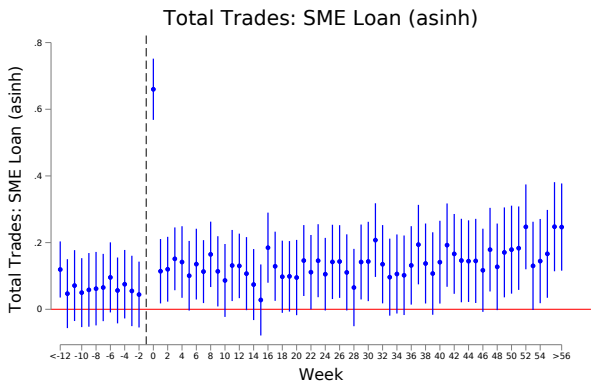
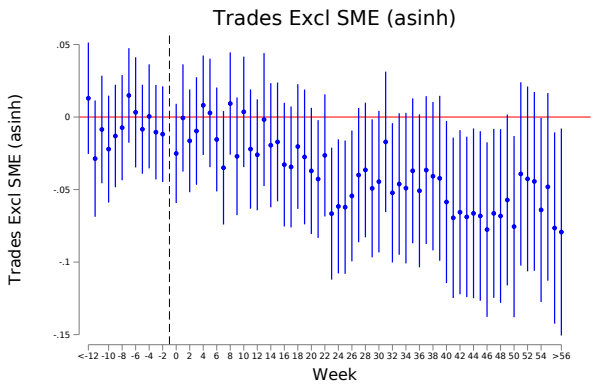


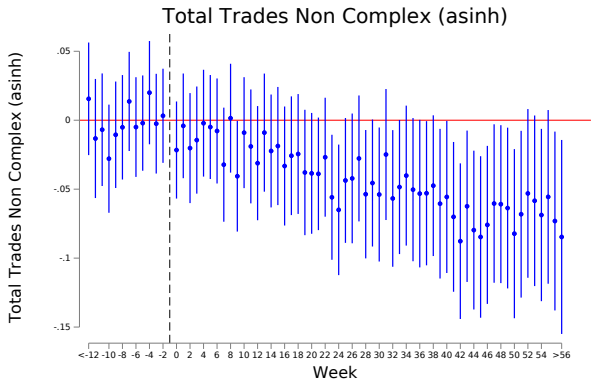
Figure 10: Kernel density distribution of average tenure in branches prior to the tech intervention. Number of branches: 449.



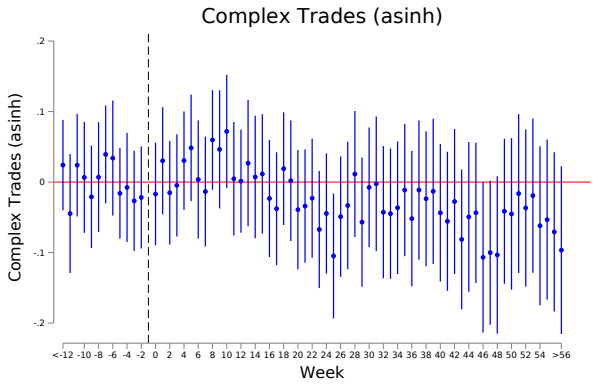
(a) Trades: SME Loans



(b) Trades: Non-SME Loans

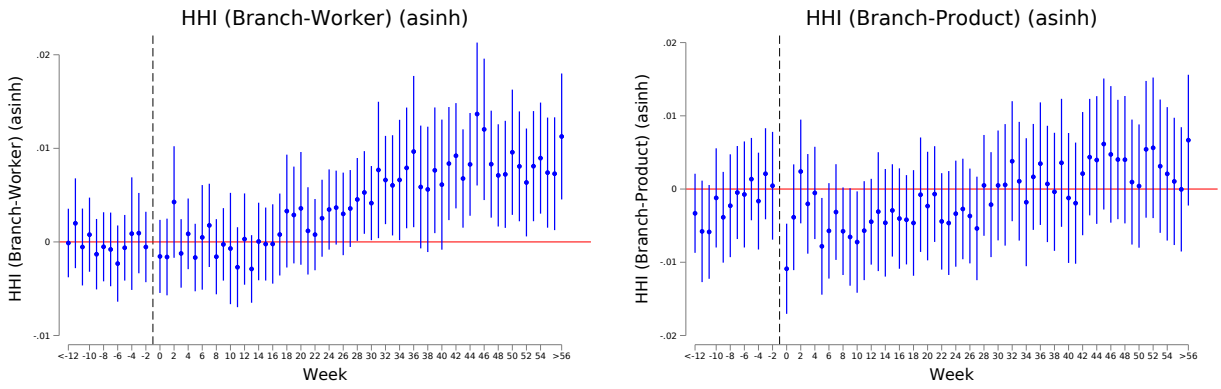


(c) Trades: Non-Complex



(d) Trades: Complex

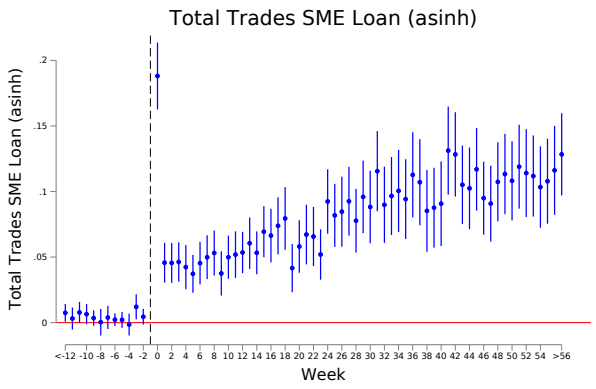
Figure 11: **Task Intervention: Trades Outcomes at the branch level.** All outcome variables are in inverse hyperbolic sine transformation.



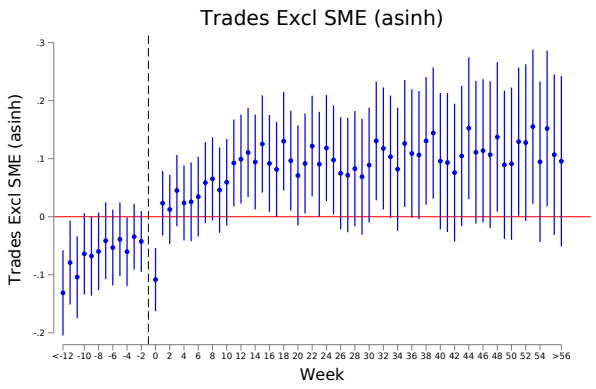
(a) HHI: Branch-Worker

(b) HHI: Branch-Product

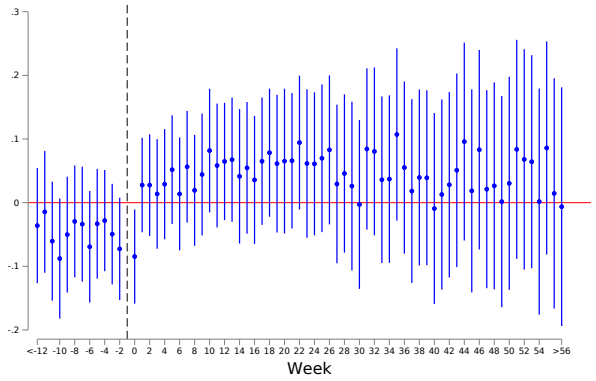
Figure 12: **Task Intervention: specialization across workers and branches.**



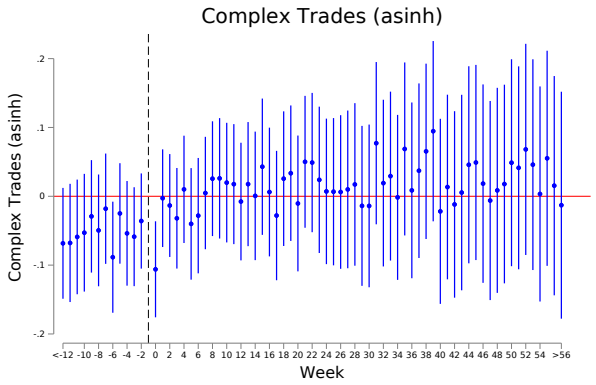
(a) Trades: SME Loans



(b) Trades excluding SME Loans

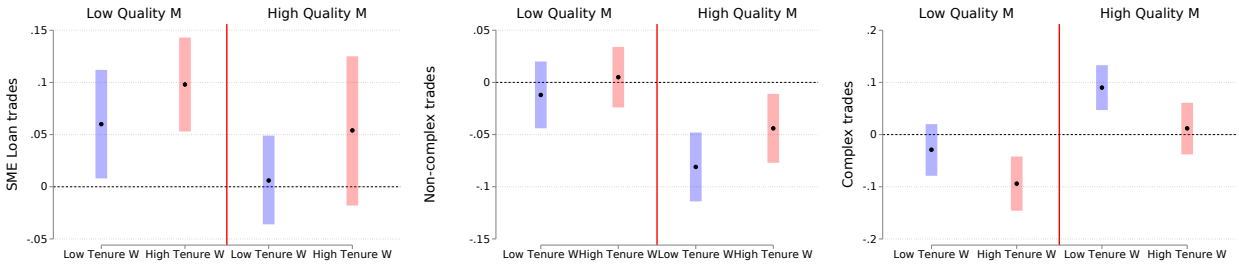


(c) Trades: Non-Complex



(d) Trades: Complex

Figure 13: **Task Intervention: Results at the worker level for Account Managers only - Trades.** All outcome variables are in inverse hyperbolic sine transformation.



(a) SME Loans

(b) Non-Complex Trades

(c) Complex Trades

Figure 14: **Task intervention: cross heterogeneity of worker tenure and manager value added.**

10. 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.

	(1)	(2)
VARIABLES	IHS(Trades)	IHS(Trades-empl)
Tech Shock	0.141***	0.0967***
	(0.0204)	(0.0152)
Observations	69,465	69,244
Mean	4.349	1.819
Std.Dev	1.110	0.652

Week and Branch FEs included. SE clustered by Branch

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

Table 4: Changes in Trades and Productivity. All outcome variables are in IHS. Column (1) shows the total number of trades performed in a branch/week. Column (2) shows productivity in a branch/week, defined as the number of total trades divided by the total number of workers ever branch/week.

	(1)	(2)
VARIABLES	IHS(Non-Complex Trades)	IHS(Complex Trades)
Tech Shock	0.227***	-0.0106
	(0.0258)	(0.0184)
Observations	69,465	69,465
Mean	3.692	3.468
Std.Dev	1.113	1.283

Week and Branch FEs included. SE clustered by Branch

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

Table 5: Changes in workers' task composition. All outcome variables are in IHS. Column (1) shows the total number of Non-Complex (Mobile) trades performed in a branch/week. Column (2) shows the total number of Complex (Non Mobile) trades performed in a branch/week.

	(1)	(2)
	Reallocation in Trades	Reallocation in Space
Tech Shock	0.0236***	0.257***
	(0.00889)	(0.0264)
Observations	69,238	69,238
Mean	0.144	0.642
Std. Dev	0.809	1.211

Week and Branch FEs included. SE clustered by Branch

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

Table 6: **Tech Intervention: Worker reallocation.** Outcome variables estimated in levels. Reallocation of workers who were hired at least three months before making their first trade, indicating a shift from positions where they were not doing trades to positions where they perform at least one trade. Reallocation in space: the number of workers whose branch changed compared to the previous week.

	(1)	(2)	(3)
	IHS(Trades)	IHS(Non-Complex Trades)	IHS(Complex Trades)
Tech Shock	0.202***	0.282***	0.0297
	(0.0245)	(0.0309)	(0.0210)
Tech Shock X Tenure (p50)	-0.118***	-0.108***	-0.0792***
	(0.0209)	(0.0252)	(0.0197)
Observations	69,465	69,465	69,465
Mean (pre)	4.349	3.692	3.468
Std. Dev (pre)	1.110	1.113	1.283
LinCom	0.0830	0.174	-0.0500
SE(LinCom)	0.0220	0.0270	0.0210

Week and Branch FEs included. SE clustered by Branch

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

Table 7: **Tech Intervention: Effect of ex-ante high-tenure on main outcome variables.** Heterogeneity analysis from equation (3) on average tenure estimated only for the pre period. The heterogeneity measure is a dummy equal to 1 if average tenure before the introduction of the banking app is above median.

	(1)	(2)	(3)
	IHS(Trades)	IHS(Non-Complex Trades)	IHS(Complex Trades)
Tech Shock	0.116***	0.208***	-0.0405*
	(0.0207)	(0.0262)	(0.0207)
Tech Shock X Manager Quality AKM (p50)	0.0685***	0.0532**	0.0695***
	(0.0219)	(0.0261)	(0.0201)
Observations	68,612	68,612	68,612
Mean (pre)	4.349	3.692	3.468
Std. Dev (pre)	1.110	1.113	1.283
LinCom	0.184	0.261	0.0290
SE(LinCom)	0.0250	0.0320	0.0220

Week and Branch FEs included. SE clustered by Branch

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

Table 8: **Tech Intervention: Effect of ex-ante high-manager quality on main outcome variables.** Heterogeneity analysis from equation (3) on manager value added θ_m from AKM equation (5). The heterogeneity measure is a dummy equal to 1 if average manager quality before the introduction of the banking app is above median.

	(1)	(2)
	Reallocation in Trades	Reallocation in Space
Tech Shock	0.0123	0.223***
	(0.0101)	(0.0390)
Tech Shock X Manager Quality	0.0241***	0.0792
	(0.00797)	(0.0533)
Observations	68,540	68,540
Mean (pre)	0.144	0.642
Std. Dev (pre)	0.809	1.211
LinCom	0.0360	0.302
SE(LinCom)	0.0100	0.0360

Week and Branch FEs included. SE clustered by Branch

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

Table 9: **Tech Intervention: Effect of ex-ante high-manager quality on Reallocation in Trades and in Space variables.** Reallocation in tasks: Outcome variables estimated in levels. Reallocation of workers who were hired at least three months before making their first trade, indicating a shift from positions where they were not doing trades to positions where they perform at least one trade. Reallocation in space: the number of workers whose home branch changed compared to the previous week. Home branches are defined weekly according to the number of transactions done in a given week in a specific branch. Workers are considered reallocated if they are no longer observed in previous week's home branch but are observed elsewhere.

	(1)	(2)	(3)
VARIABLES	IHS(Trades)	IHS(Non-Complex Trades)	IHS(Complex Trades)
Tech Shock	0.184***	0.204***	0.126***
	(0.0284)	(0.0306)	(0.0313)
Observations	381,403	381,403	381,403
Mean	2.586	1.876	1.756
Std.Dev	1.095	1.221	1.155

Week and Worker FEs included. SE clustered by Worker

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

Table 10: **Tech Intervention: Worker Level Main Outcomes**. Changes in workers' overall trades and task composition All outcome variables are in IHS. Column (1) shows the total number of trades performed by a worker on a week. Column (2) shows the total number of Non-Complex (Mobile) trades performed by a worker on a week. Column (3) shows the total number of Complex (Non Mobile) trades performed by a worker on a week.

	(1)	(2)	(3)
VARIABLES	IHS(Trades)	IHS(Non-Complex Trades)	IHS(Complex Trades)
Tech Shock	0.248***	0.259***	0.177***
	(0.0295)	(0.0316)	(0.0321)
Tech Shock X Tenure	-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

Table 11: **Tech Intervention: Effect of ex-ante high-tenure on main outcome variables at the worker level.** Heterogeneity analysis that follows the spirit of equation (3), but at the worker level, on average tenure estimated only for the pre period. The heterogeneity measure is a dummy equal to 1 if average tenure before the introduction of the banking app is above median.

	(1)	(2)	(3)
VARIABLES	IHS(Trades)	IHS(Non-Complex Trades)	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

Table 12: **Tech Intervention: Effect of ex-ante high-manager quality on main outcome variables at the worker level.** Heterogeneity analysis follows the spirit of (3), but at the worker level, on manager value added θ_m from AKM equation (5). The heterogeneity measure is a dummy equal to 1 if average manager quality before the introduction of the banking app 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 13: **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.

	(1)	(2)
	Lateral Moves Out (HR) AMs (asinh)	Lateral Moves Out (HR) All Workers (asinh)
Task Shock	0.0723***	-0.2143
	(0.0227)	(0.1369)
Observations	1,408	1,408
R-squared	0.2539	0.4137
Dependant Mean Asinh	0.0220	0.2836
Dependant Mean Level	0.0220	0.2836

Table 14: **Task Intervention: Worker Reallocation.** Using the personnel records, we measure worker reallocation by counting the total number of employees who transfer from a branch to a back office. Reporting the coefficient from differences-in-differences model: $y_{b,t} = \beta TaskShock_{b,t} + \alpha_b + \gamma_t + \varepsilon_{b,t}$.

	(1)	(2)	(3)	(4)	(5)	(6)
	AM (asinh)	Advisor (asinh)	Supernumerary (asinh)	BT (asinh)	Manager (asinh)	Others (asinh)
Panel A: Worker Hiring						
Task Shock	0.0004	-0.0002	0.0001*	-0.0009	0.0002	0.0002
	(0.0011)	(0.0002)	(0.0001)	(0.0006)	(0.0001)	(0.0004)
Observations	77,830	77,830	77,830	77,830	77,830	77,830
R-squared	0.0198	0.0082	0.0073	0.0288	0.0072	0.0090
Dependent Mean	0.0044	0.0010	0.0003	0.0048	0.0008	0.0011
Panel B: Worker Exit						
Task Shock	0.0000	0.0004	-0.0000	0.0000	0.0017*	0.0008
	(0.0002)	(0.0007)	(0.0001)	(0.0002)	(0.0010)	(0.0010)
Observations	77,830	77,830	77,830	77,830	77,830	77,830
R-squared	0.0110	0.0107	0.0082	0.0145	0.0152	0.0132
Dependent Mean	0.0002	0.0005	0.0000	0.0002	0.0016	0.0019

Table 15: **Task Intervention: Worker Entry and Exit.** Worker hiring captures the number of new employees in each branch-week. The hiring date is recorded in the personnel records. Worker exit is constructed by identifying the last recorded transaction of each worker and verifying their absence in the personnel records. Reporting the coefficient from differences-in-differences model: $y_{b,t} = \beta TaskShock_{b,t} + \alpha_b + \gamma_t + \varepsilon_{b,t}$.

	Trades			
	(1)	(2)	(3)	(4)
	All	SME Loan	Non Complex	Complex
Task Shock	-0.0159	0.0368	-0.0403**	0.0399
	(0.0173)	(0.0253)	(0.0189)	(0.0266)
1.Task Shock × 1.Tenure	-0.0009	0.0459	0.0251	-0.0890***
	(0.0189)	(0.0341)	(0.0196)	(0.0314)
Observations	74,844	74,844	74,844	74,844
R-squared	0.8002	0.3800	0.7820	0.6916
Dependant Mean	3.6121	0.6961	3.3553	2.1005

Table 16: **Task Intervention: Heterogeneity in tenure.** We classify branches into above and below median tenure according to the average tenure of all workers in the branch present in the four weeks prior to the intervention.

	Trades			
	(1)	(2)	(3)	(4)
	All	SME Loan	Non Complex	Complex
Task Shock	-0.0188	0.0743***	-0.0094	-0.0745**
	(0.0179)	(0.0262)	(0.0180)	(0.0301)
1.Task Shock × 1.Management	-0.0198	-0.0541	-0.0617***	0.1224***
	(0.0188)	(0.0346)	(0.0195)	(0.0308)
Observations	72,915	72,915	72,915	72,915
R-squared	0.8002	0.3807	0.7827	0.6923
Dependant Mean	3.6121	0.6961	3.3553	2.1005

Table 17: **Task Intervention: Heterogeneity in manager quality.**

VARIABLES	(1) Trades	(2) Trades No SME	(3) Complex Trades
Task Shock	0.1585***	0.1527***	0.1013***
	(0.0308)	(0.0312)	(0.0319)
Task Shock x Tenure	-0.0906***	-0.0904***	-0.1131***
	(0.0274)	(0.0290)	(0.0311)
Observations	153,744	153,744	153,744
R-squared	0.4108	0.4439	0.3549
Worker Lincomb	0.0680 **	0.0620 **	-0.0120
Standard Error	0.0300	0.0300	0.0300
Dependent Mean	2.6183	2.4636	1.1733

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: **Task Intervention: Worker heterogeneity in tenure, worker level results on the sample of account managers.**

VARIABLES	(1) Trades	(2) Trades No SME	(3) Complex Trades
Task Shock	0.1027***	0.0981***	-0.0354
	(0.0284)	(0.0291)	(0.0294)
Task Shock x Management	0.0247	0.0219	0.1621***
	(0.0267)	(0.0283)	(0.0299)
Observations	157,815	157,815	157,815
R-squared	0.4112	0.4456	0.3579
Manager Lincomb	0.1270 ***	0.1200 ***	0.1270 ***
Standard Error	0.0300	0.0300	0.0310
Dependent Mean	2.6183	2.4636	1.1733

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: **Task Intervention: heterogeneity in manager productivity, worker level results on the sample of account managers.**