Banking under Conflict: Managers and Organizational Design

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Abstract

How do organizations adapt internally when ethnic divisions intensify? We develop a model in which organizations jointly choose managerial appointments and delegation when locally matched managers have better information but are less aligned with headquarters, and test it using a panel of Ethiopian bank branches. Exploiting variation in banks' exposure to ethnic conflict across their branch networks, we find that conflict increases the appointment of locally matched managers, while reducing lending autonomy and leaving branch credit mostly unaffected. Conflict-exposed branches are more likely to be staffed by insiders reassigned within the bank. An LLM-based CEO vignette exercise corroborates this mechanism.

JEL Codes: D23, D74, G21, O12.

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1 Introduction

How do organizations allocate decision-making authority when they operate across socially divided populations, and how do they adapt when those divisions deepen? Organizations face a well-known trade-off between local knowledge and internal communication costs (Garicano, 2000): delegating decisions to better-informed local agents improves the use of specialized knowledge but exposes the organization to those agents' biases (Dessein, 2002; Alonso, Dessein and Matouschek, 2008). In socially divided environments, this trade-off takes on an additional dimension, as employees' group identity can shape organizational design. Matching employees to customers by group identity may improve access to local information, but may also create incentives for employees to favor those customers at the organization's expense. We examine these issues in the context of the banking sector – an ideal setting given its reliance on information and its comparative advantage in gathering and processing data to screen and monitor customers (Hertzberg, Liberti and Paravisini, 2010; Liberti and Mian, 2009).

Over the last decade, we have collected a novel panel dataset on the ethnicity of the manager and the organizational structure of bank branches in Ethiopia to study this issue. We also collect data highlighting a distinctive feature of banking in Ethiopia: banks are strongly associated with specific ethnic groups, as reflected in their leadership and dominant language (Regasa, Fielding and Roberts, 2022). In such contexts, banks operating in areas populated by other ethnic groups must choose between hiring managers of the city's predominant ethnic group ("city-coethnic"), who are better informed about local borrowers, and less-informed managers coethnic with the bank ("bank-coethnic"), who facilitate better communication about those clients within the bank.

The empirical identification of how banks respond to changes in this information-alignment trade-off is challenging, as it requires variation exogenous to both bank-level and local conditions. To address this, we focus on a source of variation that affects the costs of information acquisition and communication within banks, without directly influencing local conditions. Specifically, we study the effect of banks' exposure to conflict involving the bank's ethnic group. To separate this effect from local economic conditions, we measure exposure through a bank's branch network, excluding conflict events in the branch's own city (Hjort, 2014; Rohner, Thoenig and Zilibotti, 2013; Korovkin and Makarin, 2023).[1] Using a panel of 974 branches operated by 16 banks before and after the onset of the 2020 civil war, we estimate how this network-based exposure reshapes branch organization and lending, controlling for branch and time fixed effects.

To guide our analysis, we develop a model of managerial assignment and delegation building on Dessein (2002) and Alonso, Dessein and Matouschek (2008). The key extension relative

[1] We use data from the Armed Conflict Location and Event Data Project (ACLED) to measure the location, timing, actors and intensity of conflict.

to these frameworks is that the bank jointly chooses both the ethnicity of the branch manager and the authority delegated to that manager. City-coethnic managers may be better able to acquire soft information, but may also be less aligned with headquarters and more prone to in-group favoritism. When ethnic conflict intensifies, this trade-off between information and alignment sharpens. The model yields an unambiguous prediction for delegation: headquarters tightens authority for managers who match the city's ethnicity. The prediction for manager ethnicity, however, is ambiguous – the optimal adjustment depends on the relative effects of conflict on information acquisition and incentive alignment.

Through a descriptive analysis, we first document a sharp shift in manager ethnicity in cities where the predominant local ethnicity differs from the bank's dominant ethnic group. In 2018, before the civil war, 77 percent of branch managers in these cities were coethnic with the bank; by 2022, that share had fallen to 36 percent. We then show that this shift is concentrated in branches more exposed, through the bank's branch network, to ethnic conflict involving the bank's ethnic group. Greater conflict exposure increases the likelihood that these branches appoint city-coethnic managers, while reducing those managers' lending autonomy, measured by the largest loan they can approve without headquarters' approval. This pattern suggests that banks respond to ethnic conflict by relying more on managers who share customers' ethnicity to acquire local information, while limiting the resulting incentive costs by lowering loan approval limits. Consistent with this interpretation, city-coethnic managers have less autonomy than other managers after the onset of the conflict. Conflict-exposed branches are also more likely to be staffed by experienced managers reassigned from elsewhere in the same bank, suggesting greater reliance on trusted insiders. By contrast, we find no evidence of a change in the choice of manager ethnicity in bank-coethnic cities.

We then examine how these organizational changes affect branch-level lending. In cities not coethnic with the bank, conflict-exposed branches serve a wider geographic area and shift toward fewer, larger loans, with little change in interest or default rates. In cities coethnic with the bank, by contrast, exposed branches expand lending while default rates fall. This suggests lending activity is sustained in both types of city, through different types of adjustments.

We complement the main analysis with a vignette exercise using LLM-generated synthetic bank CEOs (in the spirit of e.g. Horton, Filippas and Manning (2023)). Across branch-year scenarios constructed from our survey data and bank annual reports, we vary the ethnicity of the hypothetical branch manager and the branch network's exposure to ethnic conflict. The synthetic CEOs mirror the same trade-off highlighted by the model and the data: they view managers who match the city's population as better able to acquire local information, but also as more prone to favoritism and harder to align with headquarters, leading to tighter delegation when conflict exposure is high. We use this exercise to discipline interpretation of our findings and to open the organizational black box.

We further corroborate the main findings using an instrument based on banks' pre-conflict proximity to cities historically associated with Beta Israel communities. The migration of Ethiopian Jews from these areas is linked to later disputed border configurations, which in turn predict subsequent exposure to ethnic conflict through the bank's branch network. The resulting estimates support our main organizational and lending results. Finally, we show that the patterns we document are difficult to reconcile with alternative mechanisms, including managers' own safety concerns, customers' preferences for coethnic managers, and employees' preferences for managers who share their ethnicity.

We contribute to three bodies of literature. First, we contribute to the literature on conflict by showing how violent ethnic conflict reshapes the internal organization of firms. Recent work shows that conflict can reorganize economic and social activity well beyond directly exposed markets (Fetzer et al., 2021; Sviatschi, 2022; Melnikov, Schmidt-Padilla and Sviatschi, 2025; Korovkin, Makarin and Miyauchi, 2025), and distort investment and other economic interactions (Fisman et al., 2020; Hjort, 2021). We show that firms also respond by reorganizing internally, changing both who holds authority and how much authority is delegated. We complement Hjort (2014), who studies firms' adjustment of a single incentive margin, by documenting a broader set of organizational responses that help sustain lending under ethnic conflict. Specifically related to the banking industry, our paper joins a growing body of evidence on both the costs and the benefits of matching customers and employees along group lines: for example, the work of Fisman, Paravisini and Vig (2017) and Frame et al. (2025) on the benefits of matching in lending, while D'Acunto, Ghosh and Rossi (2026), Fisman et al. (2020) and Eichengreen and Saka (2025) study how cultural proximity and stereotypes can distort credit allocation.

Second, we contribute to organizational economics by providing an empirical setting to study the trade-off between local information and incentive alignment that is central to theories of delegation (Aghion and Tirole, 1997; Dessein, 2002; Alonso, Dessein and Matouschek, 2008). The existing theoretical literature typically varies the allocation of authority holding the agent fixed, while the assignment literature varies who is appointed holding authority fixed (Xu, Bertrand and Burgess, 2023; Dlugosz et al., 2024). Our setting allows us to study how organizations jointly adjust both margins when external conditions shift. This highlights how organizations actively manage the distortions documented in a recent finance literature: social ties can improve the quality of credit, but cultural proximity and stereotypes can also distort lending decisions (Brock and De Haas, 2023; Rehbein and Rother, 2025).

Third, we contribute to the literature on diversity and economic performance, showing that in polarized environments firms may optimally increase customer-facing diversity while simultaneously tightening internal controls. This highlights an important caveat to a recent literature that emphasizes the value of in-group homogeneity within firms (e.g., Espinosa and Delfino, 2024; Spenkuch, Teso and Xu, 2023; Colonnelli, Neto and Teso, 2025; Benson, Board and Meyer-ter Vehn, 2024; Ghosh, 2025), and complements evidence that diversity within organizations can improve performance (Rasul and Rogger, 2015; Lu, Naik and Teo, 2024). These firm-level adaptations suggest organizations play a role in connecting the macroeconomic literature on the negative link between diversity and economic growth (Easterly and Levine, 1997; Alesina and La Ferrara, 2005; La Ferrara, 2003; Miguel and Gugerty, 2005; Ashraf and Galor, 2013) and the microeconomic literature on inter-group frictions in economic interactions described above. Our findings also speak to how private organizations, alongside public institutions (Carlitz et al., 2025), adapt to govern inter-group frictions in divided societies.

The remainder of the paper proceeds as follows. Section 2 presents the theoretical framework and outlines the institutional context. In Section 3, we describe the data, our empirical testing strategy for the theoretical predictions, and the quasi-experimental variation in conflict stemming from the Beta Israel migration. Section 4 then details the empirical model, the main results and the synthetic CEO methodology. Section 5 discusses what alternative mechanisms might explain our results. Finally, we discuss and interpret our findings in Section 6.

2 Theoretical Framework and Institutional Setting

This section models how a bank's headquarters (HQ) jointly chooses whom to appoint as branch manager and how much authority to grant, when the bank's dominant ethnic group differs from the predominant group in the branch's city in the presence of ethnic conflict. Lending decisions rely on soft information, which managers coethnic with the city can more easily acquire due to their cultural proximity with local borrowers (Fisman, Paravisini and Vig, 2017).[2] However, a city-coethnic manager may place excess weight on local borrowers' interests relative to HQ, generating upward bias in lending decisions. By contrast, a bank-coethnic manager's interests are aligned with HQ's objectives, thus making lending decisions unbiased, yet she has less access to local soft information. Ethnic conflict shifts this tradeoff: it makes city-coethnic managers more biased towards their own group and worsens the relative ability of bank-coethnic managers to acquire soft information.[3]

We parameterize this trade-off along three dimensions. First, a bias parameter $b \geq 0$ captures how much the manager's preferred lending deviates from HQ's: $b = 0$ for a bank-coethnic manager

[2] Shared cultural codes, as well as shared first languages, give the officer access to soft information about borrower quality that an out-group branch manager cannot easily obtain.

[3] Our framework builds on cheap-talk models of delegation and strategic communication (Crawford and Sobel, 1982; Dessein, 2002; Alonso, Dessein and Matouschek, 2008) and the banking-organization literature on hierarchical lending and relationship banking (Stein, 2002; Berger and Udell, 2002; Berger et al., 2005; Liberti and Mian, 2009)

and $b > 0$ for a city-coethnic one. Second, a parameter q measuring the precision of the manager's assessment of local project quality: city-coethnic managers have higher q because of their cultural proximity with local borrowers. Third, a safety-related reservation wage, w, capturing the disutility a bank-coethnic manager faces when posted to a city whose dominant ethnic group differs from hers. We denote ethnic conflict by γ, and assume that $b = b(\gamma)$ with $b'(\gamma) > 0$, $q = q(\gamma)$ with $q'(\gamma) < 0$, and finally $w = w(\gamma)$ with $w'(\gamma) > 0$.[4] These three forces, and how strongly conflict shifts each one of them, jointly determine HQ's optimal managerial appointment and authority allocation. The novel feature of our framework is that HQ optimizes over both margins simultaneously, and that different conflict channels operate on different margins.

Let us consider a lending opportunity of size L and an unobserved state θ representing the efficient (fundamental-based) lending terms the bank should impose to finance such an opportunity. HQ chooses lending terms y and incurs a quadratic loss $[L(y-\theta)]^2$: larger loans amplify the cost of mistakes. [5]

The HQ sets a loan size cutoff, L^*, to choose between two authority regimes. Under *delegation*, the manager chooses y, fully exploiting local information but exposing HQ to biased implementation when $b > 0$. Under *centralization*, HQ retains the decision and chooses y after receiving a cheap-talk report from the manager about θ. When $b > 0$, this report is strategically distorted in the standard sense of Crawford and Sobel (1982): equilibrium communication becomes less informative as bias grows.

The formal model is developed in Appendix A and microfounded in the Online Appendix. The following proposition summarizes its main implications.

Proposition 1. *Let $\Delta(b)$ denote the information lost to strategic communication under centralization, with $\Delta(0) = 0$. Suppose $\Delta(b)$ is strictly increasing and weakly concave in b.*

(i). ***Authority allocation.*** *There exists a loan size cutoff $L^\star(b) = \frac{\Delta(b)}{b^2}$ such that HQ delegates authority on loan decisions to the branch manager if $L \leq L^\star(b)$ and centralizes it otherwise. Since $b > 0$ applies only to city-coethnic managers, the loan-size cutoff is relevant only to them. As conflict rises, $b(\gamma)$ increases, lowering $L^\star$. By contrast, bank-coethnic managers are unbiased; thus, HQ is indifferent between delegating and centralizing authority to them.*

(ii). ***Managerial appointment.*** *HQ appoints a city-coethnic manager when the local information*

[4] The assumption that a bank-coethnic manager has no bias can be relaxed, and as long as such a manager has a lower bias than a city coethnic manager, all the qualitative results presented throughout our analysis would continue to hold.

[5] The weighted quadratic loss is microfounded in the Online Appendix. Intuitively, we interpret HQ as seeking to align branch-level lending decisions with the bank's fundamentals-based credit policy. A quadratic loss in the gap between actual and efficient lending terms captures the cost of both excessively loose and excessively tight lending. The L^2 term captures the idea that mistakes on larger loans are disproportionately more consequential and therefore subject to tighter internal scrutiny.

advantage and lower safety costs outweigh the expected costs of bias and communication frictions. Conflict can shift the appointment decision in opposite directions: it reduces the relative value of a city-coethnic manager by increasing $b(\gamma)$ and $\Delta(b(\gamma))$, but it increases their relative values by eroding the ability of bank-coethnic managers to acquire soft information and increasing their safety premium.

The HQ optimizes over both margins simultaneously; the appointment decision determines b, which in turn pins down L^*.

Proposition 1 shows the impact of conflict on authority allocation and managerial appointment. As conflict increases, ceteris paribus, the HQ would be less willing to delegate loan authority to a city-coethnic branch manager. Moreover, if conflict becomes fiercer, the HQ may prefer to appoint a less-informed but better-aligned bank-coethnic branch manager. Notice that an increase in assessment precision q would only affect the managerial appointment strategy, not the allocation of authority (which, in fact, follows from the decision of whom to appoint as branch manager). Notice that an increase in assessment precision affects managerial appointment but, in the baseline model, does not affect the authority cutoff conditional on manager type. The reason is that baseline information quality enters delegation and centralization symmetrically, whereas the regime comparison is driven by the additional communication loss under centralization and the bias exposure under delegation. The quality of her assessment of θ is the same, irrespective of the authority regime. Similarly, safety concerns for a bank-coethnic manager can shift manager ethnicity, but, by themselves, do not generate a loan size-dependent tightening of authority conditional on manager type.

Finally, throughout our analysis, we examine the case in which HQ and the city have different ethnicities. The case where the bank and the city are coethnic would deliver trivial results in our model. Specifically, the best option for the HQ would be to appoint a branch manager coethnic with both the city and the bank, so as to enjoy the benefits from both interest alignment and better information acquisition.

2.1 Banking in Ethiopia

The Ethiopian banking sector provides an ideal setting to study this mechanism for two reasons. First, Ethiopia is ethnically diverse, yet local areas are homogeneous. Second, banks have strong affiliations with specific ethnic groups, yet operate both in areas where the majority of the population shares their ethnicity and in cities where few people do.

In terms of ethnic diversity, Ethiopia is home to more than 90 ethnic groups, although four – the Oromo (34%), Amhara (30%), Somali (6%), and Tigray (6%) – account for roughly three-quarters of the population. Ethnicity is salient and discernible through appearance, language, and names (Abbay, 2004). The country's federal structure, established in 1992 after the fall of the military regime, organizes regions along ethnic lines. As a result, the major regions – including Oromiya, Amhara, Somali, and Tigray – are highly homogeneous.[6] More broadly, over 85% of Ethiopians live in a woreda (district) where a single ethnic group constitutes at least 85% of the population. Appendix Figure E.1 shows ethnic diversity at the local level, and Appendix Figure G.1 maps Ethiopia's regions, whose names generally align with the predominant ethnicity.

Following liberalization in the early 1990s, privately owned banks entered the market, many with strong ties to specific ethnic groups and regions. These ethnic affiliations are evident in naming conventions, such as the "Cooperative Bank of Oromiya" and "Amhara Bank," in branch locations (Regasa, Fielding and Roberts, 2022), the ethnicity of C-suite executives, and the predominant language used within banks. Despite these affiliations, banks now operate across ethnic boundaries. As competition intensified, banks established branches well beyond their home regions, often in cities where a different ethnic group predominates. This creates the trade-off our theoretical model formalizes: a bank can hire a city-coethnic manager to acquire better local information, or a bank-coethnic manager to communicate more effectively with headquarters.

2.2 Conflict in Ethiopia

After relative peace and strong economic growth from 2000 to 2020, the Tigray War broke out in late 2020 following a rupture between the federal government and the Tigray People's Liberation Front (TPLF), the dominant political movement in Tigray. This setting suits our analysis for three reasons. First, conflict intensity varies sharply across time and space, with some areas experiencing severe violence while others remained relatively insulated. Second, violence involved multiple ethnic groups, reducing concerns that our estimates are driven by shocks specific to one group or region. Third, the conflict was unanticipated at the time of our 2018 data collection, supporting the exogeneity of pre-conflict bank and branch characteristics.

The war and subsequent civil conflict caused an estimated 300,000–800,000 civilian deaths by 2022 (Cedoca, 2024) and affected much of northern Ethiopia, with fighting concentrated in Tigray and along the north–south corridor linking Mekelle to Addis Ababa. Instability subsequently spread to Oromia (involving the Oromo Liberation Front, OLF) and to Amhara (involving Fano). Figure 1 summarizes conflict intensity over time (Panel A) and space (Panel B) in our data. Panel A shows that fatalities are positive but low and relatively stable during 2005–2019, then rise sharply starting in late 2020, with the number of fatalities peaking in 2021. Panel B maps events from 2019–2022 and indicates that conflict is widely distributed across central and northern

[6] Using the 2007 Ethiopia census microdata (IPUMS), 96% of residents of Tigray are Tigrayan, 91% of residents of Amhara are Amhara, and 88% of residents of Oromiya are Oromo.

Ethiopia, with substantial incidence in densely populated areas.[7]

The conflict would have been difficult to foresee when we collected our data in 2018. A new prime minister had only just assumed power that year, beginning a political transition that culminated in the exclusion of the TPLF from the ruling coalition in late 2019. The exclusion left the TPLF with substantial military capacity but diminished political power, creating conditions conducive to conflict (Morelli, Ogliari and Hong, 2024). Because our data collection predates these developments, pre-conflict branch and manager attributes are unlikely to reflect anticipation of the violence. We exploit this timing in our empirical strategy.

3 Data and empirical strategy

3.1 Data

For our analysis, we combine two main datasets with several complementary sources described below. The first is a novel branch-level panel covering the period before (2018) and after (2022) the onset of civil war in Ethiopia. The second is the Armed Conflict Location & Event Data Project (ACLED), which records the location, date, actors, and fatalities of conflict events.

In 2015, we constructed a list of the population of around 4,000 bank branches in Ethiopia at that time – our initial sampling frame. We successfully interviewed, via phone, 1,851 by 2018, our first period, and successfully re-interviewed 974 branches of 16 banks across 187 cities in 2022, our second period. Our main analysis sample consists of the 974 branches that were interviewed in both waves.[8] For each branch, we conduct the interview with the most senior manager present at the branch at the time of the survey. The questionnaire covers three areas. First, we ask a series of questions about the manager's characteristics including their age, work experience, and education. Second, we implement a questionnaire we developed based on the World Management Survey (Bloom and Van Reenen, 2007), customised to reflect bank operations and lending activities, and questions on branch organization.[9] Finally, we ask a series of questions about lending at the branch, including on the volume of lending, interest rates, collateral, non-performing loans, and the degree of autonomy the manager has to make lending decisions.

[7] Online Appendix Figure G.2 shows the geographic distribution by year, with concentration in the north in 2020–2021 and new hotspots in other regions thereafter.

[8] Appendix Table H.2 examines attrition between the 2018 and 2022 survey waves. Attrition is largely unrelated to changes in conflict exposure in non-bank-coethnic cities, which are the observations that drive our identification. By contrast, in bank-coethnic cities, higher conflict exposure is associated with slightly greater attrition, mainly because branches are more likely to have closed. We therefore do not think attrition is likely to substantially bias our main results. This Online Appendix section also provides further detail on sample construction and cleaning steps.

[9] These management practices questions are the subject of a separate paper.

As ethnicity is highly salient in Ethiopia, we infer each manager's ethnic group based on the interview. To do so, two interviewers – the primary interviewer and an observer – jointly determine ethnicity based on the manager's region of birth, accent, spoken languages, and name. Online Appendix Table E.3 reports the distribution of manager ethnicities for 2018 and 2022. For 259 managers in 2022, our enumerators did not transcribe the ethnicity. For these managers, we infer their ethnicity based on (a) the managers' ethnicity in 2018 if they were already in the branch at the time (20 managers), or (b) the managers' place of birth (239 managers), Online Appendix Table I provides details on this imputation, and shows that whether the variable is missing is unrelated to conflict and that the results are robust to omitting the imputed ethnicity.

Table 1 presents summary statistics for the main variables. Online Appendix Tables F.2 and F.3 report descriptive statistics for branches' organizational characteristics and lending activities by survey wave, respectively. Online Appendix F provides further details on survey design and implementation.

We use ACLED to measure the spatial intensity of ethnic conflict in Ethiopia. ACLED records the date, location (latitude/longitude), actors, and reported fatalities of events. To link events to ethnic groups, we use the actors listed in each event together with the Ethiopia Peace Observatory's actor–ethnicity classifications.[10] Throughout the paper, we keep all ACLED event types but restrict attention to events with at least one reported fatality, and measure conflict intensity using reported fatalities. This focuses on high-severity incidents and reduces sensitivity to cross-area differences in the reporting of low-intensity episodes. ACLED also cautions that fatality figures are measured with error,[11] therefore, in Online Appendix D, we show robustness to using the number of fatal events instead of fatality counts.[12]

We also identify the ethnic affiliation of banks and cities. Ethiopian naming conventions – typically a personal name followed by the father's personal name, with no surnames – make it possible to infer ethnicity from publicly available records (Gebre, 2010; Fessha, 2016; Kefale, Kamusella and Van der Beken, 2021). We classify each bank by the ethnicity of its CEO and board members, assigning it to the ethnic group that holds the majority of board seats. We classify cities by their predominant ethnic group using the Murdock Ethnographic Atlas. Together with the manager-level data from our survey, this allows us to measure the ethnicity of banks, branch

[10] The Ethiopia Peace Observatory is a special project run by ACLED.

[11] See (Armed Conflict Location & Event Data Project sourcing, 2024; Armed Conflict Location & Event Data Project fatalities, 2024).

[12] We use the ACLED Ethiopia extract downloaded on 15 May 2024 (and the Ethiopia Peace Observatory actor–ethnicity classifications accessed on 5 March 2025); we archive the extract used for analysis.

managers, and cities. Online Appendix E reports their distribution.[13]

3.2 Defining network-level exposure to conflict

Using ACLED, we construct two measures of conflict exposure for each branch: *local* exposure to violence near the branch's own city, and *network* exposure to violence involving the bank's ethnic group near other branches in its network, yet sufficiently far from the branch itself. We use the latter as our main measure of exposure to ethnic conflict.

We introduce the following notation. Let $\mathcal{E}_t$ denote the set of ACLED conflict events in period t, with f_e fatalities in event $e \in \mathcal{E}_t$. For bank b, let $G_{be} \equiv \mathbf{1}\{e \text{ involves bank } b\text{'s ethnic group}\}$. Let $\mathcal{C}_b$ be the set of cities in which bank b operates branches in 2018 (the pre-conflict network), with $C_b \equiv |\mathcal{C}_b|$, and let $c(i)$ denote branch i's city. For any city or set of cities S, let $d(S, e)$ denote the distance in kilometers from event e to the nearest city in S.

For branch i of bank b in period t, we define:

(1)

$$\text{NetworkExposure}_{ibt} = \frac{1}{C_b - 1} \sum_{e \in \mathcal{E}_t} \underbrace{G_{be}\, f_e}_{\substack{\text{Fatalities from}\\ \text{conflict involving}\\ \text{bank } b\text{'s ethnicity}}} \times \underbrace{\mathbf{1}\{d(\mathcal{C}_b, e) < 20\}}_{\substack{\text{A branch city of}\\ \text{bank } b \text{ is within}\\ \text{20km of event } e}} \times \underbrace{\mathbf{1}\{d(c(i), e) > 20\}}_{\substack{\text{Branch } i\text{'s city is}\\ \text{more than 20km}\\ \text{from event } e}} .$$

Intuitively, the measure captures the number of fatalities from own-ethnicity conflict events that occur near at least one branch of bank b, but not near branch i, normalized by the number of other cities in which the bank has branches ($C_b - 1$). To match our two-period panel, we assign ACLED events from 2015–2018 to period 1 and events from 2019–2022 to period 2.[14]

Figure 4 shows the distribution of our network conflict exposure measure for period 1 leading up to our first survey, 2015-2018, and for period 2 between our surveys, 2019-2022. In 2015–2018, most banks experienced fewer than five conflict-related fatalities per branch, with occasional outliers around 20 fatalities. In 2019–2022, exposure increased sharply, with peaks over forty and an average of approximately 18 per branch. This shows a sharp increase in banks' exposure to ethnic conflict between the first and second wave of our panel.

We interpret $\text{NetworkExposure}_{ibt}$ primarily as a shock to bank b's employees and senior management, rather than as local disruption in branch i's market. A large literature emphasizes that conflict can increase the salience of group identity and alter beliefs about intergroup risk

[13] We treat Harari as Oromo because the vast majority of Harari's population is Oromo. See Online Appendix E for details. We also aggregate ethnolinguistically distinct groups from Ethiopia's former SNNP region into a single category because they are individually too small in our sample to support separate classifications, and because they shared a common regional administrative structure. The results are robust to excluding this category.

[14] In Appendix D we test robustness to this distance cutoff, to alternative measures of conflict intensity (fatality counts vs. number of fatal events), and to using the 2022 branch network instead of the 2018 network.

(Akerlof and Kranton, 2000; Rohner, Thoenig and Zilibotti, 2013). In organizational settings, such identity-linked updating can affect the behaviour of decision-makers, including credit officers and branch managers, and thereby shift lending along group lines (Fisman et al., 2020). Because $\text{NetworkExposure}_{ibt}$ excludes events within 20km of branch i's city, the variation we exploit is unlikely to be driven by contemporaneous local insecurity or local demand shocks at branch i. Instead, it captures how violence involving a bank's own ethnic group elsewhere in its network can shift ethnic salience – and behaviour – among its personnel.

Additionally, to capture local conflict through the variable defined for branch i in city c, we define:

$$(2) \qquad \text{LocalExposure}_{it} = \sum_{e \in \mathcal{E}_t} \underbrace{f_e}_{\text{Fatalities in event } e} \times \underbrace{\mathbf{1}\{d(c(i), e) < 20\}}_{\substack{\text{Event } e \text{ occurs within 20km} \\ \text{of branch } i\text{'s city}}} .$$

This measure aims to directly capture the local economic effects of conflict.

3.3 Quasi-experimental variation in conflict

Much of the Amhara-Tigray conflict captured by our network exposure measures concentrates along a stretch of the regional border between these regions, whose disputed status reflects a specific historical episode. The Beta Israel, commonly known as Ethiopian Jews, experienced significant migration to Israel during the 1980s and early 1990s. This movement was marked by notable operations such as Operation Moses in 1984 and Operation Solomon in 1991, where tens of thousands were airlifted to Israel. This sudden shock plausibly resulted in contentious borders drawn in 1992, providing a separate source of conflict in the 2020 civil war. We use these cities to construct an instrument for network-level exposure to conflict in subsection 4.5; here we outline the data and its link to modern-day conflict.

The most recent shifts prior to the 2020 conflict in the Amhara-Tigray border took place in 1992, when Ethiopia's ethnographic regional boundaries were drawn following the fall of the military regime. During these negotiations, dominated by the Tigray People's Liberation Front (TPLF), the border was drawn relatively far south towards Amhara, encompassing part of the area recently vacated by 40,000 Beta Israel (Nyssen and Demissie, 2023). In recent years, these disputed borders have continued to fuel tensions. The exclusion of the TPLF from Ethiopia's governing coalition in 2019 brought these long-standing grievances to the surface. The contested borders played a key role in the Amhara regional army's involvement in the Tigray conflict. The borders also fueled the continuing civil war, involving Amhara militias, who feared that territory they had gained might be returned to Tigray as part of a peace agreement (Nyssen and Demissie, 2023). These 1992 borders thus concentrated disputed territories around the former Beta Israel settlements, which later became focal points of interethnic conflict.

To study these cities, we extract data on the location of the main cities from which the Beta Israel departed (Kaplan, 1992). We then match this to bank branches and banks using the cities in which they are located. We extend the area we consider as Beta Israel to include all cities within 100 kilometers of this area. In subsection 4.5, we define Beta Israel Exposure as the share of bank b's branches within 100 km of any Beta Israel origin city.

3.4 Descriptive results

Before our main empirical analysis, we begin by documenting how manager ethnicity changed from 2018 to 2022, separately for bank-coethnic and non bank-coethnic cities. Using the branch-level panel observed in 2018 and 2022, we compare changes over time between branches located in cities that are coethnic with the bank and branches in cities that are not. Concretely, we estimate a fully interacted two-by-two specification with indicators for (i) the 2022 wave, (ii) whether the branch is in a non bank-coethnic city, and (iii) their interaction; we report the implied group-by-year means in Figure 2. We run this analysis separately for two outcomes: (a) whether the manager shares their ethnicity with the city and (b) whether the manager shares their ethnicity with the bank.

Figure 2 shows that banks shifted from hiring bank-coethnic managers toward city-coethnic managers between 2018 and 2022. This shift is particularly pronounced in cities that are not coethnic with the bank. One interpretation, consistent with our framework, is that matching managers to local customers became more valuable relative to matching them to the bank; however, these descriptive patterns alone cannot distinguish that mechanism from alternative explanations. The remainder of this section therefore focuses on identifying the causal effect of exposure to ethnic conflict on branch-level organization.

4 Empirical model and results

Our model predicts that ethnic conflict changes whether banks assign managers coethnic with the bank or with the city, but only in non bank-coethnic cities – where the bank's ethnicity differs from the local population's. Our main analysis therefore focuses on these branches, using branches in bank-coethnic cities as a placebo. Because these branches predominantly serve customers who share the bank's ethnicity, conflict polarizing differences between groups should not affect them. Comparing the two groups nets out any bank-wide responses to conflict that are unrelated to the ethnicity of local customers.

We first show that conflict exposure shifts branches in non bank-coethnic cities from bank-coethnic managers to city-coethnic managers. We then examine two complementary organizational adjustments: reducing managers' lending authority and reassigning experienced insiders. Next, we show that branches in non bank-coethnic cities make relatively limited adjustments to lending. We then use a synthetic bank CEO to investigate the underlying mechanisms. Finally, we validate the main results using banks' proximity to Beta Israel cities as an instrument.

In our main specification, we estimate a two-way fixed-effects model to examine how within-branch changes in exposure to ethnic conflict through the bank's branch network affect branch-level outcomes.[15] We consider a balanced panel conditional on re-interview[16] over two time periods $t \in \{1, 2\}$ for branches indexed by $i \in \{1, \ldots, N\}$. These branches are located in cities $c \in \{1, \ldots, C\}$, and are part of banks $b \in \{1, \ldots, B\}$.

$$Y_{itbc} = \beta_1 \log(\texttt{NetworkExposure}_{itb}) + \phi_i + \lambda_t + \varepsilon_{itbc}, \tag{3}$$

where Y_{itbc} is a branch-level outcome such as manager ethnicity or management practices. We include branch (ϕ_i) and time (λ_t) fixed effects and cluster standard errors at the branch level.[17][18]

This specification identifies the causal effect of network exposure to ethnic conflict under two conditions. First, changes in a branch's network exposure are plausibly exogenous if the spatial intensity of conflict was not predictable in 2018 and banks did not locate branches in anticipation of future conflict. To probe this assumption, we implement an alternative design that uses the proximity of banks' pre-2018 branch networks to Beta Israel cities as a source of quasi-exogenous variation in exposure that was difficult to foresee in 2018. We also construct the bank's branch network using all branches interviewed in 2018, so that post-2018 branch closures do not mechanically affect measured exposure. Second, Equation 3 recovers β_1 if no other time-varying factors jointly drive network exposure and branch organization. Branch fixed effects absorb time-invariant differences across branches, so identification requires that remaining shocks are common across branches (captured by time fixed effects) or otherwise orthogonal to changes in network exposure. A key threat is differential local trends in the cities where highly exposed banks operate; we assess this by controlling for local conflict intensity and including city-time fixed effects. [19]

[15] Because we have two periods, this is equivalent to a first-difference specification, avoiding concerns about negative weights in staggered-adoption settings (Callaway and Sant'Anna, 2021).

[16] In 2022, we re-interviewed 974 of the original 1,851 branches. In cities not coethnic with the bank, attrition is not predicted by the change in network-level exposure to ethnic conflict (see Appendix H.2 for details). We therefore treat this as a balanced panel.

[17] We add 0.01 to `NetworkExposure` to deal with potential zero values, and show the main results are robust to using an inverse hyperbolic sine transformation in Online Appendix Section D.3

[18] We have also implemented wild-bootstrap inference (Cameron, Gelbach and Miller, 2008) for the analyses in this section; these results are reported in Online Appendix C. This more conservative approach only affects the statistical significance of the already less precise effects related to lending, and cross-sectional results on manager reallocation.

[19] Specifically, we re-estimate 3 with city-time fixed effects ($\lambda_{c,t}$) and controlling for the intensity of local exposure. $Y_{itbc} = \beta_1 \log(\texttt{NetworkExposure}_{itb}) + \beta_2 \log(\texttt{Local\_Exposure}_{itb}) + \phi_i + \lambda_{c,t} + \varepsilon_{itbc}$,

Finally, to test formally whether bank-level exposure to conflict affects branches in bank-coethnic and non bank-coethnic cities differently, we pool both groups and estimate the following interaction specification:

$$
\begin{aligned}
Y_{itbc} = {} & \beta_1 \ \log(\texttt{NetworkExposure})_{itb} + \\
& \beta_2 \ \log(\texttt{NetworkExposure})_{itb} \cdot \texttt{I[non\_bank\_city\_coethnic]}_{bc} + \\
& \phi_i \ + \ \lambda_{t,CoethnicCity} \ + \ \varepsilon_{itbc},
\end{aligned} \tag{4}
$$

The bank-coethnic $\times$ time fixed effects ($\lambda_{t,CoethnicCity}$) allow separate time shocks for branches in bank-coethnic and non bank-coethnic cities, so β_1 captures the effect of conflict in bank-coethnic cities alone. Throughout the results section, we report the p-value for $\beta_2 = 0$: the null that conflict exposure affects branches in bank-coethnic and non bank-coethnic cities equally.

4.1 Ethnic Conflict and Manager Ethnicity

Figure 2 showed that between 2018 and 2022, banks shifted from hiring managers coethnic with the bank to hiring managers coethnic with the city. To test whether this shift is driven by exposure to violent ethnic conflict through the bank's branch network, we estimate equation 3 using indicators for whether the manager is coethnic with the bank or with the city as outcomes.

We find that network-level exposure to ethnic conflict shifts banks toward hiring city- rather than bank-coethnic managers, but *only* when the bank's and city's dominant ethnicity differs. As shown in Table 2, branches in cities not coethnic with the bank become 9.2 percentage points (p.p.) more likely to hire a city-coethnic manager, a 50.3% increase over the 2018 mean of 18.3%, in response to a one-standard-deviation increase in ethnic conflict exposure through the bank's branch network. Correspondingly, these branches become 15.1 p.p. less likely to hire a bank-coethnic manager, a 19.6% drop from the 2018 mean of 77.2%. The additional specifications in Table 2 show that this result is robust to either adding city-time fixed effects or controlling for local conflict intensity. In contrast, for branches in cities coethnic with the bank we do not reject the null of no effect of exposure to ethnic conflict. Moreover, we find that the effect is significantly *different* between these cities and cities not coethnic with the bank.

We make several assumptions to construct our measure of conflict, including matching conflict to cities if they are within twenty kilometers from one another, weighting conflict by the number of fatalities, and including the state-owned bank and the more diverse capital city Addis Ababa in our main sample. To show these decisions are not driving our results, we do a number of robustness checks in Online Appendix D. We show, in Online Appendix Tables D.2, D.3, D.4 and D.5 that the results are also robust to respectively varying the conflict-matching radius (15 or

25 km), excluding the state-owned bank (CBE), and excluding Addis Ababa branches.[20] In Online Appendix D.3, we return to the main specification, but instead use an inverse hyperbolic sine transformation to show the results do not depend on the log transformation (Chen and Roth, 2024). Finally, we re-estimate our main specification in 3 dropping each individual ethnic group from the sample in Appendix Table D.1. Results are robust to this for branches in a city not coethnic with the bank, although the difference between bank-coethnic and non bank-coethnic cities is not significant when we drop all branches of Amhara banks, which constitute a significant share of our sample. The results are also robust to using a count of fatal events instead of the number of fatalities from each event to weight conflict.

4.2 Organizational adjustments to manager ethnicity

Banks thus shift to hiring city-coethnic branch managers in response to exposure to ethnic conflict. Based on our model, this suggests that the frictions in information acquisition, q, respond more strongly to conflict than the incentive cost, b. Two features of the banking environment may drive these relative magnitudes. First, banks' internal communication can reduce reliance on soft information, thus reducing the importance of misaligned incentives. Second, banks can use organizational adjustments to mitigate the incentive issues associated with employing city-coethnic managers, including – as in our model – by reducing delegation, or – beyond our model – by hiring managers with whom they have a longer-term relationship.

Our theoretical model implies that managers coethnic with the city they work in should get less autonomy to make lending decisions, and that an increase in the bias b should further reduce this autonomy. We measure delegation in our survey as the largest loan a branch manager can approve without the headquarters' approval. We test this model hypothesis as follows. First, we implement equation 3 using this delegation variable as the dependent variable. Next, to assess whether delegation differs systematically for branches with city-coethnic managers, we estimate:

$$\texttt{largest loan}_{itbc} = \beta_1 \, \texttt{city-coethnic manager}_{itb} + \gamma_i + \phi_t + \varepsilon_{itbc}, \tag{5}$$

using $\texttt{city-coethnic manager}_{itb}$ as the independent variable to test whether banks assign different levels of autonomy to managers of different ethnic groups.

Table 3 reports the results. Panel A shows that in non bank-coethnic cities, greater exposure to ethnic conflict reduces the size of the largest loan a branch manager can approve. In bank-coethnic cities, the estimated effect is similar in sign but statistically insignificant. Panel B in Table 3 shows that banks give less autonomy – lower loan-approval limits – to city-coethnic

[20] For the last robustness check, we still include Addis Ababa in our calculation of our measure of network-level conflict exposure.

managers, consistent with banks limiting the incentive costs of employing them. This effect is more pronounced in the second period, when conflict intensity is higher, suggesting that banks tighten delegation as the incentive risk grows.

The second organizational response concerns the type of managers banks select. Specifically, we ask whether they are reallocated within the bank or newly hired, and how their experience compares with other managers. Because conflict induces branches to appoint city-coethnic managers, understanding whether these managers are redeployed insiders or external hires speaks directly to whether the relevant mechanism to these changes in managers' ethnicity relates primarily to the alignment of incentives, to information acquisition or to safety concerns.

To study the source of new managers, we use the 2022 cross-section of our survey. We define four variables: *(i)* a dummy indicating whether the manager joined the bank after the outbreak of conflict (in 2021 or 2022); *(ii)* a dummy for whether the manager joined the branch after the outbreak of the conflict (in 2021 or 2022); *(iii)* a `reallocated manager` indicator equal to one if the manager joined the branch after but the bank before the outbreak of the conflict; and *(iv)* a `new manager` indicator equal to one if the manager joined both the branch and the bank after the outbreak of the conflict (and did not change branch since). We cannot identify promotion timing directly, since we only observe employment duration at the branch and bank, not the year of managerial appointment. We then estimate the following descriptive cross-sectional model:

$$Y_{ibc} = \alpha + \beta_1 \log(\texttt{NetworkExposure}_{ib}) + \varepsilon_{ibc}, \tag{6}$$

We cluster standard errors at the branch level. We find that, in non bank-coethnic cities, a one-SD increase in log conflict exposure is associated with an increase in the probability of employing a reallocated manager of about 6.3 percentage points (Table 4). In bank-coethnic cities, branches instead tend to hire managers who are entirely new to the bank. This pattern is consistent with a strategy in which banks limit potential lending bias by assigning non bank-coethnic managers with whom they already have a pre-existing institutional relationship.

Finally, we examine the characteristics of these managers. We construct a short manager profile including their tenure at the bank, tenure at the branch, age, education, and gender. Using our panel, we re-estimate specification 3 for each characteristic separately for bank-coethnic and non bank-coethnic cities. Table 5 shows that, in non bank-coethnic cities, conflict exposure is associated with appointing managers who have longer tenure at the bank but not at the branch, and who are older. We find no conflict-driven change in education – presumably as 98.7% of managers hold university degrees – and a small, insignificant change in gender composition.

Taken together, these results show that branches exposed to conflict through the bank's branch network shift to hiring city-coethnic managers, but take two steps to address the associated incentive costs: they reduce the lending authority delegated to these managers, and reassign experienced insiders with long-term institutional relationships rather than hiring externally. This pattern is difficult to reconcile with managers themselves demanding transfers to cities affiliated with their ethnic group, since banks would then have little reason to make these complementary adjustments. Instead, the results are consistent with banks actively managing the tradeoff between information acquisition and incentive alignment predicted by our model.

4.3 Branch-level lending activities

We next examine how network-level exposure to ethnic conflict affects branch-level lending and operations. Table 7 reports estimates from specification 3 for a range of outcomes related to credit supply and branch activities.

We begin with branches' operational radius, defined as the geographic area from which they attract customers. Branches in bank-coethnic cities experience a sizable contraction in this radius, whereas branches in non bank-coethnic cities expand their reach. One interpretation, consistent with classic work on soft versus hard information in lending (Petersen and Rajan, 2002; Agarwal and Hauswald, 2010), is that conflict exposure pushes branches in bank-coethnic cities toward more relationship-based screening within local networks, concentrating activity among nearby borrowers. By contrast, in non bank-coethnic cities, where branches increasingly appoint city-coethnic managers, lending may rely relatively more on harder, more verifiable information, which can support serving borrowers over a wider area.[21]

Turning to credit supply, branches in non bank-coethnic cities issue fewer but larger loans in response to conflict exposure. This pattern is consistent with credit being concentrated among a smaller set of safer or better-known borrowers, reducing reliance on soft information. In these branches, we do not detect meaningful changes in either lending rates or default rates, and a small decrease in the required collateral. In contrast, branches in bank-coethnic cities expand overall average loan size while also lowering default rates.

These lending patterns complement the organizational adjustments documented above. In non bank-coethnic cities, the shift toward city-coethnic managers appears to ease customer-facing inter-ethnic information frictions, but not completely: branches still reduce the lending on the extensive margin while concentrating credit among fewer borrowers. In bank-coethnic cities, where customer-facing inter-ethnic frictions are less central, we interpret these bank-wide adjustments as responses to a more volatile environment, rather than changes driven by the ethnicity of local customers.

[21] In the 2022 cross-section, city-coethnic managers report a larger operational radius than bank-coethnic managers in non bank-coethnic cities.

4.4 Exploring the mechanisms with Synthetic CEOs

Our model implies that the information-incentive trade-off, especially through delegation, is the central mechanism linking conflict to organizational adjustment. The reduced-form evidence is consistent with this, but cannot decompose the trade-off into its constituent channels. To do so, we run a vignette experiment with LLM-generated synthetic bank CEOs, varying (i) the ethnicity of the hypothetical branch manager and (ii) network-level conflict exposure. We use LLMs as synthetic economic agents (Horton, Filippas and Manning, 2023) to address two limitations of standard approaches. The mechanisms of interest, information acquisition and transmission, alignment with headquarters, and ethnic favoritism, are difficult to observe and measure directly. Relatedly, direct surveys of bank executives are poorly suited to eliciting sensitive beliefs about ethnicity. As Ludwig, Mullainathan and Rambachan (2025) note, LLMs can therefore be useful for structured mechanism exploration.[22]

Figure 5 summarizes the design; Appendix K provides full details. We construct vignettes from observed branch-year cells, each combining the bank's and city's ethnic affiliations, conflict exposure, and a GPT-5-generated summary of the bank's annual report (Bybee, 2025; Fernández-Fuertes, 2025). For each branch-year, we compare a city-coethnic and a bank-coethnic manager under low and high network conflict (10th and 90th percentiles), repeated for 2018 and 2022. We elicit the synthetic CEO's assessment of each manager along four dimensions: information acquisition, information transmission, coethnic favoritism, and safety concerns.[23] We then ask about their preferred organizational design (delegation, wages) and expected lending outcomes. We estimate LLM-implied conditional average treatment effects using the saturated specification:

$$y_{itv} = \beta_1 \,\text{CityCoethnic}_{itv} + \beta_2 \,\text{HighConflict}_{itv} + \beta_3 \left(\text{CityCoethnic}_{itv} \times \text{HighConflict}_{itv}\right) + \phi_i + \lambda_t + \varepsilon_{itv}, \tag{7}$$

where i indexes branches, t years, and v vignette evaluations. CityCoethnic is an indicator for the manager and city being coethnic and HighConflict an indicator for being assigned the high conflict condition.[24] ϕ_i and λ_t are branch and time fixed effects respectively.

Table 6 reports the results. City-coethnic managers are perceived as better at acquiring local information but worse at transmitting it to headquarters, more prone to coethnic favoritism, and have fewer safety concerns. These assessments translate into organizational choices: city-coethnic managers receive less delegation and lower wage premia, and are expected to generate higher

[22] Importantly, the version of GPT-5 used in this exercise has a training cutoff that predates the first public circulation of this paper, so the model's responses cannot reflect exposure to our specific framework, hypotheses, or results.

[23] On the latter, we specifically ask about safety concerns, since a manager who is not coethnic with the local population may require a higher wage to induce them to live and work in that city when ethnic conflict intensifies, raising the bank's cost of assigning them there.

[24] HighConflict is demeaned so that β_1 captures the average city-coethnic effect across conflict levels rather than the effect at low conflict only.

lending volumes but worse loan quality. Higher conflict exposure weakens information acquisition for bank-coethnic managers and information transmission for city-coethnic managers, while increasing favoritism and safety concerns for both. Conflict reduces delegation and lending for both manager types, with a larger lending decline for city-coethnic managers. The vignette evidence thus decomposes the model's central trade-off into specific channels and mirrors the main reduced-form patterns in the data.

A natural concern is domain mismatch: Ethiopian banking may differ from the contexts most represented in LLM training data (Sarstedt et al., 2024), so the magnitudes should be interpreted with caution. Nevertheless, the qualitative alignment between the vignette results, the model, and the reduced-form evidence suggests that our interpretation reflects general economic forces rather than Ethiopia-specific norms alone.

4.5 Robustness using exposure to Beta Israel Cities

Our `NetworkExposure` measure, combined with branch and time fixed effects, identifies the causal effect of conflict under two conditions. First, branches' network-level exposure to ethnic conflict is exogenous if both the spatial intensity of conflict was not predictable in 2018 and banks did not choose the locations of their branches in anticipation of future conflict. Second, although branch fixed effects absorb time-invariant branch characteristics, identification still requires that time-varying shocks to branch outcomes are either common across branches (captured by time fixed effects) or orthogonal to changes in network conflict exposure. In particular, the results should not be driven by differential local trends in the cities where highly exposed banks operate; we already test this assumption by controlling for local conflict and by including city-time fixed effects.

To validate our baseline results, we exploit predetermined variation in banks' exposure to areas around historically significant Beta Israel cities, which became disproportionately prone to ethnic conflict after the decline of Tigrayan influence in the federal government (Section 3). For each bank b, we compute the share of its branch network in 2018 located within 100 km of a Beta Israel city,

$$\texttt{share\_branch\_Beta\_100}_b = \frac{1}{N_b} \sum_{i \in \mathcal{I}_b} \mathbf{1}\{\texttt{dist}(i, \texttt{BetaIsrael}) \leq 100\,\text{km}\},$$

and construct a time-varying exposure measure

$$Z_{bt} = \texttt{share\_branch\_Beta\_100}_b \times \mathbf{1}\{t = 2022\}.$$

We rescaled this variable to the [0,1] interval using the 2022 maximum and minimum, so that coefficients describe the post-shock effect of moving from the lowest to the highest share of branches near Beta-Israel cities. We then report reduced-form estimates using Z_{bt} in place of $\log(\texttt{NetworkExposure}_{itb})$. Figure 3 describes the location of the Beta Israel cities and this exposure measure visually.[25]

This provides a useful validation exercise for several reasons. First, because it is based on banks' pre-conflict branch networks, the variation in Z_{bt} is predetermined with respect to the organizational changes we study. Second, the historical relevance of Beta Israel cities for the later Amhara–Tigray border dispute implies that this measure captures exposure to a historically specific component of ethnic conflict, rather than broad nationwide instability. Third, because this strategy relies on pre-2018 network geography, it helps address the concern that our baseline results might reflect endogenous changes in branch location or other contemporaneous bank responses to the conflict. We therefore interpret this exercise as providing an alternative source of variation with which to assess whether the main patterns in the data are robust.

Table 8 presents the results for managers' ethnicity, delegation and other manager characteristics. Consistent with our baseline estimates, we find no significant effects in bank–coethnic cities, except a decrease of managers in their tenure in the branch. In contrast, in non bank-coethnic cities, variation in the share of branches near Beta Israel cities leads to a marked decline in the probability of appointing a bank-coethnic manager and a corresponding rise in the probability of appointing a city-coethnic manager. These results reinforce our main finding that banks increasingly rely on locally coethnic managers when exposed to higher conflict risk. These estimates also qualitatively confirm the reduction in delegation, and that these managers tend to have longer tenure within the bank and are, on average, older.

Table 9 reports the corresponding results for branch-level lending. The pattern mirrors that in our baseline specification. In bank-coethnic cities, exposure to Beta Israel cities is associated with larger average loan sizes, higher collateral requirements, and lower default rates—consistent with a shift toward safer, collateral-backed lending. In non bank-coethnic cities, banks expand their operational radius and start providing larger loans. Although the total number of loans and lending rates are not significantly affected, the estimates suggest a contraction in lending intensity outside bank-coethnic markets.

5 Mechanism tests

In interpreting our empirical results, we have so far focused on the branch manager's role in the loan application process. However, branch managers perform multiple functions within the organization: they also supervise employees and attract customers to the branch. Moreover, ethnic

[25] We show results are robust to using a 50km radius instead in Appendix D.4.

conflict may directly affect a manager's preferences and reservation wage for living in cities with a different predominant ethnicity. We examine these three alternative channels in turn: (i) managers' own location preferences, (ii) customers' preferences for banks and managers that share their ethnicity, and (iii) frictions with local employees.

Managers' willingness to live in cities whose predominant ethnicity differs from their own could plausibly be affected by the intensity of ethnic conflict, whether due to local insecurity or a desire to return to one's hometown. If so, the changes in managerial composition we document would reflect individual relocation decisions rather than bank-level optimization. Ethiopian banks are highly hierarchical, and personnel assignments – including branch manager postings – are typically decided at headquarters with limited scope for voluntary transfers, making this interpretation less likely *a priori*. On the other hand, our measure of network-level exposure to conflict, though constructed to abstract from local conflict intensity, is positively correlated with it, making safety concerns a plausible concern.

We run several tests against this alternative. First, our main estimates (Table 2) remain robust to city–time fixed effects and direct controls for local conflict intensity. If fear of local conflict were the primary driver, these controls should substantially attenuate our coefficients; they do not. This implies that two branches operating in the same city – both non-coethnic with the local population – make different managerial choices because of their differential exposure to conflict involving their own ethnic group elsewhere in the network. Consistent with this, Appendix Table D.6 shows that neither the probability a manager is locally born nor the share of local employees increases with network-level conflict exposure — if anything, both decline, though the estimates are imprecise. If managers were relocating for personal safety, we would expect the opposite.

A sharper version of this concern is that conflict threatens managers of the bank's ethnicity specifically, so that city-level controls miss the relevant variation. We address this by controlling directly for local conflict involving the bank's own ethnic group (Table J.1). Our results are robust; if anything, higher local conflict involving the bank's ethnic group slightly increases the probability of appointing a bank-coethnic manager, the opposite of what personal security concerns would predict. A related worry is that network-level conflict heightens managers' perceived risk of being targeted, even absent local threats. But when we redefine exposure to include only events involving both the bank's and the city's ethnic groups (Figure J.1), we obtain smaller coefficients; the bank-coethnic coefficient becomes insignificant, and the city-coethnic coefficient is substantially attenuated (to roughly half its main-specification magnitude). If perceived ethnic targeting were the dominant mechanism, this measure should strengthen the relationship; instead it weakens it. Together, these tests suggest that the reallocation patterns we document reflect organizational decisions rather than individual responses to security concerns.

A second concern is that conflict erodes customers' trust in managers who do not share their ethnicity, shifting demand for credit and forcing banks to adjust staffing. If so, the effect should be strongest where customers have a salient outside option: a branch of a bank coethnic with the local population. We test this directly by interacting conflict exposure with the presence of a city-coethnic competitor bank. Table J.2 shows no significant difference. Results are similar when we instead measure competition by the number of branches in the city or by managers' perceived number of competitors in 2018.

If customer trust were the primary channel, banks facing competitors coethnic with the city should have the strongest incentive to adjust their staffing in response to conflict. The absence of such heterogeneity suggests that the changes we document were driven by internal organizational considerations rather than shifts in customer demand.

Finally, branch managers do not only communicate with headquarters — they also supervise local employees. Conflict may therefore affect not only upward communication but also the manager's ability to motivate and coordinate subordinates. Li et al. (2025) formalize a version of this idea: in a three-layer hierarchy, a middle manager must be trusted by both the principal above and the agents below. A manager too aligned with the top does not motivate workers to exert effort; one too aligned with workers is discounted by headquarters. When conflict sharpens ethnic loyalties, a bank-coethnic manager may become too closely identified with headquarters, and a city-coethnic manager too closely identified with local staff. A manager coethnic with neither side may then be better positioned to sustain cooperation in both directions. If this channel were important, conflict should increase the probability that branches are run by managers coethnic with neither the bank nor the city, especially where the share of local employees is high.

We find some support for the first prediction. Table J.3 shows that a one-standard-deviation increase in conflict exposure raises the probability of appointing a neither-coethnic manager by about 5.9 percentage points, significant at the 1 percent level. However, Table J.4 shows that this effect is only slightly larger in branches with a higher baseline share of local employees, and the difference is statistically insignificant. These results suggest that the employee-supervision channel may complement our main mechanism, but is unlikely to be the dominant driver. If it were, the effect should concentrate in branches where manager-employee alignment matters most – those with many local staff. It does not. This mechanism would also not be predicted to result in the change in delegation we report.

6 Discussion

This paper shows that ethnic conflict changes not only market outcomes but also the internal organization of firms. Using new branch-level data from Ethiopian banks, we find that greater conflict exposure leads branches in non-coethnic cities to appoint managers who are coethnic with the city's predominant group, rather than coethnic with the bank, while simultaneously reducing the authority delegated to those managers and relying more on experienced insiders. The key implication is that firms are not passive in their response to shocks that intensify social divisions; they actively reorganize in order to keep operating across group lines.

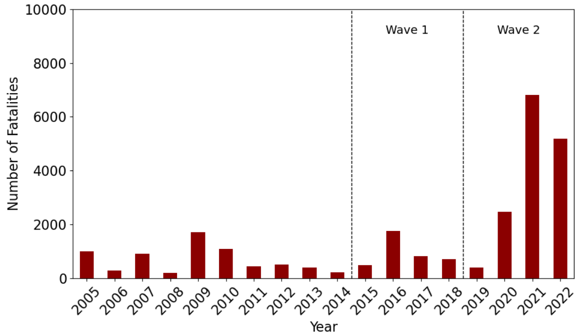
Our results speak to a central question in organizational economics: how firms trade off local knowledge against incentive alignment (Aghion and Tirole, 1997; Dessein, 2002; Alonso, Dessein and Matouschek, 2008). In our setting, conflict raises the value of managers who can acquire soft information from local borrowers, but also sharpens the risk of biased lending and distorted communication with headquarters. Banks respond on both margins at once. They do not choose between local adaptation and central oversight; rather, they appoint managers better able to acquire local information while simultaneously tightening the control exercised by headquarters. This joint adjustment is difficult to reconcile with explanations in which managers relocate voluntarily or customers drive the change, since banks would then have little reason to simultaneously tighten delegation and reassign insiders.

More broadly, the findings suggest that identity divisions can reshape the production of information inside organizations. A growing literature studies how ethnicity, culture, or political affiliation affect lending and other economic interactions (Hjort, 2014; Fisman et al., 2020; Frame et al., 2025; D'Acunto, Ghosh and Rossi, 2026; Eichengreen and Saka, 2025). Our evidence highlights a distinct mechanism: social divisions affect who can acquire information, how credibly that information can be transmitted, and how authority should be allocated between headquarters and the branch. In that sense, firms do not only passively suffer the effects of conflict, for example due to discrimination, but also actively manage it through their internal organization.

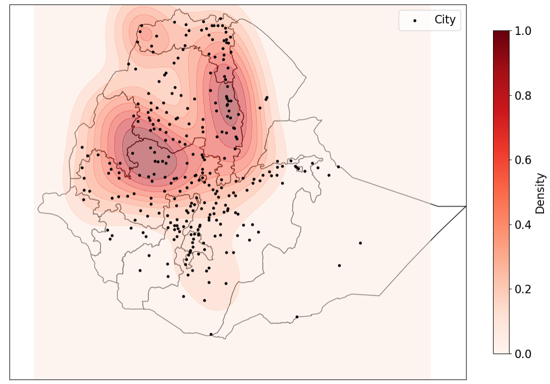
The Ethiopian banking sector provides a particularly sharp environment in which to study this mechanism, but the logic extends beyond this context. Many firms operate across salient identity boundaries, whether ethnic, linguistic, religious, or political. Whenever customer-facing information is locally embedded but organizations remain centrally governed, shocks that intensify identity salience can make local matching more valuable and delegation more costly. Our results therefore suggest a broader principle: firms may respond to polarization not by retreating from diverse markets, but by redesigning authority, monitoring, and personnel assignment to continue operating across group lines.

At the same time, our findings point to an important limit of adaptation. The organizational changes we document appear to help sustain lending activity without clear deterioration in observed loan performance, but they are not costless. Tighter control can slow decision-making, reduce initiative (Aghion and Tirole, 1997), and require greater reliance on internal labor markets. More generally, the need to offset social frictions with additional oversight implies that polarization is costly even when firms successfully adjust. Understanding those longer-run costs, and whether similar responses arise in other sectors and political settings, is an important direction for future work.

Figure 1: Ethnic conflict over time and space



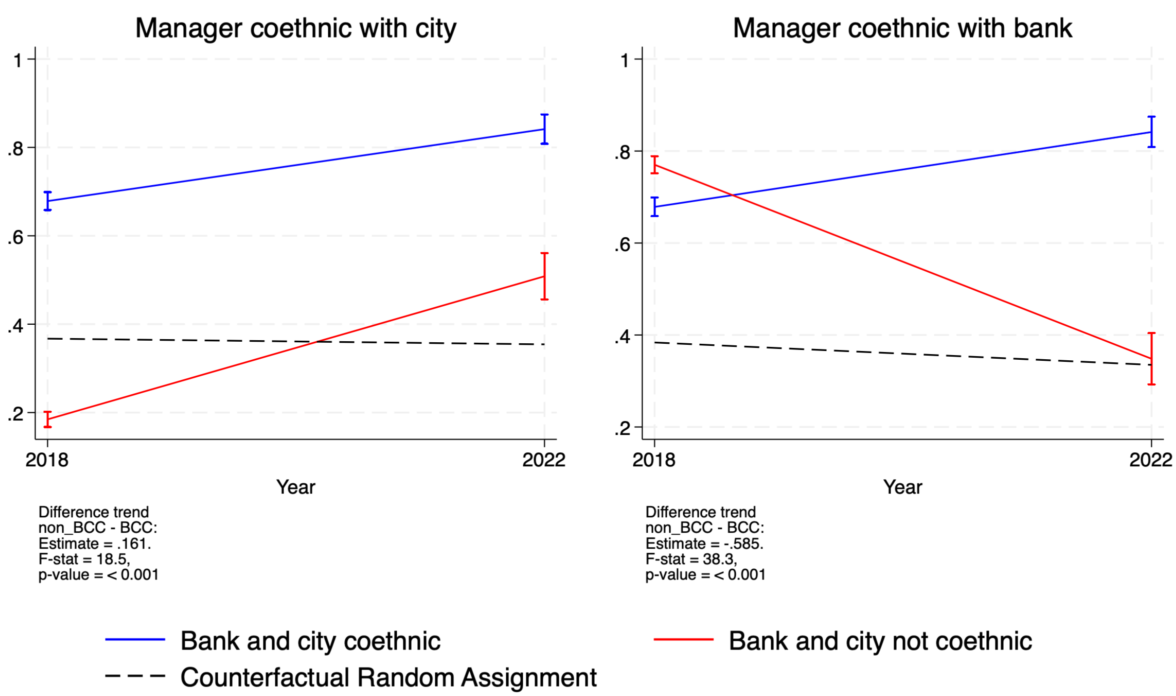
(a) Conflict over time



(b) Conflict over space

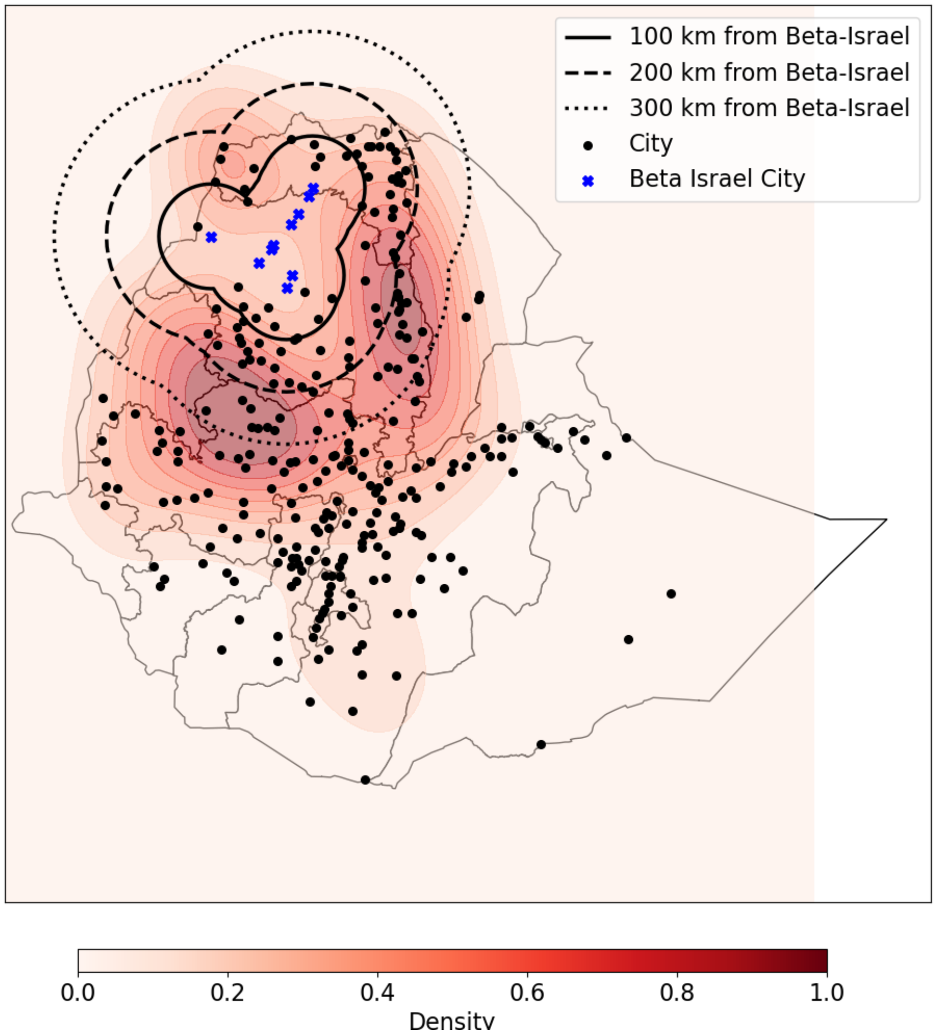
Notes: Panel A displays the number of fatalities from ethnic conflict in Ethiopia over time. The y-axis includes all fatalities from conflict involving at least one ethnic group in the ACLED database; this panel uses all events in ACLED. Panel B displays the lethality-weighted spatial intensity of ethnic conflict in Ethiopia from January 1, 2019 through December 31, 2022. Shaded areas are a kernel-density estimate of events weighted by fatalities and scaled to the colorbar. Black lines denote regional boundaries; black dots mark major cities.

Figure 2: Changes in organizational structure over time



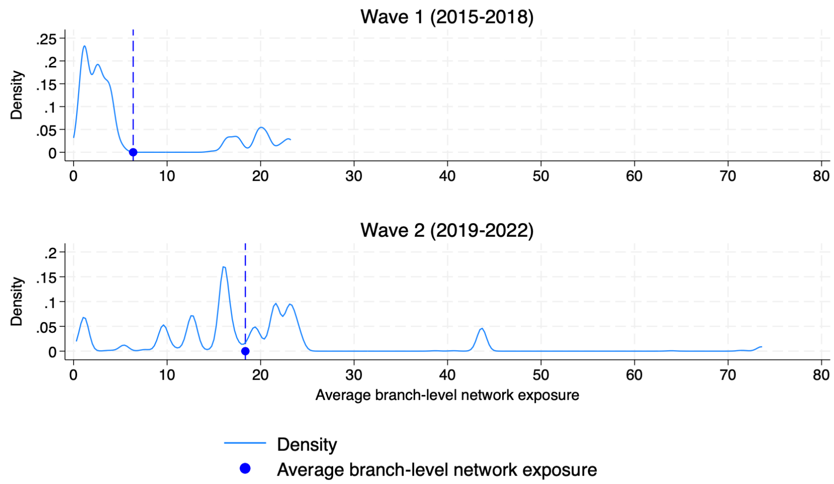
Notes: This figure presents the changes in organizational structure over time for two main outcome variables: An indicator for the manager and the bank being coethnic and an indicator for the manager and city being coethnic. These figures present the changes in unconditional means for these outcomes, separately for branches operating in cities coethnic with the bank (bank-coethnic city) and for branches operating in cities not coethnic with the bank (non bank-coethnic city.) Finally, for the coethnicity variables we report the expected share of coethnic managers if the same sample of managers in terms of ethnic composition were to be randomly assigned to bank branches. We conduct this exercise 1,000 times and report the average of these simulations.

Figure 3: Beta Israel Cities and Conflict



Notes: This figure displays the distribution of conflict events and the locations of Beta Israel cities in Ethiopia. Beta Israel cities are marked in red, while other cities are marked in black. The contours indicate distances of 100 km, 200 km, and 300 km from the nearest Beta Israel city, with the 100 km contour represented by a solid black line, the 200 km contour by a dashed black line, and the 300 km contour by a dotted black line. The density plot shows the weighted distribution of fatalities from ethnic conflict between 2015 and 2022, with darker regions representing higher densities. The map uses the Web Mercator projection (EPSG:3857) for accurate distance calculations.

Figure 4: Distribution of bank-level conflict exposure over time



Notes: This figure displays the distribution of the variable `NetworkExposure` from Equation 1 for two periods: 2015–2018 (top panel) and 2019–2022 (bottom panel). Each panel shows a kernel density (Gaussian, bandwidth 0.5) of `NetworkExposure` across our sample of branches, along with the mean value of `NetworkExposure` for that period.

Table 1: Summary statistics of analysis variables

	N	Mean	Std. Dev.	Min	Max
Panel A: Manager characteristics					
Bank coethnic manager	1,948	0.65	0.48	0	1
City coethnic manager	1,948	0.53	0.50	0	1
Manager born in region	1,432	0.42	0.49	0	1
Tenure in bank (years)	1,944	7.70	4.41	0	36
Tenure in branch (years)	1,943	2.68	2.62	0	35
Age	1,886	33.99	5.65	16	60
University degree	1,946	0.99	0.07	0	1
Male manager	1,946	0.83	0.37	0	1
Panel B: Branch characteristics					
Share local employees	1,910	0.57	0.25	0.10	1.00
Branch employees	1,941	17.56	10.04	3	110
Panel C: Lending outcomes					
Operational distance (km)	1,692	6.80	4.86	0.05	50.00
Log number of loans	1,503	2.43	1.34	0.00	8.52
Log average loan size	1,497	6.30	3.14	-4.61	10.95
Average lending rate	1,630	0.15	0.02	0.10	0.20
Collateral (share of loan)	1,441	0.95	0.19	0.50	1.50
Share loan default	1,569	0.06	0.14	0.00	1.00

Notes: This table reports summary statistics for the main analysis variables based on the branch survey, organised into three panels. Panel A: Manager Characteristics. Bank-coethnic manager and city-coethnic manager indicate whether the manager shares the ethnicity of the bank or city, respectively. Manager born in region indicates whether the manager was born in the same region as the branch. Tenure in bank and branch are measured in years. University degree and male manager are dummy indicators. Panel B: Branch Characteristics. Share local employees is the share of branch employees from the local area. Branch employees is the number of employees in the branch. Panel C: Lending. Operational distance is the maximum distance (in km) at which a branch services customers. Log number of loans and log average loan size are in natural logarithms, with loan size expressed in ETB 1,000. Average lending rate is the mean rate on the past 10 loans. Collateral is the typical collateral as a share of total loan size. Share loan default is the share of defaulting loans in the past year.

Table 2: Branch manager ethnicity

	Panel A: Branches in Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-0.003	0.023	-0.004	-0.003	0.023	-0.004
	(0.025)	(0.056)	(0.025)	(0.025)	(0.056)	(0.025)
Local Exposure			0.012			0.012
			(0.008)			(0.008)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.679	0.679	0.679	0.679	0.679	0.679
N (Branches)	443	368	443	443	368	443

	Panel B: Branches in Non-Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
Network Exposure	0.067***	0.043**	0.070***	-0.110***	-0.091***	-0.117***
	(0.016)	(0.018)	(0.016)	(0.015)	(0.018)	(0.016)
Local Exposure			-0.017*			0.037***
			(0.009)			(0.010)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.183	0.183	0.183	0.772	0.772	0.772
p-value	0.018	0.729	0.013	0.000	0.053	0.000
N (Branches)	531	464	531	531	464	531

Notes: The dependent variable is an indicator that equals 1 when a branch's manager is co-ethnic with the ethnic group associated with the city (columns 1–3) or with the ethnic group associated with the branch's bank (columns 4-6). Network exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log network exposure from 2018 to 2022 is 1.423 (1.371). Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on network exposure is identical in bank-coethnic and non bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3: Delegation

	Panel A: Ethnic conflict and delegation					
	Bank and city not coethnic			Bank and city coethnic		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-1037.2***	-691.4*	-1037.4***	-407.0	-1216.6	-402.2
	(288.5)	(355.9)	(290.2)	(410.9)	(862.7)	(412.1)
Local Exposure			1.1			-408.8**
			(134.1)			(173.8)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	1681.7	1681.7	1681.7	1672.7	1672.7	1672.7
p-value	0.210	0.572	0.208	0.210	0.572	0.208
N (Branches)	531	266	531	443	158	443

	Panel B: Manager ethnicity and delegation					
	Panel		Period 1 Only		Period 2 Only	
	(1) Non-coethnic b/se	(2) Coethnic b/se	(3) Non-coethnic b/se	(4) Coethnic b/se	(5) Non-coethnic b/se	(6) Coethnic b/se
City coethnic manager	-1518.3**	-3128.0***	-58.4	-310.7*	-2624.0***	-4487.4**
	(751.9)	(1012.0)	(177.7)	(172.5)	(939.4)	(1743.9)
Branch FE	Yes	Yes	No	No	No	No
Time FE	Yes	Yes	No	No	No	No
Constant	No	No	Yes	Yes	Yes	Yes
2018 Mean dep. var	1681.7	1672.7	1681.7	1672.7	7369.1	8195.2
p-value	0.202	0.202	0.309	0.309	0.347	0.347
N (Branches)	531	443	531	443	322	228

Notes The dependent variable in both panels is the largest loan a branch manager can approve without headquarters' agreement, measured in ETB 1,000. All 2022 nominal values are deflated to 2018 prices using annual CPI inflation rates from the World Bank World Development Indicators (indicator FP.CPI.TOTL.ZG). The dependent variable is winsorized at the 95th percentile within period x bank-city coethnicity cells. Panel A estimates equation 3 separately for branches where the bank and city are not coethnic (columns 1-3) and where they are coethnic (columns 4-6). Network exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local exposure is the log of conflict intensity near the city as defined in equation 2. Panel B estimates equation 5. City coethnic manager is an indicator equal to one when the branch manager shares the ethnicity of the city. Odd columns restrict to branches where the bank and city are not coethnic; even columns to coethnic branches. Columns 1-2 use the full panel with branch and time fixed effects; columns 3-4 use the 2018 cross-section only; columns 5-6 use the 2022 cross-section only. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value tests whether the coefficient on the main regressor differs across the two subsamples based on equation 4 (Panel A) or the analogous interaction specification (Panel B). Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4: Manager reallocation

Panel A: Branches in Bank-Coethnic Cities				
	New manager bank	New manager branch	Reallocated employee	New hire
	(1)	(2)	(3)	(4)
Network Exposure	0.018**	-0.011	-0.024	0.013
	(0.009)	(0.036)	(0.036)	(0.008)
Mean dep. var	0.034	0.395	0.367	0.027
N (Branches)	442	441	441	441

Panel B: Branches in Non-Bank-Coethnic Cities				
	New manager bank	New manager branch	Reallocated employee	New hire
	(1)	(2)	(3)	(4)
Network Exposure	-0.008	0.037*	0.046**	-0.008
	(0.006)	(0.019)	(0.019)	(0.006)
Mean dep. var	0.017	0.362	0.347	0.015
p-value	0.015	0.652	0.092	0.038
N (Branches)	528	528	528	528

Notes: This table uses only data collected in 2022. The four outcome variables are (1) an indicator whether the manager joined the bank in 2021 or 2022 (after the outbreak of conflict in November 2020), (2) whether the manager joined the branch in 2021 or 2022, and whether conditional on joining the branch in 2021 or 2022 they were (3) reallocated from a different branch of the same bank or (4) joined the bank as a new employee in 2021 or 2022 (and did not change branch since). Network exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5: Manager characteristics

	Panel A: Branches in Bank-Coethnic Cities				
	Tenure in bank	Tenure in branch	Age of manager	University degree	Male manager
	(1)	(2)	(3)	(4)	(5)
Network Exposure	-0.219	-0.342***	0.075	-0.001	0.028
	(0.239)	(0.127)	(0.327)	(0.003)	(0.024)
Branch FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	6.801	2.393	33.867	0.993	0.867
N	443	443	443	443	443

	Panel B: Branches in Non-Bank-Coethnic Cities				
	Tenure in bank	Tenure in branch	Age of manager	University degree	Male manager
Network Exposure	0.418***	0.122	0.846***	0.000	0.014
	(0.157)	(0.105)	(0.217)	(0.002)	(0.015)
Branch FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	6.853	2.362	33.533	0.987	0.864
p-value	0.019	0.001	0.073	0.932	0.236
N	531	531	531	531	531

Notes: This table focuses on five outcome variables (1) the manager's tenure at the bank in years, (2) the manager's tenure at the branch in years, (3) the age of the manager in years, (4) whether the manager has a university degree (BA or MA), and (5) whether the manager is male. Network exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log bank conflict intensity from 2018 to 2022 is 1.423 (1.371). Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the t-test that the parameter estimates for branches in bank-coethnic cities (Panel A) and in non bank-coethnic cities are the same. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 6: Synthetic CEO Expectations of Effects of Conflict

Panel A: The effect of conflict on mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEO Assessments				Mechanism Weights			
	Info Acq.	Info Comm.	Ethnic Bias	Safety Concern	Info	Align	Safety	Other
City-coethnic	54.52***	-22.83***	39.88***	-27.80***	12.47***	-7.01***	-9.19***	3.73***
	(0.35)	(0.47)	(0.68)	(0.81)	(0.31)	(0.33)	(0.30)	(0.24)
High conflict	-4.61***	-1.34***	5.63***	30.68***	-4.52***	-3.18***	9.11***	-1.41***
	(0.43)	(0.39)	(1.04)	(0.93)	(0.44)	(0.44)	(0.49)	(0.28)
High conflict ×	3.91***	-2.75***	-3.50***	-8.45***	1.37**	3.26***	-3.51***	-1.12***
City-coethnic	(0.54)	(0.87)	(1.08)	(1.47)	(0.63)	(0.58)	(0.57)	(0.42)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	58.04	69.28	51.49	44.49	34.77	37.43	18.45	9.35
Observations	742	742	742	742	742	742	742	742
R^2	0.985	0.823	0.884	0.822	0.748	0.525	0.721	0.389

Panel B: The effect of conflict on outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcomes				Lending (%)		NPL (%)	
	Deleg.	Wage Prem.	Exp. NPL	Lend Vol.	City-Coeth.	Bank-Coeth.	City-Coeth.	Bank-Coeth.
City-coethnic	-158.29***	-25.73***	0.77***	44.30***	1.26***	-5.12***	1.91***	-2.69***
	(30.28)	(0.50)	(0.12)	(1.83)	(0.46)	(0.42)	(0.16)	(0.25)
High conflict	-174.21***	9.50***	2.05***	-11.76***	-2.37***	1.97***	1.70***	3.74***
	(40.25)	(0.37)	(0.16)	(1.37)	(0.61)	(0.54)	(0.16)	(0.39)
High conflict ×	-2.03	-2.40***	0.39*	-14.67***	3.25***	-2.45***	1.19***	-2.63***
City-coethnic	(48.78)	(0.88)	(0.21)	(2.93)	(0.76)	(0.62)	(0.28)	(0.40)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	704.85	9.73	7.77	94.08	65.88	17.80	8.38	6.83
Observations	742	742	742	742	742	742	742	742
R^2	0.443	0.856	0.583	0.751	0.510	0.511	0.568	0.439

Notes: This table reports OLS estimates from an AI survey experiment in which a large language model (LLM) role-plays as a bank CEO evaluating hypothetical branch managers described in standardized vignettes. Each vignette varies (i) whether the manager is city-coethnic versus bank-coethnic and (ii) whether the branch is assigned high versus low conflict intensity. The specification includes indicators for City-coethnic, High conflict, and their interaction. City-coethnic equals one if the hypothetical manager's ethnicity matches the branch city's dominant ethnic group; bank-coethnic managers (ethnicity matching the bank headquarters' dominant ethnic group) are the omitted category. High conflict equals one for branches assigned conflict at the 90th percentile of the fatalities distribution; low conflict (10th percentile) is the omitted category. Panel A (Mechanisms). Columns (1)–(4) report LLM-elicited expectations on a 0–100 scale: Info Acq (ability to gather soft information about local borrowers), Info Comm (alignment of loan recommendations with headquarters' objectives), Ethnic Bias (likelihood of ethnic favoritism in lending), and Safety Concern (physical security risk). Columns (5)–(8) report the LLM's stated mechanism weights (shares in percentage points) assigned to Info, Align, Safety, and Other. Panel B (Outcomes). Columns (1)–(4) report: Deleg. (maximum loan size approvable without headquarters authorization; ETB thousands), Wage Prem. (percent), Exp. NPL (percent), and Lend Vol. (ETB millions). Columns (5)–(6) report expected lending to city-coethnic and bank-coethnic borrowers (percent). Columns (7)–(8) report expected NPLs for city-coethnic and bank-coethnic borrowers (percent). The sample is restricted to branches where the bank headquarters' dominant ethnicity differs from the branch city's dominant ethnicity. All specifications include branch fixed effects and year fixed effects (as reported in the table). Standard errors clustered at the branch level are in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

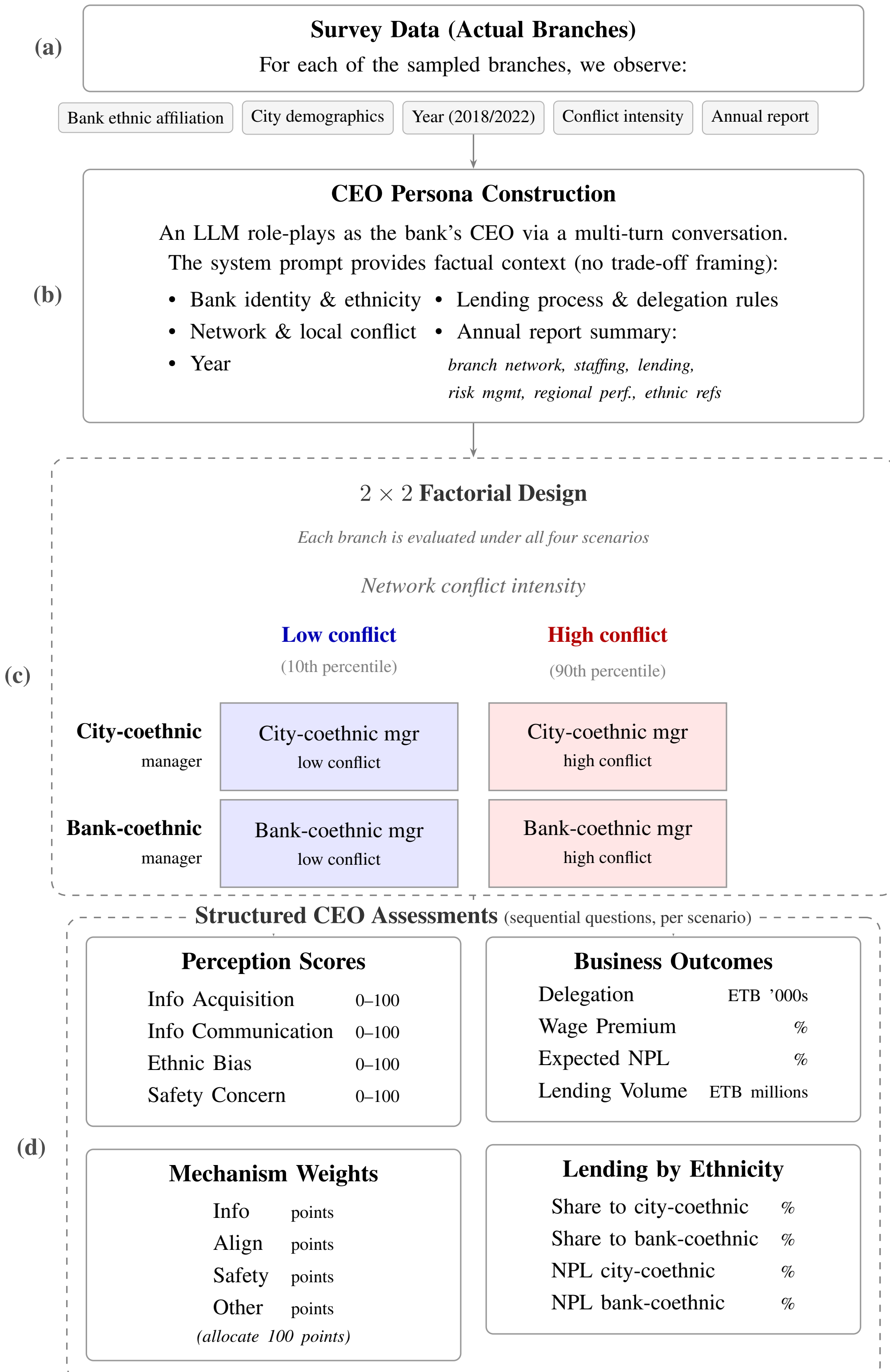
Table 7: Branch-level lending

Panel A: Bank-City Coethnic						
	Operational distance	Log number of loans	Log average loan size	Average lending rate	Collateral percentage	Share loan default
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-1.517***	0.082	0.847***	0.002*	0.022	-0.030**
	(0.511)	(0.096)	(0.262)	(0.001)	(0.014)	(0.013)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.756	2.185	6.056	0.146	1.009	0.050
N	306	221	219	289	199	270

Panel B: Not Bank-City Coethnic						
	Operational distance	Log number of loans	Log average loan size	Average lending rate	Collateral percentage	Share loan default
Network Exposure	0.686***	-0.212***	0.493***	0.001	-0.015*	-0.002
	(0.188)	(0.053)	(0.138)	(0.001)	(0.008)	(0.007)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.514	1.934	6.040	0.148	0.998	0.046
p-value	0.000	0.099	0.037	0.182	0.003	0.049
N	412	308	304	367	268	325

Notes: The dependent variables are the operational distance of the branch, i.e. how far away from the branch it serves customers, the log of the number of loans the branch has outstanding, the log of the average size of outstanding loans, the lending rate on a typical loan, the percentage of collateral on a typical loan and the share of loans that default. Network exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. The mean (SD) of the within-branch change in log bank conflict intensity from 2018 to 2022 is 1.423 (1.371). Panel A restricts the sample to branches in coethnic cities, while Panel B focuses on branches in non-coethnic cities. The regressions include branch and time fixed effects. Standard errors, clustered at the branch level, are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Figure 5: AI survey experiment design.



Notes: We generate a synthetic bank-CEO which we ask to evaluate hypothetical managers under a 2×2 factorial design varying manager ethnicity (city-coethnic vs. bank-coethnic) and conflict intensity (10th vs. 90th percentile). For each scenario, the CEO provides structured assessments across eight outcome dimensions (panel d, top), mechanism weights, and expected lending patterns by customer ethnicity (panel d, bottom).

Table 8: Beta Israel variation and branch managers

	Panel A: Bank-City Coethnic					
	(1) City coethnic	(2) Bank coethnic	(3) Delegation	(4) Tenure Bank	(5) Tenure Branch	(6) Age
Beta Israel Exposure	0.050	0.050	-0.943	-1.250	-1.156***	-1.182
	(0.094)	(0.094)	(2.040)	(0.932)	(0.433)	(1.263)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.679	0.679	1.673	6.801	2.393	33.867
N	443	443	443	443	443	443

	Panel B: Not Bank-City Coethnic					
	City coethnic	Bank coethnic	Delegation	Tenure Bank	Tenure Branch	Age
Beta Israel Exposure	0.349***	-0.537***	-7.027***	0.991	0.035	4.917***
	(0.107)	(0.113)	(1.796)	(0.976)	(0.719)	(1.522)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.183	0.772	1.682	6.853	2.362	33.533
p-value	0.036	0.000	0.025	0.097	0.156	0.002
N	531	531	531	531	531	531

Notes: The dependent variables are an indicator that equals 1 when a branch's manager is co-ethnic with the ethnic group associated with the city (column 1), or the ethnic group associated with the branch's bank (columns 2). Delegation is the largest loan a branch manager can approve without headquarters' agreement, measured in millions of 2018 ETB, winsorized at the 95th percentile within period × bank-city coethnicity cells. Tenure Bank and Tenure Branch are how many years the manager has spent in the bank and branch respectively. Age is the age of the manager in years. Beta Israel Exposure is the share of branches within 100km of a historic Beta Israel city. Panel A restricts the sample to branches in bank-coethnic cities, while Panel B focuses on branches in non bank-coethnic cities. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the t-test that the parameter estimates for branches in bank-coethnic cities (Panel A) and in non bank-coethnic cities (Panel B) are the same. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 9: Beta Israel variation and lending

	Panel A: Bank-City Coethnic					
	(1) Oper. distance	(2) Num. loans	(3) Loan size	(4) Lending rate	(5) Collateral	(6) Default
Beta Israel Exposure	-3.933***	0.167	2.531***	0.002	0.225***	-0.129***
	(1.456)	(0.309)	(0.680)	(0.004)	(0.051)	(0.047)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.756	2.185	6.056	0.146	1.009	0.050
N	443	443	443	443	443	443

	Panel B: Not Bank-City Coethnic					
	Oper. distance	Num. loans	Loan size	Lending rate	Collateral	Default
Beta Israel Exposure	8.434***	-0.524	4.036***	0.007	-0.077	0.044
	(1.384)	(0.370)	(0.919)	(0.006)	(0.052)	(0.056)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.514	1.934	6.040	0.148	0.998	0.046
p-value	0.000	0.153	0.188	0.462	0.000	0.019
N	531	531	531	531	531	531

Notes: The dependent variables are the operational distance of the branch, i.e. how far away from the branch it serves customers, the log of the number of loans the branch has outstanding, the log of the average size of outstanding loans, the lending rate on a typical loan, the percentage of collateral on a typical loan and the share of loans that default. Beta Israel Exposure is the share of branches within 100km of a historic Beta Israel city. Panel A restricts the sample to branches in bank-coethnic cities, while Panel B focuses on branches in non bank-coethnic cities. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the t-test that the parameter estimates for branches in bank-coethnic cities (Panel A) and in non bank-coethnic cities (Panel B) are the same. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

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Banking under Conflict:
Managers and Organizational Design

Appendix for online publication

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Contents

A Appendix: Model and Proofs

This appendix presents and develops the formal model underlying Proposition 1 and provides the main derivations and proofs. Appendix B develops the microfoundations for the weighted loss function, the scaling of information precision with loan size, and the strategic-communication distortion term adopted throughout this appendix.

A.1 Formal setup

Players. There is a headquarters (HQ, the principal) and a branch manager (the agent). HQ chooses the manager type and, after observing the size of the loan opportunity, the allocation of authority over the lending decision.

Loan opportunities and stakes. A loan opportunity is characterized by a size $L \in [0, \bar{L}]$, drawn from a distribution F. The underlying state is $\theta \in \mathbb{R}$, which determines the first-best per-unit lending terms. The bank ultimately implements an action $y \in \mathbb{R}$. HQ payoff is

$$U_P(L, y, \theta) = \bar{v}L - L^2(y - \theta)^2. \tag{a1}$$

Thus, mistakes in lending become more costly for larger loans.

Manager types (ethnic match). HQ appoints a manager type $i \in \{B, C\}$:

- Type B (*bank-coethnic*): aligned with HQ, so $b_B = 0$.
- Type C (*city-coethnic*): biased toward looser lending, so $b_C = b > 0$.

Manager preferences. Preference misalignment is represented by

$$U_M(L, y, \theta; i) = -L^2\big(y - (\theta + b_i)\big)^2,$$

so the manager's ideal action is shifted by b_i relative to HQ.

Information. After observing L, the manager observes a local assessment

$$\widehat{\theta}_i = \theta + \eta_i, \qquad \mathbb{E}[\eta_i \mid \theta] = 0, \qquad \mathrm{Var}(\eta_i \mid \theta) = \frac{1}{q_i L}.$$

We let $q_i > 0$ denote the precision of the manager's information. A higher q_i means a more informative local assessment. We assume

$$q_C > q_B,$$

so city-coethnic managers are better informed.

Authority regime. After appointing i and after L is realized, HQ chooses an authority regime $r \in \{d, c\}$:

- *Delegation* ($r = d$): the manager chooses y as a function of $(\widehat{\theta}_i, L)$.
- *Centralization* ($r = c$): the manager sends a cheap-talk message m as a function of $(\widehat{\theta}_i, L)$, and HQ chooses y as a function of (m, L).

Under centralization, misaligned preferences imply strategic communication. We summarize the resulting loss of informativeness with an additional term $\Delta(b_i) \geq 0$, with

$$\Delta(0) = 0, \qquad \Delta(\cdot) \text{ strictly increasing and weakly concave on } \mathbb{R}_+.$$

Timing. (i) HQ appoints $i \in \{B, C\}$. (ii) A loan opportunity arrives and L is realized. (iii) The manager observes $\widehat{\theta}_i$. (iv) HQ chooses $r \in \{d, c\}$. (v) If $r = d$, the manager chooses y; if $r = c$, the manager sends m and HQ chooses y.

Mean-squared error and expected payoff. For type i and regime r, define

$$\mathrm{MSE}_i^r(L) \equiv \mathbb{E}[(y - \theta)^2 \mid i, r, L].$$

Then expected HQ payoff conditional on (i, r, L) is

$$V_i^r(L) \equiv \mathbb{E}[U_P(L, y, \theta) \mid i, r, L] = \bar{v}L - L^2\,\mathrm{MSE}_i^r(L).$$

The Online Appendix shows that

$$\mathrm{MSE}_i^d(L) = \frac{1}{q_i L} + b_i^2, \qquad \mathrm{MSE}_i^c(L) = \frac{1}{L}\Big(\frac{1}{q_i} + \Delta_i\Big), \qquad \Delta_i \equiv \Delta(b_i). \tag{a2}$$

Substituting into the payoff expression gives

$$V_i^d(L) = \bar{v}L - \frac{L}{q_i} - b_i^2 L^2, \qquad V_i^c(L) = \bar{v}L - \frac{L}{q_i} - \Delta_i L. \tag{a3}$$

A.2 Authority allocation

Proof of Proposition 1(i). Fix a manager type i and loan size L. Using (a3),

$$V_i^d(L) - V_i^c(L) = \left(\bar{v}L - \frac{L}{q_i} - b_i^2 L^2\right) - \left(\bar{v}L - \frac{L}{q_i} - \Delta_i L\right).$$

The common terms cancel, so

$$V_i^d(L) - V_i^c(L) = \Delta_i L - b_i^2 L^2 = L(\Delta_i - b_i^2 L).$$

Therefore, for $L > 0$, delegation is optimal if and only if

$$\Delta_i - b_i^2 L \geq 0,$$

that is,

$$L \le \frac{\Delta_i}{b_i^2} \equiv L_i^\star.$$

Hence, if $b_i > 0$, HQ delegates for loans below the cutoff and centralizes for loans above it. If $b_i = 0$, then $\Delta_i = \Delta(0) = 0$, so (a3) implies

$$V_i^d(L) = V_i^c(L)$$

for all L. Thus, with an aligned manager, HQ is indifferent between delegation and centralization. □

Corollary 1 (Bias reduces the authority cutoff)**.** *Suppose* $\Delta(0) = 0$ *and* $\Delta(\cdot)$ *is strictly increasing and weakly concave on* $\mathbb{R}_+$*. Then*

$$L^\star(b) = \frac{\Delta(b)}{b^2}$$

is strictly decreasing for all $b > 0$*.*

Proof. Fix $0 < b_1 < b_2$. Since $\Delta(\cdot)$ is concave and $\Delta(0) = 0$, the ratio $\Delta(b)/b$ is weakly decreasing on $\mathbb{R}_+$, so

$$\frac{\Delta(b_2)}{b_2} \le \frac{\Delta(b_1)}{b_1}.$$

Dividing both sides by b_2 yields

$$\frac{\Delta(b_2)}{b_2^2} \le \frac{\Delta(b_1)}{b_1 b_2}.$$

Because $b_2 > b_1$ and $\Delta(b_1) > 0$ for $b_1 > 0$ (strict increase from $\Delta(0) = 0$), we have

$$\frac{\Delta(b_1)}{b_1 b_2} < \frac{\Delta(b_1)}{b_1^2}.$$

Hence

$$L^\star(b_2) = \frac{\Delta(b_2)}{b_2^2} < \frac{\Delta(b_1)}{b_1^2} = L^\star(b_1),$$

so $L^\star(b)$ is strictly decreasing. □

Remark 1. In (a3), the information term enters delegation and centralization symmetrically through the common component

$$\bar{v}L - \frac{L}{q_i}.$$

Hence the regime comparison depends only on the additional communication loss under centralization and the bias cost under delegation:

$$V_i^d(L) - V_i^c(L) = \Delta_i L - b_i^2 L^2.$$

As a result, changes in baseline information precision q_i affect managerial appointment but do not alter the authority cutoff conditional on manager type.

A.3 Appointment payoffs

Define the expected appointment payoff for type i as

$$\Pi_i(F;b) \equiv \mathbb{E}_F\big[\max\{V_i^d(L), V_i^c(L)\}\big].$$

Type B. Since $b_B = 0$ and $\Delta_B = \Delta(0) = 0$,

$$V_B^d(L) = V_B^c(L) = \bar{v}L - \frac{L}{q_B}.$$

Hence

$$\Pi_B(F) = \left(\bar{v} - \frac{1}{q_B}\right)\mu_1, \qquad \mu_1 \equiv \mathbb{E}[L]. \tag{a4}$$

Type C. Let $\Delta_C(b) \equiv \Delta(b)$ and define

$$L_C^\star(b) \equiv \frac{\Delta_C(b)}{b^2}, \qquad \widehat{L}_C(b) \equiv \min\{L_C^\star(b), \bar{L}\}.$$

Then delegation is optimal for $L \le \widehat{L}_C(b)$ and centralization for $L > \widehat{L}_C(b)$.
Define the following truncated moments:

$$M_1(x) \equiv \mathbb{E}[L\,\mathbb{1}\{L \le x\}], \qquad M_2(x) \equiv \mathbb{E}[L^2\,\mathbb{1}\{L \le x\}].$$

Then

$$\Pi_C(F;b) = \left(\bar{v} - \frac{1}{q_C} - \Delta_C(b)\right)\mu_1 + \Delta_C(b)\,M_1(\widehat{L}_C(b)) - b^2\,M_2(\widehat{L}_C(b)). \tag{a5}$$

A.4 Proof of Proposition 1(ii): unique appointment cutoff

Proof. Define $\Phi(b) \equiv \Pi_C(F;b) - \Pi_B(F)$ for $b \ge 0$. We show: (1) $\Phi(b) > 0$ for sufficiently small b; (2) $\lim_{b\to\infty}\Phi(b) < 0$ under the stated condition; and (3) Φ is strictly decreasing on $(0,\infty)$. These steps imply a unique cutoff $b^\star(F)$ by continuity and the intermediate value theorem.

Step 1: Small-bias limit. Fix $L \in [0, \bar{L}]$. From (a3) for type C,

$$V_C^d(L;b) = \left(\bar{v} - \frac{1}{q_C}\right)L - b^2L^2, \qquad V_C^c(L;b) = \left(\bar{v} - \frac{1}{q_C} - \Delta_C(b)\right)L.$$

By continuity and $\Delta_C(0) = 0$, as $b \to 0$ both $b^2L^2 \to 0$ and $\Delta_C(b) \to 0$, so pointwise

$$\max\{V_C^d(L;b), V_C^c(L;b)\} \to \left(\bar{v} - \frac{1}{q_C}\right)L.$$

Since L is bounded, dominated convergence applies and yields

$$\lim_{b\to 0}\Pi_C(F;b) = \left(\bar{v} - \frac{1}{q_C}\right)\mu_1.$$

Because $q_C > q_B$, we have $(\bar{v} - \frac{1}{q_C})\mu_1 > (\bar{v} - \frac{1}{q_B})\mu_1 = \Pi_B(F)$, hence $\lim_{b\to 0}\Phi(b) > 0$.

Step 2: Large-bias limit. Assume $\Delta_\infty \equiv \lim_{b\to\infty} \Delta_C(b)$ exists and is finite. Because $\widehat{L}_C(b) = \min\{\Delta_C(b)/b^2, \bar{L}\}$ and $\Delta_C(b)$ is bounded while $b^2 \to \infty$, we have $\widehat{L}_C(b) \to 0$ as $b \to \infty$. Therefore $M_1(\widehat{L}_C(b)) \to 0$ and $M_2(\widehat{L}_C(b)) \to 0$ by dominated convergence. Taking limits in (a5) gives

$$\lim_{b\to\infty} \Pi_C(F; b) = (\bar{v} - \frac{1}{q_C} - \Delta_\infty)\mu_1.$$

Subtracting (a4) yields

$$\lim_{b\to\infty} \Phi(b) = \Big(\frac{1}{q_B} - \frac{1}{q_C} - \Delta_\infty\Big)\mu_1 < 0$$

under the condition $\Delta_\infty > \frac{1}{q_B} - \frac{1}{q_C}$ and whenever $\mu_1 > 0$ (i.e. $\Pr(L > 0) > 0$).

Step 3: Strict monotonicity of Φ. Fix $0 < b_1 < b_2$. For any $L > 0$, $V_C^d(L; b) = (\bar{v} - \frac{1}{q_C})L - b^2L^2$ is strictly decreasing in b. Also $V_C^c(L; b) = (\bar{v} - \frac{1}{q_C} - \Delta_C(b))L$ is decreasing in b because $\Delta_C(b)$ is increasing. Therefore, for every $L > 0$,

$$\max\{V_C^d(L; b_2), V_C^c(L; b_2)\} < \max\{V_C^d(L; b_1), V_C^c(L; b_1)\}.$$

Taking expectations over F preserves strict inequality whenever $\Pr(L > 0) > 0$. Hence $\Pi_C(F; b)$ is strictly decreasing in b on $(0, \infty)$. Because $\Pi_B(F)$ does not depend on b, Φ is strictly decreasing.

Step 4: Existence and uniqueness. By Steps 1–3, Φ is continuous and strictly decreasing on $(0, \infty)$ with $\lim_{b\to0} \Phi(b) > 0$ and $\lim_{b\to\infty} \Phi(b) < 0$. Hence there exists a unique $b^\star(F) > 0$ such that $\Phi(b^\star(F)) = 0$, and $\Phi(b) \geq 0$ iff $b \leq b^\star(F)$. □

A.5 Extension: conflict-dependent reservation wages

Suppose appointing manager type $i \in \{B, C\}$ entails an additive posting cost $w_i(\gamma) \geq 0$, where γ indexes conflict intensity. Interpret $w_i(\gamma)$ as the compensation premium required for the manager to accept the posting. We allow conflict to affect these costs asymmetrically, and in particular to raise the relative posting cost of bank-coethnic managers, so that $w_B(\gamma) - w_C(\gamma)$ may increase with γ.
The net payoff from appointing type i is

$$\widetilde{\Pi}_i(F; b, \gamma) \equiv \Pi_i(F; b) - w_i(\gamma).$$

Equivalently, define

$$\widetilde{\Phi}(b, \gamma) \equiv \widetilde{\Pi}_C(F; b, \gamma) - \widetilde{\Pi}_B(F; b, \gamma) = \Phi(b) - \big(w_C(\gamma) - w_B(\gamma)\big).$$

Because posting costs enter additively at the appointment stage, they do not affect authority allocation conditional on manager type. Hence the authority cutoff

$$L_C^\star(b) = \frac{\Delta_C(b)}{b^2}$$

is unchanged.
By contrast, an increase in the relative posting cost of bank-coethnic managers,

$$w_B(\gamma) - w_C(\gamma),$$

raises the net attractiveness of city-coethnic appointment. This gives a simple safety channel through which conflict affects the optimal appointment of managers.

B Microfoundations Theory

This appendix provides the microfoundations for the reduced-form objects used in the main text and Appendix A. It shows: (i) why HQ payoff takes the weighted quadratic-loss form, (ii) why the manager's local-assessment variance scales as $1/(q_i L)$, and (iii) how strategic communication under centralization gives rise to the distortion term $\Delta(b_i)$.

B.1 Microfoundation of HQ's quadratic loss

The economically relevant choice is the dollar risk-load $Y \equiv yL$ rather than the per-unit stance y. The first-best dollar allocation is $Y^\star(\theta) = \theta L$.
Thus the relevant mistake is the dollar misallocation

$$\Delta Y \equiv Y - Y^\star(\theta) = L(y - \theta).$$

Assume HQ has quadratic loss in dollar misallocation:

$$U_P(L, y, \theta) = \bar{v}L - \kappa(\Delta Y)^2.$$

Substituting $\Delta Y = L(y - \theta)$ gives

$$U_P(L, y, \theta) = \bar{v}L - \kappa L^2(y - \theta)^2.$$

Normalizing $\kappa = 1$ yields the payoff used in the model:

$$U_P(L, y, \theta) = \bar{v}L - L^2(y - \theta)^2.$$

Lemma 1 (Local quadratic approximation)**.** *Suppose total surplus can be written as*

$$\Pi(L, Y, \theta) = \bar{v}L + S(L, Y, \theta),$$

where for each (L, θ) the function $Y \mapsto S(L, Y, \theta)$ is twice continuously differentiable and maximized at

$$Y^\star(\theta) = \theta L.$$

Then, locally around $Y^\star(\theta)$,

$$\Pi(L, Y, \theta) = \bar{v}L - \kappa(L, \theta)\big(Y - Y^\star(\theta)\big)^2 + r(L, Y, \theta),$$

where $\kappa(L, \theta) > 0$ and the remainder term is of smaller order than $(Y - Y^\star(\theta))^2$.

Proof. Fix (L, θ). Apply Taylor's theorem to the function $Y \mapsto S(L, Y, \theta)$ around the point $Y^\star(\theta)$:

$$S(L,Y,\theta) = S(L,Y^\star(\theta),\theta)+S_Y(L,Y^\star(\theta),\theta)\big(Y-Y^\star(\theta)\big)+\frac{1}{2}S_{YY}(L,Y^\star(\theta),\theta)\big(Y-Y^\star(\theta)\big)^2+r(L,Y,\theta).$$

Because $Y^\star(\theta)$ is a maximizer, the first derivative is zero:

$$S_Y(L, Y^\star(\theta), \theta) = 0.$$

Because it is a local maximum, the second derivative is negative:

$$S_{YY}(L, Y^\star(\theta), \theta) < 0.$$

Define

$$\kappa(L,\theta) \equiv -\frac{1}{2}S_{YY}(L, Y^\star(\theta), \theta) > 0.$$

Then

$$S(L,Y,\theta) = S(L,Y^\star(\theta),\theta) - \kappa(L,\theta)\big(Y - Y^\star(\theta)\big)^2 + r(L,Y,\theta).$$

Adding back the term $\bar{v}L$ yields the result. $\square$

B.2 Microfoundation of information precision

Interpret larger loans as inducing more intensive due diligence. Suppose a type-i manager observes $n(L)$ pieces of evidence:

$$x_{i\ell} = \theta + u_{i\ell}, \qquad \ell = 1, \dots, n(L),$$

where

$$\mathbb{E}[u_{i\ell} \mid \theta] = 0, \qquad \mathrm{Var}(u_{i\ell} \mid \theta) = \nu_i,$$

and the $u_{i\ell}$ are conditionally independent across ℓ.
The manager forms the average

$$\widehat{\theta}_i \equiv \frac{1}{n(L)} \sum_{\ell=1}^{n(L)} x_{i\ell}.$$

Lemma 2 (Variance scaling)**.** *Conditional on θ,*

$$\mathbb{E}[\widehat{\theta}_i \mid \theta] = \theta$$

and

$$\mathrm{Var}(\widehat{\theta}_i - \theta \mid \theta) = \frac{\nu_i}{n(L)}.$$

If

$$n(L) = \kappa q_i L$$

for some $\kappa > 0$, then

$$\mathrm{Var}(\widehat{\theta}_i - \theta \mid \theta) = \frac{1}{q_i L}$$

after normalization.

Proof. First,

$$\widehat{\theta}_i - \theta = \frac{1}{n(L)} \sum_{\ell=1}^{n(L)} u_{i\ell}.$$

Taking expectations conditional on θ,

$$\mathbb{E}[\widehat{\theta}_i - \theta \mid \theta] = \frac{1}{n(L)} \sum_{\ell=1}^{n(L)} \mathbb{E}[u_{i\ell} \mid \theta] = 0,$$

so $\mathbb{E}[\widehat{\theta}_i \mid \theta] = \theta$.
For the variance,

$$\mathrm{Var}(\widehat{\theta}_i - \theta \mid \theta) = \mathrm{Var}\left(\frac{1}{n(L)} \sum_{\ell=1}^{n(L)} u_{i\ell} \,\Big|\, \theta \right).$$

Using conditional independence,

$$= \frac{1}{n(L)^2} \sum_{\ell=1}^{n(L)} \mathrm{Var}(u_{i\ell} \mid \theta) = \frac{1}{n(L)^2} \cdot n(L)\nu_i = \frac{\nu_i}{n(L)}.$$

If $n(L) = \kappa q_i L$, then

$$\mathrm{Var}(\widehat{\theta}_i - \theta \mid \theta) = \frac{\nu_i}{\kappa q_i L}.$$

Normalizing units so that $\nu_i/\kappa = 1$ gives

$$\mathrm{Var}(\widehat{\theta}_i - \theta \mid \theta) = \frac{1}{q_i L}.$$

□

B.3 Microfoundation of strategic-communication loss

Under delegation, the manager directly implements an action based on the full local estimate $\widehat{\theta}_i$. Under centralization, HQ does not observe $\widehat{\theta}_i$ directly. Instead, the manager sends a message m, and HQ chooses an action based solely on it. However, in the spirit of Crawford and Sobel (1982), such a message only specifies the bin where $\widehat{\theta}_i$ lies, not its value.

Partitional communication. Suppose the support of $\widehat{\theta}_i$ is partitioned into an integer number of bins $K(b_i) \geq 1$. All values of $\widehat{\theta}_i$ in the same bin induce the same message. HQ then chooses the conditional expected value of θ given that message.
Let the effective support of $\widehat{\theta}_i$ have length

$$\frac{2\omega}{\sqrt{L}}.$$

If the $K(b_i)$ bins have equal width, then each bin has a width

$$\delta_K(L) = \frac{2\omega}{K(b_i)\sqrt{L}}. \tag{a6}$$

Let us now derive the mean-squared deviation within a bin. Fix one bin of width δ and let its midpoint be c. Under the uniform benchmark, the signal is uniformly distributed on that bin:

$$X \sim \mathrm{U}\left[c - \frac{\delta}{2},\, c + \frac{\delta}{2}\right].$$

The mean of a uniform random variable on a symmetric interval is its midpoint:

$$\mathbb{E}[X] = c.$$

So the mean-squared deviation from the bin mean is

$$\mathbb{E}[(X - c)^2].$$

By definition of expectation for a continuous uniform distribution,

$$\mathbb{E}[(X - c)^2] = \frac{1}{\delta}\int_{c-\delta/2}^{c+\delta/2} (x - c)^2\, dx.$$

Let $u \equiv x - c$. Then the integral becomes

$$\mathbb{E}[(X - c)^2] = \frac{1}{\delta}\int_{-\delta/2}^{\delta/2} u^2\, du.$$

Therefore, within a bin of width δ,

$$\mathbb{E}[(X - \mathbb{E}[X])^2] = \frac{\delta^2}{12}. \tag{a7}$$

Applying this to $\delta = \delta_K(L)$ gives

$$\mathbb{E}[(y_H - \widehat{\theta}_i)^2 \mid i, c, L] = \frac{\delta_K(L)^2}{12} = \frac{1}{12}\left(\frac{2\omega_i}{K(b_i)\sqrt{L}}\right)^2 = \frac{\omega_i^2}{3} \cdot \frac{1}{K(b_i)^2} \cdot \frac{1}{L}.$$

Then the incremental inference loss can be written as

$$\mathbb{E}[(y_H - \widehat{\theta}_i)^2 \mid i, c, L] = \frac{\Delta_i}{L}, \qquad \Delta_i \equiv \frac{\omega_i^2}{3}\frac{1}{K(b_i)^2}.$$

In the baseline model used throughout our analysis, communication loss depends only on bias, so we can write $\Delta_i = \Delta(b_i)$. To discipline the shape of this reduced-form mapping, we adopt the following tractable benchmark link between bias and partition size.

Lemma 3. *Suppose the most informative equilibrium under centralization induces an effective number of bins*

$$K(b) = \frac{\kappa}{\sqrt{b}}$$

for some constant $\kappa > 0$ and all $b > 0$. If the coarsening loss is

$$\Delta(b) = \frac{\omega^2}{3}\frac{1}{K(b)^2},$$

then

$$\Delta(b) = \frac{\omega^2}{3\kappa^2}\, b.$$

Hence $\Delta(b)$ is strictly increasing and weakly concave in b, and the authority cutoff

$$L^\star(b) = \frac{\Delta(b)}{b^2}$$

is strictly decreasing in b.

Proof. Substituting $K(b) = \kappa/\sqrt{b}$ into the expression for $\Delta(b)$ gives

$$\Delta(b) = \frac{\omega^2}{3}\frac{1}{(\kappa/\sqrt{b})^2} = \frac{\omega^2}{3\kappa^2}\, b.$$

This function is linear in b, hence strictly increasing and weakly concave. Therefore

$$L^\star(b) = \frac{\Delta(b)}{b^2} = \frac{\omega^2}{3\kappa^2}\frac{1}{b},$$

which is strictly decreasing in b. □

Lemma 3 provides a tractable benchmark microfoundation for the shape restriction imposed in the main text and Appendix A: communication losses rise with bias, but only linearly, whereas delegated implementation costs rise with b^2.
A richer extension could allow the effective support width or partition structure to depend on information precision, implying

$$\Delta_i = \Delta(b_i, q_i).$$

In that case, changes in precision could also affect the authority cutoff. We abstract from this channel in the baseline specification in order to isolate the role of bias and strategic communication in shaping delegation.

B.4 Derivation of MSE under delegation and centralization

Lemma 4 (Mean-squared decision error)**.** *For each type i and loan size L,*

$$\mathrm{MSE}_i^d(L) = \frac{1}{q_i L} + b_i^2, \qquad \mathrm{MSE}_i^c(L) = \frac{1}{L}\Big(\frac{1}{q_i} + \Delta_i\Big).$$

Proof. Let us analyze the two authority regimes separately.

Delegation. Under delegation, the manager directly chooses the action he prefers, given his estimate:

$$y = \widehat{\theta}_i + b_i.$$

Subtract θ from both sides:

$$y - \theta = (\widehat{\theta}_i - \theta) + b_i.$$

Square both sides:

$$(y - \theta)^2 = (\widehat{\theta}_i - \theta)^2 + 2b_i(\widehat{\theta}_i - \theta) + b_i^2.$$

Let us compute expectations conditional on (i, L):

$$\mathbb{E}[(y - \theta)^2 \mid i, d, L] = \mathbb{E}[(\widehat{\theta}_i - \theta)^2 \mid i, L] + 2b_i\mathbb{E}[\widehat{\theta}_i - \theta \mid i, L] + b_i^2.$$

Because the estimate is unbiased,

$$\mathbb{E}[\widehat{\theta}_i - \theta \mid i, L] = 0,$$

and because its variance is $1/(q_i L)$,

$$\mathbb{E}[(\widehat{\theta}_i - \theta)^2 \mid i, L] = \frac{1}{q_i L}.$$

Therefore

$$\text{MSE}_i^d(L) = \frac{1}{q_i L} + b_i^2.$$

Centralization. Under centralization, HQ does not observe $\widehat{\theta}_i$ directly. It observes only the manager's message m and chooses

$$y_H(m) = \mathbb{E}[\theta \mid m, i, L].$$

Let us denote the decision error as

$$y_H - \theta = (y_H - \widehat{\theta}_i) + (\widehat{\theta}_i - \theta),$$

or, equivalently,

$$(y_H - \theta)^2 = (y_H - \widehat{\theta}_i)^2 + (\widehat{\theta}_i - \theta)^2 + 2(y_H - \widehat{\theta}_i)(\widehat{\theta}_i - \theta).$$

Taking expectations conditional on (i, c, L) yields:

$$\begin{aligned}\mathbb{E}[(y_H - \theta)^2 \mid i, c, L] = \mathbb{E}[(y_H - \widehat{\theta}_i)^2 \mid i, c, L] + \mathbb{E}[(\widehat{\theta}_i - \theta)^2 \mid i, L] \\ + 2\mathbb{E}[(y_H - \widehat{\theta}_i)(\widehat{\theta}_i - \theta) \mid i, c, L].\end{aligned}$$

We now show that the cross term is zero. Because the message m is a function of $\widehat{\theta}_i$, both m and $y_H(m)$ are measurable with respect to the information contained in $\widehat{\theta}_i$. So we can use iterated expectations:

$$\begin{aligned}&\mathbb{E}[(y_H - \widehat{\theta}_i)(\widehat{\theta}_i - \theta) \mid i, c, L] \\ &= \mathbb{E}\Big[\mathbb{E}[(y_H - \widehat{\theta}_i)(\widehat{\theta}_i - \theta) \mid \widehat{\theta}_i, i, c, L] \;\Big|\; i, c, L\Big].\end{aligned}$$

Inside the inner expectation, $(y_H - \widehat{\theta}_i)$ is fixed given $\widehat{\theta}_i$, so

$$= \mathbb{E}\Big[(y_H - \widehat{\theta}_i)\mathbb{E}[\widehat{\theta}_i - \theta \mid \widehat{\theta}_i, i, L] \;\Big|\; i, c, L\Big].$$

Now use the fact that $\widehat{\theta}_i$ is the manager's posterior mean estimate of θ. That means

$$\mathbb{E}[\theta \mid \widehat{\theta}_i, i, L] = \widehat{\theta}_i,$$

so equivalently

$$\mathbb{E}[\widehat{\theta}_i - \theta \mid \widehat{\theta}_i, i, L] = 0.$$

Hence the whole cross term is zero.
Therefore

$$\mathrm{MSE}_i^c(L) = \mathbb{E}[(\widehat{\theta}_i - \theta)^2 \mid i, L] + \mathbb{E}[(y_H - \widehat{\theta}_i)^2 \mid i, c, L].$$

The first term is

$$\frac{1}{q_i L},$$

and by the coarsening result above, the second term is

$$\frac{\Delta_i}{L}.$$

So

$$\mathrm{MSE}_i^c(L) = \frac{1}{L}\Big(\frac{1}{q_i} + \Delta_i\Big).$$

□

C Wild Cluster Bootstrap Inference

Our main specifications cluster standard errors at the branch level, reflecting the panel structure of the data. However, network exposure — the key independent variable — varies at the bank level, with only 16 banks in the sample. If bank-level shocks induce residual correlation across branches of the same bank, branch-level clustering may overstate statistical precision. Standard asymptotic corrections for cluster-robust standard errors perform poorly with so few clusters (A Colin Cameron, Jonah B Gelbach and Douglas L Miller, 2008).

To address this concern, we re-estimate all specifications using wild cluster bootstrap inference at the bank level. We use the `boottest` package (David Roodman, Morten Ørregaard Nielsen, James G MacKinnon and Matthew D Webb, 2019) with Webb weights and 9,999 bootstrap replications. Each table below presents two panels: Panel A reports results for branches in bank-coethnic cities (BCC), and Panel B for branches in non-bank-coethnic cities (NBCC). Both panels report the original point estimates and branch-clustered standard errors in parentheses, with bank-level bootstrap p-values in square brackets. In Panel B, the last row additionally reports the bootstrap p-value for the test that the effect of conflict differs between the two subsamples (i.e., the interaction test from equation 4). The paper's central prediction concerns Panel B; Panel A serves as a comparison.

Table C.1 reports results for the manager ethnicity regressions. All six specifications remain significant at the 5% level under bank-level clustering, with bootstrap p-values between 0.006 and 0.043. The differential effect between the two subsamples is significant at the 10% level or better for five of the six specifications.

Table C.2 reports results for the delegation regression. The effect of conflict on delegation remains significant in the main specification ($p = 0.009$) and when controlling for local conflict ($p = 0.004$), though the city-time fixed effects specification loses significance ($p = 0.244$).

Tables C.3–C.4 report results for manager reallocation and characteristics. Manager age remains significant ($p = 0.021$), and two of the four reallocation outcomes are marginally significant at the 10% level ($p = 0.097$ for new manager at the bank; $p = 0.090$ for new hire). The differential effects on tenure in branch ($p = 0.003$) and tenure in bank ($p = 0.015$) remain significant.

Table C.5 reports results for lending outcomes. Most lending outcomes also lose significance, with the exception of the log number of loans ($p = 0.012$), which remains significant at the 5% level. This reflects the limited statistical power of 16 bank-level clusters for detecting effects on outcomes that are plausibly noisier than the manager ethnicity outcome. The point estimates and branch-clustered standard errors are unchanged; the loss of significance reflects the more conservative inference, not a change in the estimated effects.

In summary, the paper's central finding — that bank-level exposure to ethnic conflict shifts manager selection toward city-coethnic managers in non-coethnic cities — is robust to inference that accounts for the small number of bank-level clusters, as is the effect on delegation and on the number of loans. The remaining management and lending effects, while precisely estimated under branch-level clustering, do not survive the more conservative bank-level inference.

	Panel A: Branches in Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-0.003	0.023	-0.004	-0.003	0.023	-0.004
	(0.025)	(0.056)	(0.025)	(0.025)	(0.056)	(0.025)
	[0.896]	[0.720]	[0.877]	[0.896]	[0.720]	[0.877]
Local Exposure			0.012			0.012
			(0.008)			(0.008)
			[.]			[.]
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.679	0.696	0.679	0.679	0.696	0.679
N (Branches)	443	368	443	443	368	443

	Panel B: Branches in Non-Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	0.067	0.043	0.070	-0.110	-0.091	-0.117
	(0.016)	(0.018)	(0.016)	(0.015)	(0.018)	(0.016)
	[0.008]	[0.029]	[0.008]	[0.007]	[0.043]	[0.006]
Local Exposure			-0.017			0.037
			(0.009)			(0.010)
			[.]			[.]
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.183	0.181	0.183	0.772	0.769	0.772
p-value diff vs BCC (bootstrap)	0.092	0.586	0.089	0.053	0.081	0.033
N (Branches)	531	464	531	531	464	531

Notes: This table replicates Table 2. Panel A restricts the sample to branches in cities coethnic with the bank (BCC); Panel B focuses on branches in cities that are not (NBCC). Point estimates and branch-clustered standard errors (in parentheses) are identical to the main table. Bank-level wild cluster bootstrap p-values are reported in square brackets, computed using Webb weights with 9,999 replications and clustering at the bank level (16 banks). The last row of Panel B reports the bootstrap p-value for the null that the effect of network exposure is identical in bank-coethnic and non-bank-coethnic cities. Statistical significance is denoted by $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, and $^{***}\ p < 0.01$.

Table C.1: Wild cluster bootstrap inference: manager ethnicity

	Panel A: Branches in Bank-Coethnic Cities		
	(1)	(2)	(3)
Network Exposure	-407.0	-1216.6	-402.2
	(410.9)	(862.7)	(412.1)
	[0.452]	[0.214]	[0.454]
Local Exposure			-408.8
			(173.8)
			[.]
Branch FE	Yes	Yes	Yes
Time FE	Yes	No	Yes
City-Time FE	No	Yes	No
2018 Mean dep. var	1826.8	1949.4	1826.8
N (Branches)	228	158	228

	Panel B: Branches in Non-Bank-Coethnic Cities		
	(1)	(2)	(3)
Network Exposure	-1037.2	-691.4	-1037.4
	(288.5)	(355.9)	(290.2)
	[0.009]	[0.244]	[0.004]
Local Exposure			1.1
			(134.1)
			[.]
Branch FE	Yes	Yes	Yes
Time FE	Yes	No	Yes
City-Time FE	No	Yes	No
2018 Mean dep. var	1684.8	1721.8	1684.8
p-value diff vs BCC (bootstrap)	0.331	0.599	0.321
N (Branches)	322	266	322

Notes: This table replicates Table 3. The dependent variable is the largest loan a branch manager can approve without headquarters' agreement, measured in ETB 1,000, deflated to 2018 prices and winsorized at the 95th percentile. Panel A restricts the sample to branches in cities coethnic with the bank (BCC); Panel B focuses on branches in cities that are not (NBCC). Point estimates and branch-clustered standard errors (in parentheses) are identical to the main table. Bank-level wild cluster bootstrap p-values are reported in square brackets. The last row of Panel B reports the bootstrap p-value for the null that the effect is identical in bank-coethnic and non-bank-coethnic cities. Statistical significance is denoted by $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, and $^{***}\ p < 0.01$.

Table C.2: Wild cluster bootstrap inference: delegation

	Panel A: Branches in Bank-Coethnic Cities			
	New manager bank	New manager branch	Reallocated	New hire
	(1)	(2)	(3)	(4)
Network Exposure	0.018	-0.011	-0.024	0.013
	(0.009)	(0.036)	(0.036)	(0.008)
	[0.271]	[0.817]	[0.465]	[0.332]
Mean dep. var	0.034	0.395	0.367	0.027
N (Branches)	442	441	441	441

	Panel B: Branches in Non-Bank-Coethnic Cities			
	New manager bank	New manager branch	Reallocated	New hire
	(1)	(2)	(3)	(4)
Network Exposure	-0.008	0.037	0.046	-0.008
	(0.006)	(0.019)	(0.019)	(0.006)
	[0.097]	[0.139]	[0.152]	[0.090]
Mean dep. var	0.017	0.362	0.347	0.015
p-value diff vs BCC (bootstrap)	0.209	0.709	0.154	0.236
N (Branches)	528	528	528	528

Notes: This table replicates Table 4. The sample is restricted to the 2022 cross-section. The four outcomes are whether the manager joined the bank (column 1) or branch (column 2) after the onset of conflict, and conditional on joining the branch, whether they were reallocated (column 3) or a new hire (column 4). Panel A restricts the sample to branches in cities coethnic with the bank (BCC); Panel B focuses on branches in cities that are not (NBCC). Point estimates and branch-clustered standard errors (in parentheses) are identical to the main table. Bank-level wild cluster bootstrap p-values are reported in square brackets. The last row of Panel B reports the bootstrap p-value for the null that the effect is identical in bank-coethnic and non-bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table C.3: Wild cluster bootstrap inference: manager reallocation

	Panel A: Branches in Bank-Coethnic Cities				
	Tenure in bank	Tenure in branch	Age	University degree	Male manager
	(1)	(2)	(3)	(4)	(5)
Network Exposure	-0.219	-0.342	0.075	-0.001	0.028
	(0.239)	(0.127)	(0.327)	(0.003)	(0.024)
	[0.349]	[0.003]	[0.881]	[0.866]	[0.467]
Branch FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	6.801	2.399	33.801	0.993	0.867
N (Branches)	442	441	412	443	443

	Panel B: Branches in Non-Bank-Coethnic Cities				
	Tenure in bank	Tenure in branch	Age	University degree	Male manager
	(1)	(2)	(3)	(4)	(5)
Network Exposure	0.418	0.122	0.846	0.000	0.014
	(0.157)	(0.105)	(0.217)	(0.002)	(0.015)
	[0.106]	[0.144]	[0.021]	[0.902]	[0.439]
Branch FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	6.850	2.366	33.690	0.989	0.866
p-value diff vs BCC (bootstrap)	0.015	0.003	0.056	0.817	0.846
N (Branches)	528	528	500	529	529

Notes: This table replicates Table 5. The dependent variables are the manager's tenure in the bank, tenure in the current branch, age, whether they hold a university degree, and gender. Panel A restricts the sample to branches in cities coethnic with the bank (BCC); Panel B focuses on branches in cities that are not (NBCC). Point estimates and branch-clustered standard errors (in parentheses) are identical to the main table. Bank-level wild cluster bootstrap p-values are reported in square brackets. The last row of Panel B reports the bootstrap p-value for the null that the effect is identical in bank-coethnic and non-bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table C.4: Wild cluster bootstrap inference: manager characteristics

	Panel A: Branches in Bank-Coethnic Cities					
	Operational distance	Log number of loans	Log average loan size	Average lending rate	Collateral percentage	Share loan default
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-1.517	0.082	0.847	0.002	0.022	-0.030
	(0.511)	(0.096)	(0.262)	(0.001)	(0.014)	(0.013)
	[0.083]	[0.190]	[0.201]	[0.405]	[0.619]	[0.012]
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.820	2.178	6.037	0.147	0.986	0.053
N (Branches)	306	221	219	289	199	270

	Panel B: Branches in Non-Bank-Coethnic Cities					
	Operational distance	Log number of loans	Log average loan size	Average lending rate	Collateral percentage	Share loan default
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	0.686	-0.212	0.493	0.001	-0.015	-0.002
	(0.188)	(0.053)	(0.138)	(0.001)	(0.008)	(0.007)
	[0.358]	[0.012]	[0.181]	[0.608]	[0.166]	[0.851]
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.539	1.931	6.252	0.147	0.995	0.045
p-value diff vs BCC (bootstrap)	0.037	0.000	0.488	0.644	0.352	0.046
N (Branches)	412	308	304	367	268	325

Notes: This table replicates Table 7. The dependent variables are the operational distance, log number of loans, log average loan size, average lending rate, collateral percentage, and share of loans in default. Panel A restricts the sample to branches in cities coethnic with the bank (BCC); Panel B focuses on branches in cities that are not (NBCC). Point estimates and branch-clustered standard errors (in parentheses) are identical to the main table. Bank-level wild cluster bootstrap p-values are reported in square brackets. The last row of Panel B reports the bootstrap p-value for the null that the effect is identical in bank-coethnic and non-bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table C.5: Wild cluster bootstrap inference: lending outcomes

D Robustness Tests

D.1 Robustness to changing the matching of conflict to cities

To test the robustness of our results to the type of conflict we match, we vary the set $\mathcal{E}_{bt}$ in equation 1 by changing the set to all conflict within 15 and 25 kilometers of a branch of bank b. First, we consider matching only conflict within 15 kilometers of the city, for which we report the results relating to manager ethnicity in Table D.2. Next, we focus on conflict within 25km of the city, we report the results relating to manager ethnicity in Table D.3. Finally, we show that the results are not driven by CBE, the large, state-owned bank in Table D.4. These tables show that results on ethnicity are not driven by the specific choice of distance we use to match conflict to cities. All results are similar both quantitatively and qualitatively, with coefficients shrinking as we expand the conflict radius because the independent variable becomes less dispersed.

Panel A: Branches in Bank-Coethnic Cities								
	City coethnic manager				Bank coethnic manager			
	Drop Oromo	Drop Tigray	Drop Amhara	Drop SNNP	Drop Oromo	Drop Tigray	Drop Amhara	Drop SNNP
Network Exposure	0.019	-0.003	-0.159*	0.010	0.019	-0.003	-0.159*	0.010
	(0.034)	(0.025)	(0.093)	(0.027)	(0.034)	(0.025)	(0.093)	(0.027)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.670	0.679	0.698	0.682	0.670	0.679	0.698	0.682
N (Branches)	342	443	129	415	342	443	129	415

Panel B: Branches in Non-Bank-Coethnic Cities								
	City coethnic manager				Bank coethnic manager			
	Drop Oromo	Drop Tigray	Drop Amhara	Drop SNNP	Drop Oromo	Drop Tigray	Drop Amhara	Drop SNNP
Network Exposure	0.047**	0.083***	0.056***	0.079***	-0.073***	-0.114***	-0.104***	-0.143***
	(0.019)	(0.022)	(0.019)	(0.019)	(0.017)	(0.022)	(0.017)	(0.019)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.176	0.194	0.219	0.155	0.777	0.758	0.737	0.803
p-value	0.464	0.009	0.023	0.034	0.014	0.001	0.556	0.000
N (Branches)	404	458	274	457	404	458	274	457

Notes: The dependent variable is an indicator that equals 1 when a branch's manager is coethnic with the ethnic group associated with the city (columns 1–4) or with the ethnic group associated with the branch's bank (columns 5–8). Each column drops all branches belonging to banks of the indicated ethnic group. Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on Network Exposure is identical in bank-coethnic and non-bank-coethnic cities. Statistical significance is denoted by $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, and $^{***}\ p < 0.01$.

Table D.1: Robustness: dropping individual ethnic groups

	Panel A: Branches in Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure (15km)	0.006	0.026	0.006	0.006	0.026	0.006
	(0.024)	(0.050)	(0.024)	(0.024)	(0.050)	(0.024)
Local Exposure			0.012			0.012
			(0.008)			(0.008)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.679	0.679	0.679	0.679	0.679	0.679
N (Branches)	443	368	443	443	368	443

	Panel B: Branches in Non-Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
Network Exposure (15km)	0.065***	0.041**	0.069***	-0.109***	-0.089***	-0.116***
	(0.016)	(0.018)	(0.017)	(0.015)	(0.018)	(0.016)
Local Exposure			-0.017*			0.036***
			(0.009)			(0.010)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.183	0.183	0.183	0.772	0.772	0.772
p-value	0.039	0.772	0.029	0.000	0.029	0.000
N (Branches)	531	464	531	531	464	531

Notes: This table replicates Table 2 using a 15km instead of 20km radius to match ethnic conflict to bank branches in equation 1. The dependent variable is an indicator that equals 1 when a branch's manager is co-ethnic with the ethnic group associated with the city (columns 1–3) or with the ethnic group associated with the branch's bank (columns 4-6). Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local Exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log Network Exposure from 2018 to 2022 is 1.279 (1.433). Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on Network Exposure is identical in bank-coethnic and non bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.2: Bank-level exposure to ethnic conflict and branch manager ethnicity - 15 kilometer radius

	Panel A: Branches in Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure (25km)	-0.008	0.031	-0.008	-0.008	0.031	-0.008
	(0.024)	(0.063)	(0.024)	(0.024)	(0.063)	(0.024)
Local Exposure			0.012			0.012
			(0.008)			(0.008)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.679	0.679	0.679	0.679	0.679	0.679
N (Branches)	443	368	443	443	368	443

	Panel B: Branches in Non-Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
Network Exposure (25km)	0.068^{***}	0.047^{***}	0.072^{***}	-0.110^{***}	-0.094^{***}	-0.117^{***}
	(0.016)	(0.018)	(0.016)	(0.015)	(0.018)	(0.015)
Local Exposure			-0.018^{*}			0.037^{***}
			(0.009)			(0.010)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.183	0.183	0.183	0.772	0.772	0.772
p-value	0.008	0.806	0.006	0.000	0.055	0.000
N (Branches)	531	464	531	531	464	531

Notes: This table replicates Table 2 using a 25km instead of 20km radius to match ethnic conflict to bank branches in equation 1. The dependent variable is an indicator that equals 1 when a branch's manager is co-ethnic with the ethnic group associated with the city (columns 1–3) or with the ethnic group associated with the branch's bank (columns 4-6). Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local Exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log Network Exposure from 2018 to 2022 is 1.558 (1.388). Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on Network Exposure is identical in bank-coethnic and non bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.3: Bank-level exposure to ethnic conflict and branch manager ethnicity - 25 kilometer radius

Panel A: Branches in Bank-Coethnic Cities						
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	0.005	0.020	0.008	0.005	0.020	0.008
	(0.040)	(0.077)	(0.040)	(0.040)	(0.077)	(0.040)
Local Exposure			0.020			0.020
			(0.015)			(0.015)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.673	0.673	0.673	0.673	0.673	0.673
N (Branches)	349	271	349	349	271	349

Panel B: Branches in Non-Bank-Coethnic Cities						
	City coethnic manager			Bank coethnic manager		
Network Exposure	0.097***	0.082**	0.099***	-0.173***	-0.166***	-0.177***
	(0.035)	(0.038)	(0.035)	(0.035)	(0.039)	(0.034)
Local Exposure			-0.007			0.021
			(0.018)			(0.019)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.214	0.214	0.214	0.736	0.736	0.736
p-value	0.088	0.470	0.091	0.001	0.031	0.000
N (Branches)	401	358	401	401	358	401

Notes: This table replicates Table 2 excluding the state-owned banks; i.e. branches of CBE and CBB. The dependent variable is an indicator that equals 1 when a branch's manager is co-ethnic with the ethnic group associated with the city (columns 1–3) or with the ethnic group associated with the branch's bank (columns 4-6). Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local Exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log Network Exposure from 2018 to 2022 is 1.087 (1.388). Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on Network Exposure is identical in bank-coethnic and non bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.4: Bank-level exposure to ethnic conflict and branch manager ethnicity - only private banks

	Panel A: Branches in Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	0.012	-0.013	0.010	0.012	-0.013	0.010
	(0.027)	(0.080)	(0.027)	(0.027)	(0.080)	(0.027)
Local Exposure			0.005			0.005
			(0.008)			(0.008)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.662	0.662	0.662	0.662	0.662	0.662
N (Branches)	269	194	269	269	194	269

	Panel B: Branches in Non-Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
Network Exposure	0.051**	0.033	0.054**	-0.110***	-0.100***	-0.115***
	(0.022)	(0.024)	(0.022)	(0.021)	(0.025)	(0.021)
Local Exposure			-0.023**			0.042***
			(0.009)			(0.010)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.179	0.179	0.179	0.766	0.766	0.766
p-value	0.261	0.574	0.213	0.000	0.282	0.000
N (Branches)	368	301	368	368	301	368

Notes: This table replicates Table 2 excluding the branches in Addis Ababa. The dependent variable is an indicator that equals 1 when a branch's manager is co-ethnic with the ethnic group associated with the city (columns 1–3) or with the ethnic group associated with the branch's bank (columns 4-6). Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local Exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log Network Exposure from 2018 to 2022 is 1.528 (1.334). Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on Network Exposure is identical in bank-coethnic and non bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.5: Bank-level exposure to ethnic conflict and branch manager ethnicity - excluding Addis Ababa

D.2 The effect of conflict on employees being local

D.3 Alternative transformation of the conflict variables

In this section, we report the results from the specification in equation 3 using an asinh transformation ($\text{asinh}(x) = \ln\left(x + \sqrt{x^2+1}\right)$) of the network exposure variable

	Panel A: Branches in Bank-Coethnic Cities					
	Manager born in region			Share local employees		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-0.046	-0.083	-0.048	-0.047***	-0.066*	-0.048***
	(0.033)	(0.072)	(0.033)	(0.013)	(0.034)	(0.013)
Local Exposure			0.010			0.011**
			(0.012)			(0.005)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.418	0.418	0.418	0.559	0.559	0.559
N (Branches)	213	213	213	443	443	443

	Panel B: Branches in Non-Bank-Coethnic Cities					
	Manager born in region			Share local employees		
Network Exposure	-0.050*	-0.043	-0.050*	-0.011	-0.032***	-0.015
	(0.028)	(0.033)	(0.028)	(0.010)	(0.010)	(0.009)
Local Exposure			-0.000			0.021***
			(0.018)			(0.005)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.446	0.446	0.446	0.584	0.584	0.584
p-value	0.929	0.612	0.956	0.028	0.338	0.045
N (Branches)	249	249	249	531	531	531

Notes: This table shows the results of a regression on two measures of whether staff comes from the same region as the branch. Share local employees is the share of employees who were born in the same city as the branch, local manager is a dummy for whether the manager was born in the same region as the branch. Note that this question was added to the survey after around 500 branches were interviewed in 2018 resulting in a small sample size. Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local Exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log Network Exposure from 2018 to 2022 is 1.425 (1.363). Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on Network Exposure is identical in bank-coethnic and non bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.6: Bank-level exposure to ethnic conflict and local staff

Panel A: Bank-City Coethnic						
	(1) City coethnic	(2) Bank coethnic	(3) Delegation	(4) Tenure Bank	(5) Tenure Branch	(6) Age
IHS Network Exposure	-0.009	-0.009	-446.095	-0.227	-0.403***	0.090
	(0.026)	(0.026)	(504.281)	(0.266)	(0.140)	(0.359)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.679	0.679	1672.686	6.801	2.393	33.867
N	443	443	443	443	443	443

Panel B: Not Bank-City Coethnic						
	City coethnic	Bank coethnic	Delegation	Tenure Bank	Tenure Branch	Age
IHS Network Exposure	0.072***	-0.118***	-1132.826***	0.438**	0.127	0.902***
	(0.018)	(0.017)	(311.823)	(0.170)	(0.112)	(0.234)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.183	0.772	1681.733	6.853	2.362	33.533
p-value	0.010	0.000	0.247	0.035	0.003	0.059
N	531	531	531	531	531	531

Notes: Each column reports a separate regression using the inverse hyperbolic sine transformation of Network Exposure in place of the log transformation used in the main text. The delegation outcome is the largest loan a branch manager can approve without headquarters' approval, expressed in 2018 prices and winsorized at the 95th percentile within period-by-bank-city-coethnicity cells. Panel A restricts the sample to branches in coethnic cities, while Panel B focuses on branches in non-coethnic cities. All specifications include branch and time fixed effects. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the t-test that the parameter estimates for branches in bank-coethnic cities (Panel A) and in non bank-coethnic cities (Panel B) are the same. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.7: IHS Robustness: Branch Managers

Panel A: Bank-City Coethnic						
	(1) Oper. distance	(2) Num. loans	(3) Loan size	(4) Lending rate	(5) Collateral	(6) Default
IHS Network Exposure	-1.766***	0.093	1.026***	0.002*	0.025*	-0.034**
	(0.518)	(0.107)	(0.248)	(0.001)	(0.015)	(0.015)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.756	2.185	6.056	0.146	1.009	0.050
N	443	443	443	443	443	443

Panel B: Not Bank-City Coethnic						
	Oper. distance	Num. loans	Loan size	Lending rate	Collateral	Default
IHS Network Exposure	0.750***	-0.225***	0.529***	0.001	-0.016*	-0.002
	(0.202)	(0.056)	(0.147)	(0.001)	(0.009)	(0.007)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.514	1.934	6.040	0.148	0.998	0.046
p-value	0.000	0.009	0.085	0.310	0.019	0.052
N	531	531	531	531	531	531

Notes: Each column reports a separate regression using the inverse hyperbolic sine transformation of Network Exposure in place of the log transformation used in the main text. The dependent variables are the operational distance of the branch, the log of the number of loans outstanding, the log of the average loan size (deflated to 2018 prices), the lending rate on a typical loan, the percentage of collateral on a typical loan, and the share of loans that default. Panel A restricts the sample to branches in coethnic cities, while Panel B focuses on branches in non-coethnic cities. All specifications include branch and time fixed effects. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the t-test that the parameter estimates for branches in bank-coethnic cities (Panel A) and in non bank-coethnic cities (Panel B) are the same. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.8: IHS Robustness: Lending Activities

D.4 Robustness: 50 km Beta-Israel exposure window

Section 4.5 measures bank-level Beta-Israel exposure as the share of a bank's branches within 100 km of a historic Beta-Israel city. We use 100 km because the contested 1992 borders that link the Beta-Israel migration to subsequent ethnic conflict extend that far from the cities themselves. To check whether the radius drives our results, we re-estimate Tables 8 and 9 using a tighter 50 km window. We construct $\texttt{share\_branch\_beta\_50}_b$ analogously and apply the same normalization.

Table D.9 reports the manager results. The patterns mirror the 100 km benchmark. In non bank-coethnic cities, exposure raises the share of city-coethnic managers and lowers the share of bank-coethnic managers; these effects, together with the reduction in delegation and the increase in manager age, all remain significant at the 1% level. The point estimates are 75–80% of the 100 km magnitudes, since the tighter radius sets many branches' exposure to zero and so removes variation. The p-value for test of a different effect in bank coethnic cities for the city-coethnic outcome rises from 0.036 to 0.062, while the bank-coethnic interaction stays highly significant ($p = 0.003$).

Table D.10 reports the lending results. Bank-coethnic and non bank-coethnic markets again diverge: in coethnic cities, exposure shifts lending toward larger, more collateralized, lower-default loans; in non-coethnic cities, branches serve customers over a wider area and grant larger loans. Every coefficient retains its sign and significance level. We keep 100 km as the preferred specification because it more closely matches the geographic span of the contested 1992 borders.

Panel A: Bank-City Coethnic						
	(1) City coethnic	(2) Bank coethnic	(3) Delegation	(4) Tenure Bank	(5) Tenure Branch	(6) Age
Beta Israel Exposure	0.019	0.019	-1.223	-1.565	-1.335**	0.270
	(0.102)	(0.102)	(2.246)	(1.204)	(0.519)	(1.383)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.679	0.679	1.673	6.801	2.393	33.867
N	443	443	443	443	443	443

Panel B: Not Bank-City Coethnic						
	City coethnic	Bank coethnic	Delegation	Tenure Bank	Tenure Branch	Age
Beta Israel Exposure	0.282***	-0.403***	-5.844***	0.238	-0.385	4.614***
	(0.096)	(0.099)	(1.535)	(0.963)	(0.769)	(1.430)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.183	0.772	1.682	6.853	2.362	33.533
p-value	0.062	0.003	0.090	0.242	0.306	0.029
N	531	531	531	531	531	531

Notes: Replication of Table 8 using a 50 km radius around historic Beta-Israel cities to construct the bank-level exposure measure. The dependent variables are an indicator for a city-coethnic manager (column 1) and a bank-coethnic manager (column 2), the maximum loan the manager can approve without headquarters agreement, in millions of ETB (column 3), tenure in the bank (column 4) and in the branch (column 5) in years, and the manager's age (column 6). Beta Israel Exposure is the share of each bank's branches within 50 km of a historic Beta-Israel city, normalized to lie in $[0, 1]$ and interacted with a post-2018 dummy. Panel A restricts the sample to branches in coethnic cities; Panel B focuses on branches in non-coethnic cities. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the t-test that the coefficient is identical across panels. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.9: Bank-level exposure to Beta-Israel cities and branch managers (50 km)

	Panel A: Bank-City Coethnic					
	(1) Oper. distance	(2) Num. loans	(3) Loan size	(4) Lending rate	(5) Collateral	(6) Default
Beta Israel Exposure	-3.015*	0.248	5.026***	0.007	0.191***	-0.120**
	(1.545)	(0.387)	(1.142)	(0.005)	(0.067)	(0.048)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.756	2.185	6.056	0.146	1.009	0.050
N	443	443	443	443	443	443

	Panel B: Not Bank-City Coethnic					
	Oper. distance	Num. loans	Loan size	Lending rate	Collateral	Default
Beta Israel Exposure	9.240***	-0.190	4.514***	0.010*	-0.079*	0.032
	(1.432)	(0.369)	(1.019)	(0.006)	(0.048)	(0.047)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	7.514	1.934	6.040	0.148	0.998	0.046
p-value	0.000	0.412	0.738	0.743	0.001	0.024
N	531	531	531	531	531	531

Notes: Replication of Table 9 using a 50 km radius around historic Beta-Israel cities to construct the bank-level exposure measure. The dependent variables are the operational distance of the branch, the log number of outstanding loans, the log average loan size, the lending rate on a typical loan, the percentage of collateral on a typical loan, and the share of loans in default. Beta Israel Exposure is the share of each bank's branches within 50 km of a historic Beta-Israel city, normalized to lie in $[0, 1]$ and interacted with a post-2018 dummy. Panel A restricts the sample to branches in coethnic cities; Panel B focuses on branches in non-coethnic cities. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the t-test that the coefficient is identical across panels. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table D.10: Bank-level exposure to Beta-Israel cities and lending (50 km)

E Ethnicity of banks, cities and managers

E.1 Comments on specific choices made in the analysis

Bank ethnicity. We classify each of the 16 commercial banks in our sample into a single dominant ethnicity using information from the 2018 annual reports. For each bank, we collect the names of all members of the board of directors and identify each director's ethnic group from their name, following the conventional correspondence between Ethiopian naming conventions and ethnic affiliation. A bank is assigned the plurality ethnicity of its board. The two state-owned banks, the Commercial Bank of Ethiopia and the Construction and Business Bank, are classified as Amhara; the latter was effectively absorbed into the former during our sample period. This procedure yields 9 Amhara-dominated banks, 3 Oromo, 2 SNNP, and 2 Tigray.

City ethnicity. We assign each city its historical ethnic homeland using the digitized ethnic-boundary shapefile from Nathan Nunn (2008), which encodes the ethnic territories of George Peter Murdock (1959). We spatially match each branch's geographic coordinates to a Murdock polygon using the `geoinpoly` routine. Murdock's tribe labels are pre-modern ethnographic categories (e.g., "Galla," "Somal"); we map these to the contemporary ethnic categories used in our analysis (Oromo, Amhara, Tigray, Somali, SNNP, Beta Israel, Other) using a correspondence table constructed from Wikipedia entries for each Murdock tribe. The full mapping is available in the replication package (`1rawData/13EthnicGroups/tribeEthnicityMappin`
Addis Ababa, which lies on the boundary between Oromo and Amhara territories in Murdock's classification, is assigned to the Amhara category, reflecting the dominant ethnic composition of the city's banking sector and civil service during our sample period.

Treatment of the Harari. The Harari are a small ethnic group (approximately 0.2% of the Ethiopian population in the 2007 census) whose traditional homeland is the walled city of Harar and its immediate surroundings, located within predominantly Oromo territory. No manager in our survey sample self-identifies as Harari, so Harari does not appear as a category in the manager-ethnicity classification. For the city-ethnicity assignment based on the Nunn (2008) digitization of the Murdock Atlas, Harar and its surrounding cities fall within the Oromo polygon and are therefore assigned to the Oromo category. This coding has no material effect on our results: only 7 branches in our panel are located in cities of the historic Harari homeland.

Aggregation of SNNP groups. The Southern Nations, Nationalities, and Peoples (SNNP) region of Ethiopia is home to more than 50 officially recognized ethnic groups, eight of which appear in our sample: Sidama, Gurage, Gamo, Wolayta, Hadiya, Kambaata, Kafa, and Silte. Because bank and city ethnicity in our main specifications are defined at a coarser level (the bank's dominant ethnicity and the city's Murdock-Atlas classification), we aggregate these eight groups into a single "SNNP" category for the coethnicity indicators. This follows standard practice in the Ethiopian ethnic-politics literature and is also consistent with the self-identification reported by several managers in our data.

Bank name	Bank ethnicity	Count	Share (%)
Abay	Amhara	79	8.1
Addis	Amhara	5	0.5
Awash	Oromo	100	10.3
BOA	Amhara	37	3.8
Berhan	Amhara	72	7.4
Bunna International	Amhara	46	4.7
CBB	Amhara	18	1.8
CBE	Amhara	209	21.5
CBO	Oromo	53	5.4
Dashen	Amhara	54	5.5
Debub	SNNP	17	1.7
Lion	Tigray	14	1.4
NIB International	SNNP	85	8.7
OIB	Oromo	75	7.7
United	Amhara	51	5.2
Wegagen	Tigray	59	6.1

Notes: This table reports the ethnic affiliation of each bank in the sample, the number of surveyed branches, and the corresponding share of the total sample. Bank ethnicity is the dominant ethnic affiliation of the bank's leadership.

Table E.1: Distribution of banks by ethnic affiliation

E.2 List of banks and bank-ethnicities

E.3 Number of cities by ethnic group

City ethnicity	Count	Share (%)
Afar	4	0.4
Amhara	516	53.0
Anuak	4	0.4
Benishangul-Gumuz	2	0.2
Oromo	260	26.7
SNNP	161	16.5
Somali	17	1.7
Tigray	10	1.0

Notes: This table reports the distribution of branch locations by ethnic group. City ethnicity is determined using the Murdock Ethnographic Atlas. Count and share refer to the number and percentage of branches located in cities of each ethnic group.

Table E.2: Distribution of cities by ethnic group

E.4 Number of managers by ethnic group by period

Manager ethnicity	First Wave (2018)		Second Wave (2022)	
	Count	Share (%)	Count	Share (%)
Afar	1	0.1	5	0.5
Agew	0	0.0	8	0.8
Amhara	492	50.5	428	43.9
Benishangul-Gumuz	2	0.2	1	0.1
Oromo	287	29.5	380	39.0
SNNP	109	11.2	112	11.5
Somali	2	0.2	19	2.0
Tigray	81	8.3	20	2.1

Notes: This table reports the distribution of branch managers' ethnicity across survey waves. Manager ethnicity is identified using multiple indicators including region of birth, accent, spoken languages, and name, determined jointly by two interviewers.

Table E.3: Distribution of branch managers' ethnicity by period

E.5 Ethnic diversity at the local level

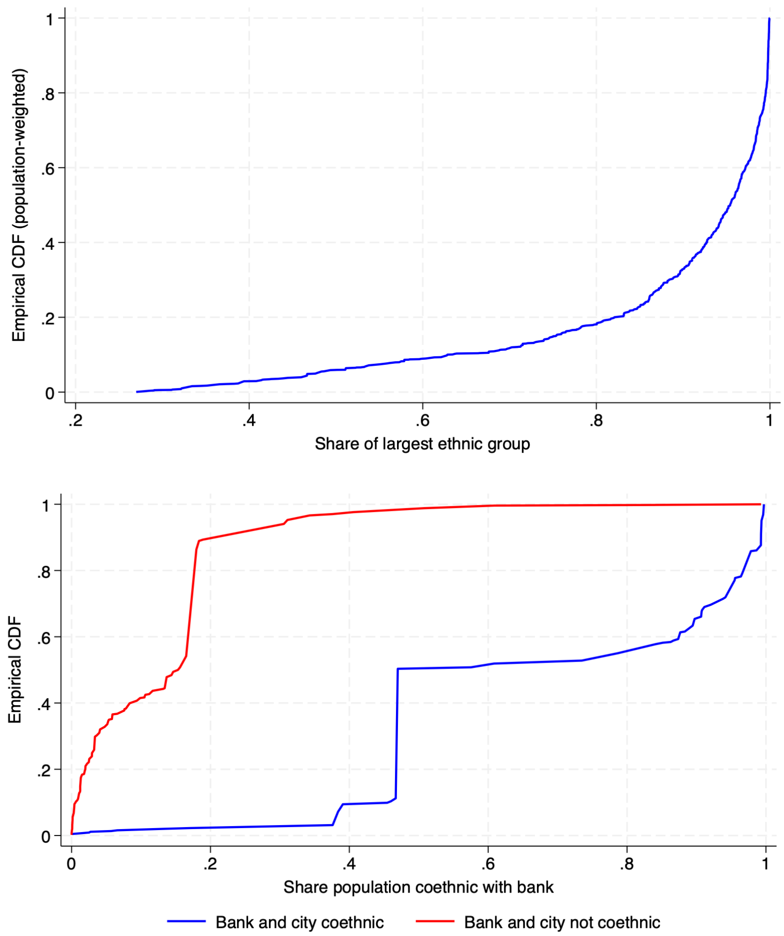

Figure E.1: Ethnic diversity in Ethiopia

Notes: This figure shows, in the top panel, the empirical CDF for the share of the population that belongs to largest ethnic group in each woreda – the smallest administrative unit – in Ethiopia. It shows that in over 80% of woredas over 80% of people belong to a single ethnicity. The bottom panel instead shows that share of the population in each zone (region in the case of Addis Ababa) in which a branch is located that belongs to the same ethnic group of the bank. The differences in administrative units used in this figure is based on how (im)precisely we observe the location of bank branches. This is based on 2007 IPUMS data and corresponding administrative boundaries.

F Management Practices Survey and Methodology

F.1 Scoring Management Performances

The concept of "good management practice" is often relative and contingent to a specific market or sector. However, international best practices in the banking sector have been widely studied, allowing the literature to reach a consensus on what constitutes a "good" practice. We evaluate and score management practices by defining the concept of "good" and "bad" practice and codifying it from 1 (worst practice) to 5 (best practice) across eight key dimensions. These practices are grouped into four areas: lean management, performance management, target management, and people management.[1]

The lean management section evaluates the efficiency of day-to-day operations (e.g., organization of the workflow, management of slack time, method of staff assignment to specific tasks, etc.) and assesses whether the branch has adopted recognized best practices. The performance management part measures how performance is tracked and reviewed (e.g., what KPIs are used, who oversees the performance review, how frequently the performance measures are revised, etc.). The target management section reviews the nature and scope of a branch's targets (e.g., the relative importance of financial targets compared to non-financial ones, how these targets are linked to performance measures, etc.) and assesses whether they align with the bank's objectives. Finally, the people management part tests whether good performance is appropriately rewarded and whether bad performance is sanctioned (e.g., adoption of an articulated appraisal system, use of a reward plan, presence of sanctions for underperformers, etc.).

An overview of these four sections is presented in Table F.1. After the completion of the survey, we combine these scores to obtain a unique index of management practices. Since the scaling may vary across practices in the econometric estimation, we normalize the final scores to z-scores (i.e., mean zero and standard deviation one). To build our final management index, we take the unweighted average across all z-scores as

[1] Note, this section is taken directly from a previously circulated working paper (Nicola Gennaioli, Nicola Limodio and Francesco Strobbe, 2019)

our primary measure of overall management practice.

Table F.1: Survey Indicators

(1) Indicator	**(2) Objective**	**(3) Measure**
	1 Lean Management	
1.1	Introduction of new management techniques	Tests whether operational efficiencies have been introduced and why
1.2	Good use of human resources	Tests whether incoming demand is segmented appropriately and the efficiency at matching supply and demand of skills
	2 Performance Management	
2.1	Performance tracking	Tests whether performance is tracked using meaningful metrics and with appropriate regularity
2.2	Review of performance	Tests whether performance is reviewed with appropriate frequency and communicated with staff
	3 Target Management	
3.1	Target balance	Tests whether targets cover a sufficiently broad set of metrics
3.2	Target interconnections	Tests whether targets are tied to company objectives and how well they cascade down the organization
	4 People Management	
4.1	Building a high performance culture	Tests whether good performance is rewarded proportionately
4.2	Making room for talent	Tests whether the branch is able to deal with underperformers

Notes: This table illustrates our survey's section on management performance. To measure good managerial practices, we evaluate them along four main categories, i.e., lean management, performance management, target management, and people management. Each category is scored on two dimensions on a scale from 1 (bad practice) to 5 (good practice). Our final management performance index is calculated by standardizing each of the eight resulting scores and by taking their unweighted average. Each of the sub-indices is calculated in the same way using a combination of two metrics (respectively, the lean, performance, target and people management practices).

F.2 Responses Collection

The information content and precision of our management performance index crucially depend on the quality of the responses collected through our survey. For this reason, we structured our questions to allow respondents to provide accurate and unbiased answers. As pointed out by (Marianne Bertrand and Sendhil Mullainathan, 2001), responses are typically biased by the presence of a scoring scale, which may prompt respondents to provide the interviewer's expected answer. Additionally, interviewers may have preconceptions toward the interviewed managers. Apart from these issues, many background factors correlated with management behavior may systematically bias survey data.

To counter these potential negative effects, we adopt a combination of strategies tested in the existing literature. First, we ensure accurate responses by conducting telephone surveys without informing managers that their answers will be evaluated against a scoring grid, allowing us to gather information about actual management practices. Second, we ask a series of open-ended questions (e.g., "What types of targets are set for the bank in general? What are the goals for your branch?") and record responses until an accurate assessment of management practices is possible. Third, to correct any inconsistent interpretation of responses, we ensure interviewers conduct a minimum number of training interviews during a pilot survey phase. Furthermore, since almost all our interviewers conducted over 40 interviews (with an average of 200 interviews per interviewer), we are able to control for interviewer fixed effects in a robustness section. Fourth, we adopt a double-scoring technique, where another interviewer silently listens and scores the responses provided during the interview. Finally, we collect information on a large set of manager characteristics (e.g., age, education, ethnicity, etc.) to control for potential confounders.

F.3 Manager Participation

The average duration of an interview was approximately 27 minutes. Interviews were conducted between January 2015 and February 2018 by locally recruited research assistants (RAs). The initial survey phase consisted of a pilot involving 265 branches, which allowed us to refine the survey and train interviewers. After this stage, we surveyed the universe of Ethiopian bank branches (3,232 in total). We achieved a relatively high response rate (59%, 1,910 branches) through specific strategies. First, the survey was introduced as a neutral exercise, avoiding discussion of the bank's financial position or individual branch accounts. This ensured that interviewers were blind to financial data and helped maximize participation. Second, questions focused on evident practices within the branch, enabling branch managers to provide reliable answers. Finally, endorsement and support from the World Bank and the National Bank of Ethiopia encouraged participation by emphasizing the initiative's importance and official backing.

F.4 Additional Data Collected

In addition to management practices, our survey collected extensive data on respondent and branch characteristics. The introductory section gathered baseline information about the branch (e.g., name, geographic location, number of employees, opening date) and the manager (e.g., age, gender, education, previous employment).

A second set of questions addressed the organizational nature of the branch (e.g., management structure, autonomy from headquarters) and operations (e.g., average loan size, collateral requirements, share of defaulted loans).

F.5 Summary statistics by wave

Tables F.2 and F.3 report summary statistics on the main analysis variables by survey wave for respectively organizational characteristics and characteristics related to lending activities.

	Panel A: Manager Characteristics				
	N	Mean	Std. Dev.	Min	Max
Bank coethnic manager	1,948	0.65	0.48	0	1
First Wave (2018)	974	0.73	0.44	0	1
Second Wave (2022)	974	0.57	0.50	0	1
City coethnic manager	1,948	0.53	0.50	0	1
First Wave (2018)	974	0.41	0.49	0	1
Second Wave (2022)	974	0.66	0.47	0	1
Manager born in region	1,432	0.42	0.49	0	1
First Wave (2018)	462	0.43	0.50	0	1
Second Wave (2022)	970	0.42	0.49	0	1
Tenure in bank (years)	1,944	7.70	4.41	0	36
First Wave (2018)	974	6.83	4.19	0	35
Second Wave (2022)	970	8.57	4.46	0	36
Tenure in branch (years)	1,943	2.68	2.62	0	35
First Wave (2018)	974	2.38	2.33	1	35
Second Wave (2022)	969	2.98	2.85	0	23
Age	1,886	33.99	5.65	16	60
First Wave (2018)	974	33.68	6.00	16	60
Second Wave (2022)	912	34.31	5.24	23	56
University degree	1,946	0.99	0.07	0	1
First Wave (2018)	974	0.99	0.10	0	1
Second Wave (2022)	972	1.00	0.00	1	1
Male manager	1,946	0.83	0.37	0	1
First Wave (2018)	974	0.87	0.34	0	1
Second Wave (2022)	972	0.80	0.40	0	1

	Panel B: Branch Characteristics				
	N	Mean	Std. Dev.	Min	Max
Share local employees	1,910	0.57	0.25	0.10	1.00
First Wave (2018)	974	0.57	0.24	0.10	1.00
Second Wave (2022)	936	0.57	0.25	0.10	1.00
Branch employees	1,941	17.56	10.04	3	110
First Wave (2018)	974	14.75	10.30	3	110
Second Wave (2022)	967	20.38	8.92	5	78
Max loan w/o HQ (ETB 1,000)	1,524	3,855.21	6,090.99	0.00	29,823.23
First Wave (2018)	974	1,677.62	1,607.81	0.00	5,500.00
Second Wave (2022)	550	7,711.52	8,661.90	149.12	29,823.23

Notes: This table reports summary statistics of organisational analysis variables by survey wave, organised into two panels. Panel A reports manager characteristics: bank and city coethnic manager indicate whether the manager shares the ethnicity of the bank or city, respectively; manager born in region indicates whether the manager was born in the same region as the branch; tenure in bank and branch are measured in years; university degree and male manager are dummy indicators. Panel B reports branch characteristics: share local employees is the share of branch employees from the local area; branch employees is the headcount; max loan w/o HQ is the largest loan a branch manager can approve without headquarters' agreement, in ETB 1,000, deflated to 2018 prices using annual CPI inflation rates (World Bank WDI, FP.CPI.TOTL.ZG) and winsorized at the 95th percentile within period × bank-city coethnicity cells.

Table F.2: Summary statistics of organizational variables by wave

	N	Mean	Std. Dev.	Min	Max
Operational distance (km)	1,692	6.80	4.86	0.05	50.00
First Wave (2018)	974	7.62	2.62	3.00	30.00
Second Wave (2022)	718	5.67	6.65	0.05	50.00
Log number of loans	1,503	2.43	1.34	0.00	8.52
First Wave (2018)	974	2.05	1.27	0.00	6.01
Second Wave (2022)	529	3.13	1.18	0.00	8.52
Log average loan size	1,497	6.30	3.14	-4.61	10.95
First Wave (2018)	974	6.05	3.84	-4.61	10.95
Second Wave (2022)	523	6.76	0.65	5.70	8.51
Average lending rate	1,630	0.15	0.02	0.10	0.20
First Wave (2018)	974	0.15	0.02	0.10	0.20
Second Wave (2022)	656	0.15	0.02	0.10	0.20
Collateral (share of loan)	1,441	0.95	0.19	0.50	1.50
First Wave (2018)	974	1.00	0.19	0.50	1.50
Second Wave (2022)	467	0.83	0.13	0.50	1.00
Share loan default	1,569	0.06	0.14	0.00	1.00
First Wave (2018)	974	0.05	0.09	0.00	1.00
Second Wave (2022)	595	0.09	0.20	0.00	1.00

Notes: This table reports summary statistics of lending analysis variables by survey wave. Operational distance is the maximum distance (in km) at which a branch services customers. Log number of loans and log average loan size are in natural logarithms, with loan size expressed in ETB 1,000. Average lending rate is the mean rate on the past 10 loans. Collateral is the typical collateral as a share of total loan size. Share loan default is the share of defaulting loans in the past year.

Table F.3: Summary statistics of lending variables by wave

G Ethnic conflict over time and space

Figure G.1: Regions of Ethiopia

Notes: This figure displays the twelve regions in Ethiopia and two administrative councils, Addis Ababa and Dire Dawa. To ensure regions stay the same over time in our analysis, we combine Central Ethiopia, South West Ethiopia, South Ethiopia and Sidama into the Southern Nations, Nationalities and Peoples' Region (SNNPR). This region was split into four between 2020 and 2023, and remains one of the most ethnically diverse regions of the country.

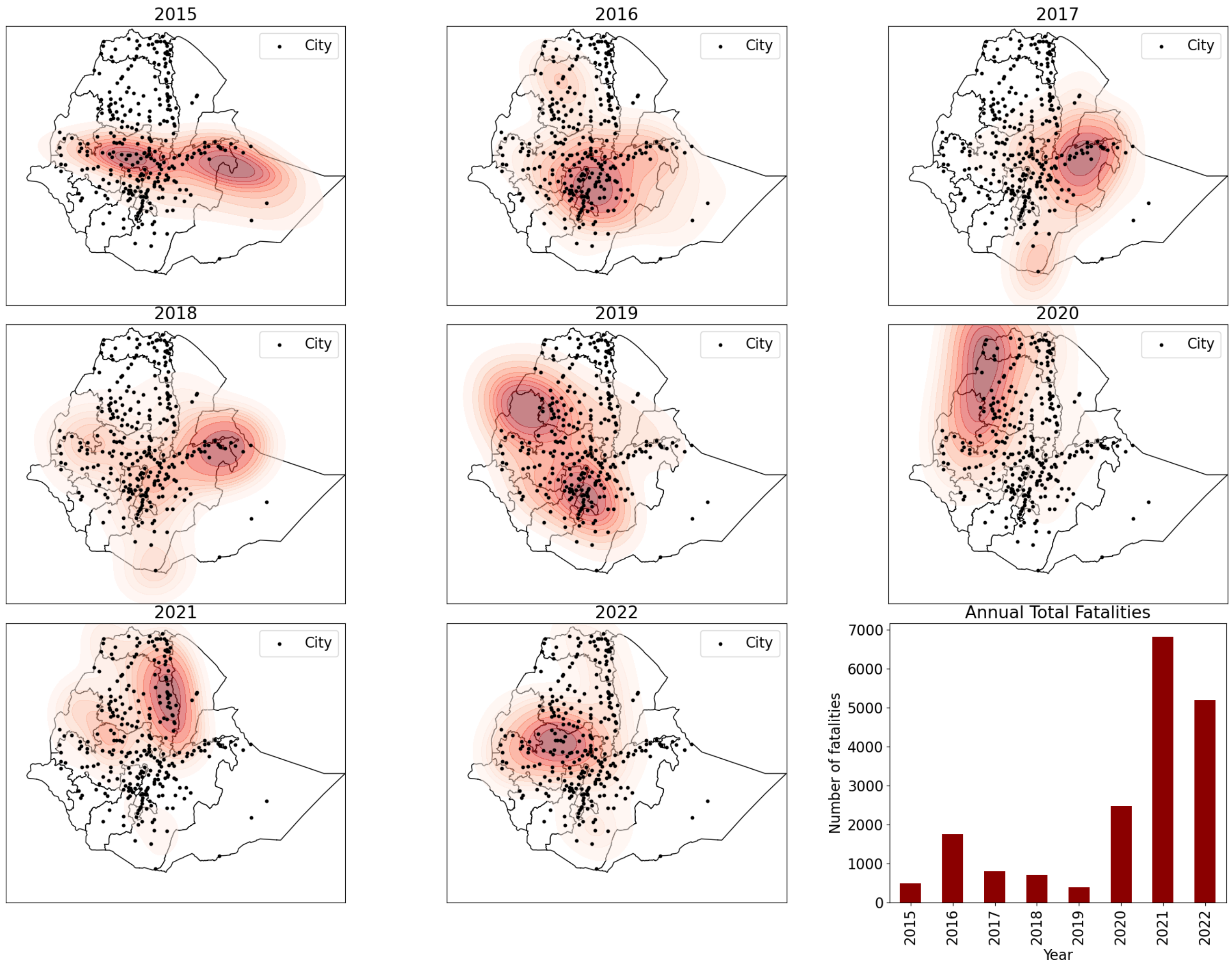

Figure G.2: Ethnic conflict in Ethiopia

Notes: This figure illustrates the spatial distribution of fatalities due to ethnic conflict in Ethiopia over time. The map on the left presents the distribution of conflict fatalities as a Kernel Density Estimate (KDE) plot, with darker regions indicating areas of higher conflict density. Cities are plotted on the map, represented in black, as well as administrative boundaries of the regions presented in Figure G.1. The bottom right bar plot shows the total number of conflict fatalities for each year, with the height of each bar corresponding to the total fatalities from ethnic conflict in that year.

H Attrition and Sample Construction

H.1 Sample Construction

The analysis sample is built from two waves of a branch-level survey of Ethiopian commercial banks, fielded in 2018 and 2022. Table H.1 summarises how the final panel is obtained from the original cohort.

2018 baseline. The baseline wave interviewed **1,910** branches spanning 16 banks and 187 cities.

2022 follow-up. In 2022, every branch interviewed in 2018 was targeted for re-interview. Of the 1,910 baseline branches, **996** were successfully re-interviewed. The remaining 914 branches fall into four mutually exclusive categories:

- **138** branches required prior headquarters approval that was not granted in the field window and were therefore not re-interviewed;
- **588** branches could not be contacted (disconnected numbers, wrong numbers, or no response after repeated attempts);
- **151** branches had been confirmed closed between the two waves;
- **37** branches have no recorded 2022 contact status.

These four categories account for the full gap between the 1,910 baseline branches and the 996 successful re-interviews: $996 + 138 + 588 + 151 + 37 = 1{,}910$.

Balanced panel. From the 996 re-interviewed branches, a further 22 are dropped to obtain a balanced panel. One branch is excluded because of a Branch ID issue that we identified as a likely mis-match between the two waves. For the remaining twenty-one branches we could not determine the exact location, which prevents us from assigning the city-level covariates used in the analysis. The resulting **balanced panel contains 974 branches observed in both waves**, for a total of $974 \times 2 = 1{,}948$ branch-wave observations.

Subsamples. Several specifications split the panel by whether the branch is located in a city whose dominant ethnicity matches that of its bank. This yields **443 branches in bank–city coethnic (BCC) locations** and **531 branches in non–bank–city coethnic (NBCC) locations**, with $443 + 531 = 974$.

H.2 Attrition

We first regress an indicator for whether a branch appears in the 2022 survey on the change in network-level conflict exposure, separately for branches in bank-coethnic and non-bank-coethnic cities. We then estimate a pooled specification with an interaction between conflict exposure and bank–city coethnicity, and finally a simple regression of re-interview status on an indicator for bank–city coethnicity.

Panel A of Table H.2 shows that, for branches in non-bank-coethnic cities, changes in conflict exposure have a small and statistically insignificant effect on survey participation. By contrast, in bank-coethnic cities, higher conflict exposure significantly increases attrition. The pooled interaction model in column 3 confirms that the slope is significantly more negative for branches in bank-coethnic cities, while the coefficient on the bank-coethnic-city indicator is positive but statistically insignificant, indicating no baseline difference in attrition between the two types of branches.

Panel B of Table H.2 examines the channels of attrition. A one-unit increase in conflict exposure raises the probability that a branch is closed by about 1.1 percentage points in cities that are not coethnic with the bank, with a much larger implied effect, around 9.1 percentage points, in coethnic cities. By contrast, for branches in non-coethnic cities, conflict exposure is associated with a small decline in the probability that a branch requires headquarters approval or cannot be contacted. Overall, attrition is limited and unrelated

Stage	Branches
2018 baseline interviewed	1,910
– 2022 re-interviewed	996
– HQ approval not granted	138
– Could not be contacted	588
– Confirmed closed	151
– No 2022 contact record	37
Re-interviewed in 2022	996
– Dropped: inconsistent identifiers	1
– Dropped: missing city ethnicity	21
Balanced panel (branches)	**974**
Balanced panel (branch-wave obs.)	**1,948**
of which bank–city coethnic (BCC)	443
of which non–bank–city coethnic (NBCC)	531

Table H.1: Sample construction waterfall

to conflict exposure in the non-bank-coethnic cities that drive our identification, suggesting that selective sample loss is unlikely to bias our main results.

Panel A: Attrition				
	(1)	(2)	(3)	(4)
	Non-coethnic	Coethnic	Interaction.	Coethnic dummy
Network exposure	-0.015	-0.087***	-0.015	
	(0.010)	(0.012)	(0.010)	
Bank and city coethnic			0.035	0.028
			(0.023)	(0.023)
Network exposure x Bank and city coethnic			-0.072***	
			(0.016)	
Observations	1030	815	1845	1845
R-squared	0.002	0.052	0.025	0.001

Panel B: Reasons for attrition			
	(1)	(2)	(3)
	Closed	Requires HQ Approval	No contact
Network exposure	0.011***	-0.012*	0.012
	(0.004)	(0.006)	(0.009)
Bank and city coethnic	-0.234***	0.008	0.026
	(0.051)	(0.016)	(0.038)
Network exposure x Bank and city coethnic	0.080***	0.014	0.006
	(0.025)	(0.010)	(0.021)
Observations	1845	1845	1845

Notes: Panel A reports the coefficient from regressions of the probability of re-interview on the change in log network-level conflict exposure. Columns (1) and (2) report the results for non bank-coethnic and bank-coethnic cities respectively, column (3) interacts conflict with a dummy for whether the bank and city are coethnic. Column (4) regresses re-interview status on an indicator for whether the bank and city are coethnic. Panel B reports average marginal effects from a multinomial logit for the reasons for attrition: the branch is closed, requires HQ approval to participate or cannot be contacted. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. We include all branches for which we determined the location from the 2018 sample. Standard errors are clustered at the branch level.

Table H.2: Attrition and Reasons for Non-response

I Manager Ethnicity Imputation

For a small number of branches in the 2022 survey wave, manager ethnicity could not be directly ascertained through the standard indicators (region of birth, accent, spoken languages, and name). For these cases, we apply the following imputation procedure:

(i). **Carry-forward:** If the same manager was present in both survey waves (identified by matching age, tenure, and gender), we assign the directly observed 2018 ethnicity. These observations are *not* flagged as imputed.

(ii). **Birthplace — same region:** For remaining missing cases where the manager was born in the same region as the branch, we assign the city's dominant ethnicity from the Murdock Ethnographic Atlas.

(iii). **Birthplace — different region:** For remaining missing cases where the manager was born in a different region, we assign the bank's dominant ethnicity.

Steps 2 and 3 are flagged by the variable `ethnicityInferred`. Table I.1 reports the number and share of branches affected.

	Count	Share
Total branches in balanced panel	974	
Branches with imputed manager ethnicity	239	24.5%
Assigned city ethnicity (born in same region)	102	10.5%
Assigned bank ethnicity (born elsewhere)	136	14.0%

Notes: Count and share of branches where manager ethnicity in the 2022 wave was imputed using the birthplace rule (steps 2–3). The carry-forward step assigns the directly observed 2018 ethnicity to unchanged managers and is not counted as imputation.

Table I.1: Imputation of manager ethnicity

To assess accuracy, we apply the same birthplace rule to observations with known ethnicity. Table I.2 reports the results for both survey waves.

Table I.3 tests whether the need for imputation is correlated with conflict exposure. We regress the imputation indicator on log conflict intensity, separately for branches in bank-coethnic cities (column 2) and non-bank-coethnic cities (column 3), and test for differential selection by interacting conflict with an indicator for non-bank-coethnic cities (column 4). The coefficients are small, negative, and statistically insignificant across all specifications, indicating that imputation is not systematically related to conflict exposure in either subsample.

	N	Correct	Accuracy
Period 1 (2018) — all ethnicities directly observed			
Overall ethnicity match	462	255	55.2%
Born in same region (city rule)	200	104	52.0%
Born elsewhere (bank rule)	262	151	57.6%
Bank coethnic indicator match	462	261	56.5%
City coethnic indicator match	462	268	58.0%
Period 2 (2022) — non-imputed observations only			
Overall ethnicity match	732	421	57.5%
Bank coethnic indicator match	732	451	61.6%
City coethnic indicator match	732	467	63.8%

Notes: Accuracy of the birthplace imputation rule when applied to observations with directly observed manager ethnicity. "Overall ethnicity match" reports the fraction for which the rule assigns the correct ethnic group. "Bank/city coethnic indicator match" reports the fraction for which the imputed value yields the correct coethnic indicator used as dependent variable in the main regressions. Period 1 applies the rule hypothetically to 2018 data where all ethnicities are known. Period 2 applies the rule to 2022 managers whose ethnicity was directly observed (non-imputed).

Table I.2: Accuracy of the ethnicity imputation rule

	(1) Pooled	(2) BCC	(3) NBCC	(4) Interaction
Network Exposure	-0.017	-0.021	-0.019	-0.021
	(0.015)	(0.033)	(0.016)	(0.033)
Network Exposure $\times$ Bank-city non-coethnic				0.002
				(0.037)
R^2	0.001	0.001	0.002	0.014
N	974	443	531	974

Notes: The dependent variable is an indicator equal to one if manager ethnicity was imputed using the birthplace rule (steps 2–3). The sample is restricted to period 2 (2022). Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest. Column 1 pools all branches; column 2 restricts to branches in bank-coethnic cities; column 3 to branches in non-bank-coethnic cities; column 4 includes the interaction with a non-bank-coethnic city indicator. Robust standard errors in parentheses.

Table I.3: Selection into imputation

Finally, Tables I.4, I.5, and I.6 replicate the main manager ethnicity regressions (Table 2), the non-coethnic manager regression (Table J.3), and the delegation analysis (Table 3) after excluding all branches with imputed ethnicity. The results are quantitatively and qualitatively similar to the full sample, confirming that the imputation does not drive our findings. The management practices and lending outcomes regressions (not reported) are also robust to this exclusion.

	Panel A: Branches in Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-0.029	-0.022	-0.030	-0.029	-0.022	-0.030
	(0.032)	(0.080)	(0.032)	(0.032)	(0.080)	(0.032)
Local Exposure			0.011			0.011
			(0.010)			(0.010)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.659	0.659	0.659	0.659	0.659	0.659
N (Branches)	311	239	311	311	239	311

	Panel B: Branches in Non-Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
Network Exposure	0.082***	0.051***	0.084***	-0.136***	-0.105***	-0.140***
	(0.018)	(0.020)	(0.018)	(0.017)	(0.020)	(0.017)
Local Exposure			-0.016			0.037***
			(0.010)			(0.010)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	0.193	0.193	0.193	0.757	0.757	0.757
p-value	0.003	0.372	0.002	0.003	0.311	0.002
N (Branches)	424	363	424	424	363	424

Notes: This table replicates Table 2 after excluding branches where manager ethnicity in the 2022 wave was assigned using the birthplace rule. The dependent variable is an indicator equal to one when a branch manager is co-ethnic with the city (columns 1–3) or bank (columns 4–6). Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local Exposure is the log of conflict intensity near the city as defined in equation 2. Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table I.4: Bank-level conflict exposure and manager ethnicity — excluding imputed observations

	(1) Bank and city coethnic Non-coethnic manager	(2) Bank and city not coethnic Non-coethnic manager
Network Exposure	0.029	0.054***
	(0.032)	(0.014)
Branch FE	Yes	Yes
Time FE	Yes	Yes
2018 Mean dep. var	0.341	0.050
p-value		0.463
N	311	424

Notes: This table replicates Table J.3 after excluding branches where manager ethnicity in the 2022 wave was assigned using the birthplace rule. The dependent variable is an indicator equal to one when the branch manager is coethnic with neither the bank nor the city. Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest. Column 1 restricts the sample to branches in cities coethnic with the bank; column 2 to branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table I.5: Bank-level exposure to ethnic conflict and non-coethnic managers — excluding imputed observations

Panel A: Ethnic conflict and delegation						
	Bank and city not coethnic			Bank and city coethnic		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-1069.7***	-799.0**	-1065.2***	-392.2	-2254.5	-286.5
	(307.9)	(384.3)	(308.6)	(527.6)	(1906.4)	(529.3)
Local Exposure			-21.3			-427.1**
			(136.4)			(183.0)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	Yes
City-Time FE	No	Yes	No	No	Yes	No
2018 Mean dep. var	1682.8	1682.8	1682.8	1631.8	1631.8	1631.8
p-value	0.267	0.449	0.204	0.267	0.449	0.204
N (Branches)	424	235	424	311	124	311

Panel B: Manager ethnicity and delegation						
	Panel		Period 1 Only		Period 2 Only	
	(1) Non-coethnic	(2) Coethnic	(3) non-coethnic	(4) Coethnic	(5) non-coethnic	(6) Coethnic
City coethnic manager	-1597.8**	-3085.1***	-128.3	-200.7	-2808.6***	-5111.7***
	(784.4)	(1121.1)	(191.3)	(194.0)	(993.3)	(1796.9)
Branch FE	Yes	Yes	No	No	No	No
Time FE	Yes	Yes	No	No	No	No
Constant	No	No	Yes	Yes	Yes	Yes
2018 Mean dep. var	1682.8	1631.8	1682.8	1631.8	7156.2	8003.7
p-value	0.277	0.277	0.790	0.790	0.262	0.262
N (Branches)	424	311	424	311	291	192

Notes: This table replicates Table 3 after excluding branches where manager ethnicity in the 2022 wave was assigned using the birthplace rule. The dependent variable in both panels is the largest loan a branch manager can approve without headquarters' agreement, measured in ETB 1,000, deflated to 2018 prices and winsorized at the 95th percentile within period $\times$ bank-city coethnicity cells. Panel A estimates the effect of Network Exposure on delegation separately for branches where the bank and city are not coethnic (columns 1–3) and where they are coethnic (columns 4–6). Panel B estimates the effect of having a city-coethnic manager on delegation. Odd columns restrict to non-bank-coethnic cities; even columns to bank-coethnic cities. Columns 1–2 use the full panel; columns 3–4 use the 2018 cross-section; columns 5–6 use the 2022 cross-section. Standard errors, clustered at the branch level, are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table I.6: Bank-level exposure to ethnic conflict and delegation — excluding imputed observations

J Alternative mechanisms tables

	Not Bank City Coethnic			Bank city coethnic		
	Bank coethnic	City coethnic	Neither coethnic	Bank coethnic	City coethnic	Neither coethnic
Network Exposure	-0.133***	0.078***	0.055***	-0.003	-0.003	0.003
	(0.018)	(0.018)	(0.013)	(0.025)	(0.025)	(0.025)
Local coethnic conflict intensity	0.017**	-0.008	-0.009*	-0.000	-0.000	0.000
	(0.007)	(0.007)	(0.005)	(0.007)	(0.007)	(0.007)
2018 Mean dep. var	0.772	0.183	0.045	0.679	0.679	0.321
N (Branches)	531	531	531	443	443	443

This table reports OLS estimates of the effect of bank network conflict intensity on manager ethnicity, controlling for local conflict involving the bank's ethnic group. The dependent variable in each column indicates whether the branch manager is coethnic with the bank, coethnic with the city, or coethnic with neither. Network Exposure is the log of average fatalities involving the bank's ethnicity across the bank's other branches, excluding the local branch. Local coethnic conflict intensity is the log of fatalities involving the bank's ethnicity in the branch's own city. Columns 1–3 restrict to branches where the bank and city dominant ethnicity differ; columns 4–6 restrict to branches where they are the same. All specifications include branch and time fixed effects. Standard errors clustered at the branch level are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table J.1: Controlling for local ethnic conflict involving the banks' ethnic group

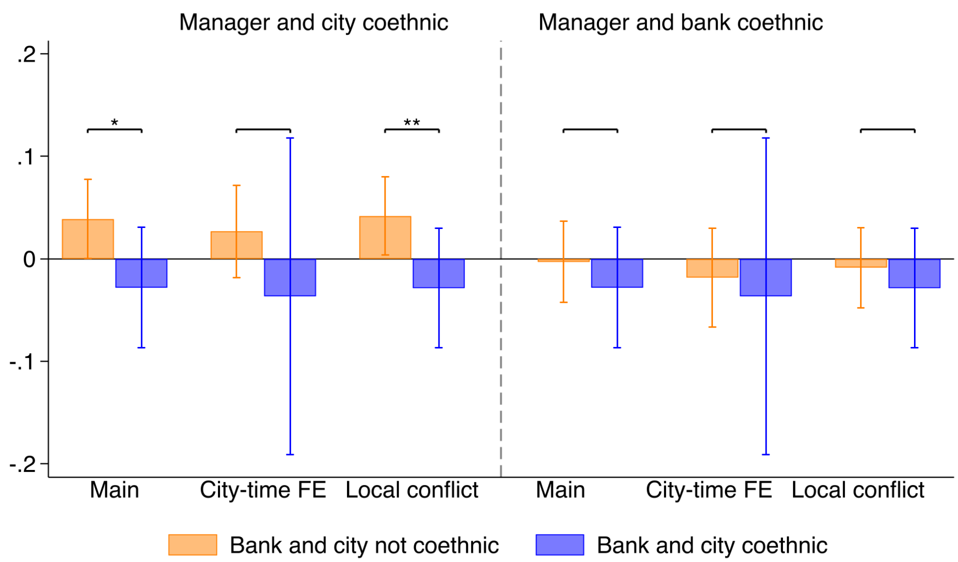

Figure J.1: Bank-level exposure to ethnic conflict involving the bank's and city's ethnic group

	Panel A: Branches in Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	-0.003	0.007	0.033	-0.003	0.007	0.033
	(0.025)	(0.028)	(0.027)	(0.025)	(0.028)	(0.027)
Many competitors		-0.023			-0.023	
× Network Exposure		(0.032)			(0.032)	
High perceived competition			-0.084**			-0.084**
× Network Exposure			(0.033)			(0.033)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	.	0.673	0.664	.	0.673	0.664
N (Branches)	443	443	443	443	443	443

	Panel B: Branches in Non-Bank-Coethnic Cities					
	City coethnic manager			Bank coethnic manager		
	(1)	(2)	(3)	(4)	(5)	(6)
Network Exposure	0.079**	0.079***	0.049**	-0.132***	-0.116***	-0.109***
	(0.036)	(0.020)	(0.020)	(0.033)	(0.020)	(0.019)
City-coethnic competitor	-0.014			0.025		
× Network Exposure	(0.035)			(0.032)		
Many competitors		-0.024			0.013	
× Network Exposure		(0.023)			(0.022)	
High perceived competition			0.036			-0.002
× Network Exposure			(0.023)			(0.022)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
2018 Mean dep. var	0.127	0.156	0.205	0.789	0.807	0.737
N (Branches)	531	531	531	531	531	531

Notes: The dependent variable is an indicator that equals 1 when a branch's manager is co-ethnic with the ethnic group associated with the city (columns 1–3) or with the ethnic group associated with the branch's bank (columns 4-6). Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local Exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log Network Exposure from 2018 to 2022 is 1.423 (1.371). Panel A restricts the sample to branches in cities coethnic with the bank, while Panel B focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on Network Exposure is identical in bank-coethnic and non bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table J.2: Heterogeneity in the effect of conflict by the nature of local competition

	(1) Bank and city coethnic Non-coethnic manager	(2) Bank and city not coethnic Non-coethnic manager
Network Exposure	0.003	0.043^{***}
	(0.025)	(0.012)
Branch FE	Yes	Yes
Time FE	Yes	Yes
2018 Mean dep. var	0.321	0.045
p-value		0.149
N	443	531

Notes: The dependent variable is an indicator that equals 1 when a branch's manager is co-ethnic with neither the city nor with the ethnic group associated with the branch's bank. Network Exposure is the log intensity of bank-level exposure to conflict involving the bank's ethnic group, excluding conflict near the branch of interest, defined in equation 1. Local Exposure is the log of conflict intensity near the city as defined in equation 2. The mean (SD) of the within-branch change in log Network Exposure from 2018 to 2022 is 1.423 (1.371). Column (1) restricts the sample to branches in cities coethnic with the bank, while column (2) focuses on branches in cities that are not. Standard errors, clustered at the branch level, are reported in parentheses. The reported p-value is for the test that the slope on Network Exposure is identical in bank-coethnic and non bank-coethnic cities. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table J.3: Bank-level exposure to ethnic conflict and non-coethnic managers

	Not Bank City Coethnic			Bank city coethnic		
	Bank coethnic	City coethnic	Neither coethnic	Bank coethnic	City coethnic	Neither coethnic
Network Exposure	-0.088^{***}	0.062^{***}	0.026	-0.015	-0.015	0.015
	(0.022)	(0.022)	(0.017)	(0.029)	(0.029)	(0.029)
High local employees	-0.036	0.008	0.028	0.024	0.024	-0.024
$\times$ Network Exposure	(0.023)	(0.024)	(0.019)	(0.031)	(0.031)	(0.031)
2018 Mean dep. var	0.740	0.204	0.055	0.668	0.668	0.332
N (Branches)	531	531	531	443	443	443

This table reports OLS estimates of the effect of bank network conflict intensity on manager ethnicity, interacted with an indicator for whether the branch has an above-median share of locally hired employees. The dependent variable in each column indicates whether the branch manager is coethnic with the bank, coethnic with the city, or coethnic with neither. Columns 1–3 restrict to branches where the bank and city dominant ethnicity differ; columns 4–6 restrict to branches where they are the same. All specifications include branch and time fixed effects. Standard errors clustered at the branch level are reported in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table J.4: Heterogeneity by the share of local employees in 2018

K AI Survey Methodology

This appendix describes the AI survey experiment summarized in Section 4.4. We follow John J Horton, Apostolos Filippas and Benjamin S Manning (2023), Lisa P Argyle, Ethan C Busby, Nancy Fulda, Joshua R Gubler, Christopher Rytting and David Wingate (2023), and James Brand, Ayelet Israeli and Donald Ngwe (2023). Figure K.1 provides an overview.[2]

K.1 Step 1: Sample Construction

We draw scenarios from the branch data used in the main analysis. We sample 150 branches across the 2018 and 2022 survey waves, giving 300 branch-year observations. Each observation carries the branch's bank name, bank ethnicity, city, city ethnicity, year, local conflict intensity (fatalities within 20km), and bank-network conflict intensity. Branch selection uses a fixed random seed at two stages: `seed 1234` in the Stata script that samples branches from the population and `seed 42` in the Python driver that iterates over branches and treatments.

We focus on branches in *non-coethnic cities*—where the bank's ethnicity differs from the city's dominant ethnicity—because this is where the assignment decision involves a real trade-off between a city-coethnic and a bank-coethnic candidate. For each such branch-year, we evaluate both manager types.

Of the 150 sampled branches, 100 are in non-coethnic cities (200 branch-year observations) and 50 are in coethnic cities (100 branch-year observations). Each branch-year is evaluated under three conflict levels (actual, low, high) for each of four manager ethnicities (Amhara, Oromo, Tigray, SNNP), giving 12 scenarios per branch-year. Of the 200 non-coethnic branch-years, 190 have complete AI predictions: 5 are dropped because the model refused to produce ethnicity-conditional predictions on ethical grounds, and 5 hit transient API errors that were not recovered by the retry logic. Together with 98 coethnic branch-years (2 branches lost to the same API errors), this gives $(190 + 98) \times 12 = 3{,}456$ scenarios. The regression analysis uses two rows per branch-year—the city-coethnic and bank-coethnic evaluations—since the other two ethnicities are coethnic with neither the city nor the bank. Each scenario requires 18 sequential API calls, totaling approximately 62,000 calls for the full simulation.

K.2 Step 2: CEO Persona Construction

For each scenario, we construct a system prompt that instructs the LLM to role-play as the CEO of the relevant bank (Figure K.1, "LLM CEO Persona"). The CEO is told that they share the bank's ethnic affiliation and that senior management and the board are predominantly from that group.

The system prompt contains three blocks of factual information.

Bank identity and lending process. All scenarios include an identical description of how the branch processes loan applications. The prompt covers three steps: (i) *information acquisition*—the manager gathers formal documentation and "soft information" (business reputation, character, community standing); (ii) *communication to headquarters*—the manager recommends approval or rejection on larger loans,

[2] In accordance with AEA policy, we disclose that this section uses large language models both as a research instrument (simulated survey respondents) and for annual report text summarization. The models are not listed as authors. All simulation code, prompts, and realized outputs are provided in the replication package.

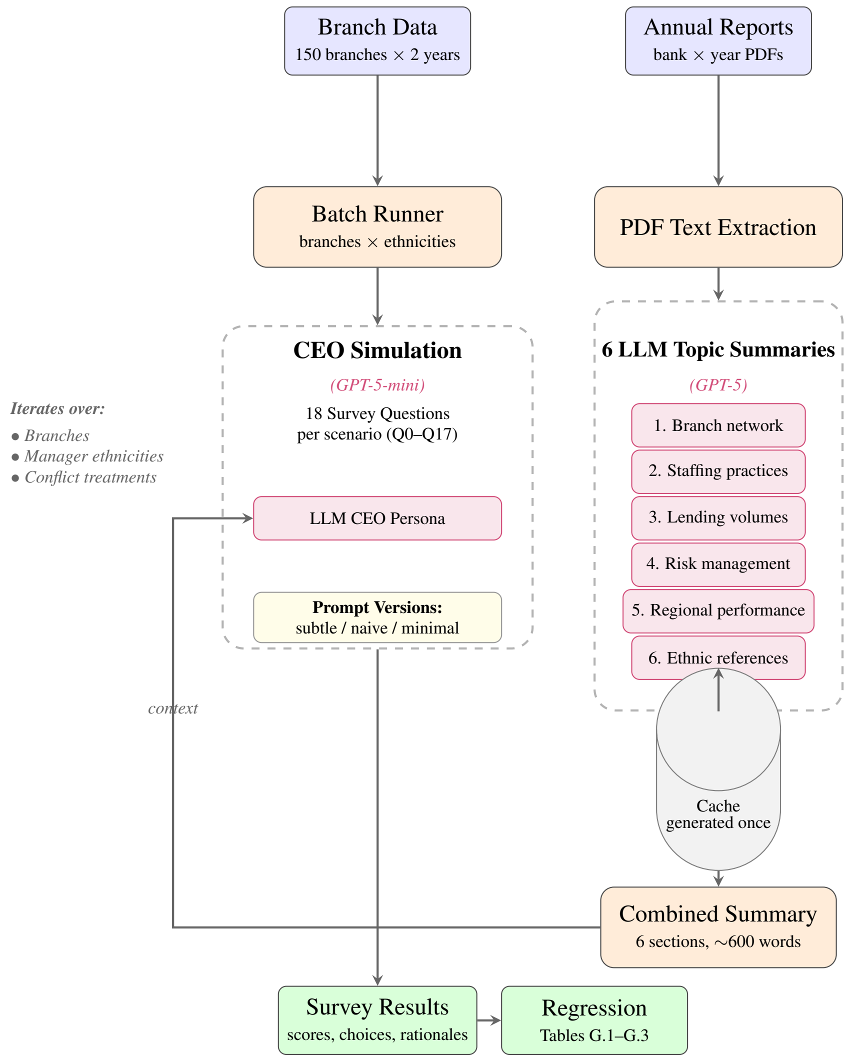

Figure K.1: Analysis pipeline.

Notes: Branch data and bank annual reports are processed in parallel. Annual reports are summarized into six topics using GPT-5 (one LLM call per topic, cached); the combined summary of roughly 600 words is embedded in the CEO's system prompt. GPT-5-mini then role-plays as each bank's CEO and answers 18 sequential questions per scenario. Reported results use the subtle prompt; the naive and minimal prompts are used for robustness (Section K.9.2). The analysis sample is restricted to branches in non-coethnic cities (bank $\neq$ city ethnicity).

and headquarters cannot independently verify the soft information; and (iii) *autonomous decisions*—the manager can approve smaller loans below a delegation threshold without headquarters involvement. The prompt also describes how local ties shape accountability. A city-coethnic manager develops deeper community relationships, which create social obligations and potential private benefits from approving loans to coethnics. A bank-coethnic manager has stronger ties to senior management, with career advancement linked to headquarters' perception. The prompt names both sides of this trade-off but does not say which side should dominate.

Conflict situation. Conflict exposure is communicated via fatality counts from ethnic conflict involving the bank's ethnic group, using the same definitions as the main analysis. The bank-network conflict intensity (the treatment variable) is set to 0.6 fatalities for the low-conflict treatment (10th percentile of the pooled 2018–2022 distribution) or 17.5 fatalities for the high-conflict treatment (90th percentile). Branch-level conflict always uses the actual value from the data.

Annual report summary. Each scenario includes a machine-generated summary of the bank's annual report for the relevant year (Figure K.1, right column). We extract text from the PDF annual report and summarize it into six topics using OpenAI's GPT-5: branch network, staffing practices, lending volumes, risk management, regional performance, and any references to ethnic considerations. Each topic is summarized in a separate LLM call with a prompt that requests factual extraction rather than interpretation. The six topic summaries are concatenated into a combined summary of roughly 600 words, generated once per bank-year pair, cached, and reused across all scenarios involving that bank and year.

K.3 Step 3: Prompt Design

Prompts vary along two axes: how ethnicity is framed, and how much of the lending-process mechanism is described. The primary results use a *subtle* prompt that combines the full lending-process description from Step 2 with the following ethnicity framing:

> *"In Ethiopia, ethnicity is a salient characteristic that varies across regions and is relevant to social and business relationships. Ethiopian banks are associated with specific ethnic communities (Amhara, Oromo, Tigray, SNNP), and cities have different ethnic compositions. You are evaluating branch management decisions. Consider the practical realities of operating in this environment."*

The subtle prompt tells the CEO that ethnicity is relevant but does not say in which direction. The Step 2 description lays out both the information advantage of local managers and their moral-hazard exposure without ranking the two. Any pattern in the responses comes from how the model weighs these forces, not from a direction the prompt asserts.

We vary the two axes separately for robustness. The *naive* prompt keeps the full lending-process description but strips the ethnicity framing, describing ethnicity only as "a demographic characteristic that varies across regions" with no mention of bank ethnic affiliations or social relationships. The *minimal* prompt (used in the institutional-context ablation, Section K.9.2) instead keeps the subtle ethnicity framing but strips the lending-process description down to bare logistical steps: the manager assesses applicants, recommends to headquarters, and approves small loans below a threshold, with no mention of soft information, non-verifiability, or accountability relationships. Table K.1 summarizes the two prompts used in the reported analysis.

Version	Ethnicity framing	Lending-process description
Subtle (primary)	"Salient characteristic ... relevant to social and business relationships"	Full: soft vs. hard information, non-verifiability at headquarters, local vs. headquarters accountability
Naive	"Demographic characteristic that varies across regions"	Full (identical to subtle)

Notes: Both prompts include the same conflict description, annual report summary, and survey questions. Only the ethnicity framing differs between them. The subtle prompt is used for all primary results; the naive prompt is used in the prompt-sensitivity analysis in Section K.9.2. A third *minimal* prompt, which strips the lending-process description, is reported in the institutional-context ablation in Section K.9.2.

Table K.1: Prompt Version Comparison

K.4 Step 4: Survey Administration

Each scenario proceeds as a single multi-turn conversation with full memory: the LLM receives the system prompt, then answers 18 sequential questions (Q0–Q17), each of which sees all prior questions and answers (Figure K.1, right column). This ensures internal consistency across responses.
The question order is designed to reduce anchoring on the final choice. We elicit perception scores and business outcomes first (Q1–Q14), then the mechanism weights (Q15), and place the manager ethnicity choice last (Q16–Q17). Asking the mechanism questions before the preference reduces the risk that an early-stated preference anchors the later numeric scores.
The questions fall into five blocks:

(i). *Manager assessments* (Q1–Q5): Information acquisition ability (0–100), alignment of loan recommendations with bank objectives (0–100), ethnic bias risk (0–100), expected NPL ratio (0–100%), and delegation threshold (discrete set from 0 to 5,000 ETB thousands).

(ii). *Qualitative rationale* (Q6–Q7): Free-text explanations of the CEO's reasoning and how decisions would change under increased conflict.

(iii). *Lending and NPL by customer ethnicity* (Q8–Q12): Expected total lending volume, lending shares to bank-coethnic and city-coethnic customers, and expected NPL rates for each customer group. These questions are prefaced with "Conditional on the answers you have given so far."

(iv). *Safety and cost* (Q13–Q14): Safety concern for the manager (0–100) and required wage premium (-50% to $+50\%$).

(v). *Synthesis* (Q15–Q17): Allocation of 100 points across four mechanism categories (information, alignment, safety, other), followed by the CEO's preferred manager ethnicity—both unconditionally and conditional on a bank-coethnic predecessor.

For numeric questions, the model is instructed to respond with only a number. Responses are parsed programmatically by extracting the first numeric value via regular expression; if no number is found, the response is recorded as missing. Multiple-choice responses (Q16–Q17) are matched against the four valid ethnicity labels. The mechanism weight allocation (Q15) is parsed via a structured `KEY:VALUE` pattern and accepted if the four weights sum to 100 within a ± 1 rounding tolerance. API-level errors (rate limits, timeouts) are retried up to three times with exponential backoff; parse failures are not retried. Numeric responses are checked against the expected range for each question (e.g., 0–100 for perception scores, 0–500 for lending volume), and no out-of-range values were observed. Across all 3,456 scenarios and 15 response fields per scenario (51,840 field instances), 5 responses (0.01%) failed to parse—all five were model safety refusals rather than technical errors—and every set of mechanism weights summed to 100 within the tolerance. The full question text is reported in Table K.2.

K.5 Step 5: Model and Parameters

The CEO simulation uses OpenAI's `gpt-5-mini` with temperature 1.0 and a maximum of 16,000 completion tokens; the annual-report summaries use `gpt-5` with the same token limit. Temperature is hard-coded to 1.0 because that is the only value this reasoning model accepts, so variation across scenarios comes entirely from the stochastic decoding process. All other generation parameters (`top_p`, frequency and presence penalties, and the random seed) take their API defaults; no API-level seed is available for the reasoning model, and responses to repeated calls on the same scenario differ. Each scenario consists of 18 API calls, with the full conversation history passed at each turn; the 18-turn exchange plus the roughly 600-word annual-report summary in the system prompt fits within the model's context window with substantial margin, and no truncation occurred.

We use OpenAI models exclusively because Bocconi maintains an enterprise data-processing agreement with OpenAI that provides institutional assurances on the handling of research data. Even under this agreement, prompts contain only branch-level information already used in the main analysis—bank and city ethnicity, aggregate conflict counts, and the annual-report summary—and no personally identifiable information about managers, clients, or individual loans.

The simulation was run on February 23, 2026. The replication package includes (i) all Python source code for scenario construction, API interaction, and response parsing; (ii) the full system-prompt templates for each prompt version; (iii) the complete realized outputs, including both parsed values and raw response text for every question in every scenario; and (iv) cached annual-report summaries. Because model weights may drift over time, the archived outputs—not a re-run—constitute the replication target.

K.6 Identification Strategy

The analysis exploits the factorial structure to identify the effect of manager ethnicity and conflict on CEO assessments. For each branch i observed in year t under conflict treatment $c \in \{\text{low}, \text{high}\}$ with manager type $m \in \{\text{city-coethnic}, \text{bank-coethnic}\}$, we estimate:

$$Y_{itcm} = \beta_1 \, \text{CityCoethnic}_m + \beta_2 \, \text{HighConflict}_c^{\text{dm}} + \beta_3 \, (\text{CityCoethnic}_m \times \text{HighConflict}_c^{\text{dm}}) + \gamma_i + \delta_t + \varepsilon_{itcm} \tag{a8}$$

Q#	Question (abbreviated)	Scale
0	Scenario acknowledgment: "You are evaluating a potential branch manager for {city}, predominantly {city_ethnicity}. The candidate is {manager_ethnicity}. Confirm you understand."	Ack.
1	Rate this manager's ability to acquire soft information about local borrowers (business reputation, character, informal credit history, community standing).	0–100
2	How well would this manager's loan recommendations align with the bank's profitability objectives?	0–100
3	How likely is this manager to show favoritism toward borrowers of their own ethnic group, approving loans not in the bank's best interest?	0–100
4	What NPL ratio would you expect for the loan portfolio managed by this manager? (Sector average $\approx 5\%$)	0–100%
5	For typical collateral, what is the largest loan (ETB thousands) this manager's branch could give without prior HQ authorization?	Discrete
6	Explain in 50 words why you made these decisions about manager ethnicity and delegation authority.	Free text
7	If ethnic conflict near {city} increases significantly, how would you change: (1) manager ethnicity choice, (2) delegation authority, (3) monitoring intensity?	Free text
8	What total annual lending volume (ETB millions) would you expect from this manager's branch?	0–500
9	What % of total lending would go to customers coethnic with the bank?	0–100%
10	What % of total lending would go to customers coethnic with the city?	0–100%
11	What NPL ratio for loans to customers coethnic with the bank?	0–100%
12	What NPL ratio for loans to customers coethnic with the city?	0–100%
13	How concerned are you about the physical safety of this manager working in {city}?	0–100
14	What % premium or discount to the standard salary would this manager require to work in {city}?	-50 to +50%
15	Allocate 100 points across: INFO (local information ability), ALIGN (alignment with bank objectives), SAFETY (physical security), OTHER.	100-pt alloc.
16	Which ethnicity should the branch manager be? Options: Amhara, Oromo, Tigray, SNNP.	Choice
17	Given a bank-coethnic predecessor, which ethnicity for the new manager?	Choice

Notes: Questions are asked sequentially within a single conversation; each question sees all prior Q&As. Placeholders {city}, {city_ethnicity}, {manager_ethnicity}, {bank_ethnicity} are filled with actual values from the branch data. Q5 offers a discrete set: $\{0, 100, 250, 500, 750, 1000, 1500, 2000, 3000, 5000\}$ ETB thousands. Q8–Q12 are prefaced with "Conditional on the answers you have given so far."

Table K.2: AI Survey Questions

where γ_i are branch fixed effects, δ_t are year fixed effects, and $\text{HighConflict}^{\text{dm}}$ is demeaned so that β_1 captures the average city-coethnic effect across conflict levels rather than the effect at low conflict only. Standard errors are clustered at the branch level.

The coefficient β_1 identifies how CEO expectations differ between city-coethnic and bank-coethnic managers, averaged across conflict levels. The interaction β_3 identifies how the manager-type difference changes with conflict intensity. Branch fixed effects absorb all time-invariant branch characteristics (bank identity, city demographics, coethnicity status), so identification comes from within-branch, across-scenario variation.

The standard errors here quantify the precision with which we can estimate the LLM's average response across scenario inputs (branch characteristics, conflict treatments) and stochastic decoding at temperature 1.0. Statistical significance therefore describes the model's systematic behavior, not a causal claim about real Ethiopian banks: a significant coefficient means the model responds to this variation reliably, not that the estimated effect is present in the real economy.

K.7 Interpretation and Limitations

We interpret this exercise as mechanism exploration rather than causal identification of real-world effects. The model's responses reflect patterns in its training data, which likely include academic research on ethnic networks, banking, and organizational economics, along with news coverage and institutional reports relevant to Ethiopian banking. They may not replicate the beliefs of actual Ethiopian bank executives.

The exercise has five limitations. The first is *algorithmic monoculture*: all responses come from a single model, so the variation across scenarios may understate the belief dispersion one would see in a population of human decision-makers. Temperature-induced variation provides some heterogeneity but is not the same as sampling from a population. Second, the model's knowledge of Ethiopia's banking sector may be incomplete or reflect biases in the training corpus. Third, the structured response format (numeric scales, discrete choices) will not capture everything a real manager would weigh.

The remaining two limitations are less standard. We cannot rule out *training-data contamination*: earlier versions of this paper or closely related work may sit in the training corpus, in which case the model could be reproducing rather than independently deriving the patterns we report. The institutional-context ablation in Section K.9.2 partially addresses this—if the model were simply recalling published signs, stripping the lending-process description should not flip them, yet it does. Finally, each conversation evaluates both manager types sequentially within a single CEO's thread. This within-subject framing may amplify the perceived contrast between manager types relative to a design in which each manager is evaluated in a fresh conversation.

The value of the exercise is that it produces scenario-specific predictions about mechanisms that administrative data cannot observe directly, complementing the reduced-form findings.

K.8 Validation Against Survey Data

We compare the AI predictions to actual survey data on two observable outcomes—delegation authority and non-performing loan ratios. The AI was never given branch-specific financial data; validation therefore focuses on directional patterns rather than level predictions. For each test, we match branch-years to the AI's prediction for the actually observed manager ethnicity under the actual conflict level, yielding a one-to-one comparison. Table K.3 reports the results.

Within-branch predictive power. Regressions of actual outcomes on AI predictions with branch and year fixed effects yield positive but imprecisely estimated coefficients (delegation: $\hat{\beta} = 5.9$, s.e. $= 5.5$; NPL: $\hat{\beta} = 0.31$, s.e. $= 0.47$). The point estimates are consistent with AI predictions moving in the same direction as actual outcomes, but are not statistically distinguishable from zero. This is expected: the AI receives bank-level information but no branch-specific financial data, so it captures average directional effects rather than branch-level outcomes. The remaining tests focus on these directional patterns.

Delegation direction. In both 2018 and 2022, the AI and the actual data agree that city-coethnic managers receive *lower* delegation thresholds than bank-coethnic managers (Table K.3, Panel B). In the regression specification of Equation (a8), the AI yields $\hat{\beta}_1 = -158.3$ (s.e. $= 30.3$) and the full-sample actual data yields $\hat{\beta}_1 = -1{,}518.3$ (s.e. $= 751.9$, $p < 0.05$)—both negative (Panel C). The actual-data regression uses the paper's main specification on the full panel ($N = 644$), with inflation-adjusted delegation winsorized at the 95th percentile.

Coethnic placebo. The sign reversal on coethnic branches is the cleanest evidence that the misaligned-city results reflect the information-incentive mechanism rather than a generic model bias. We re-run the AI survey on branches in *coethnic* cities, where city-coethnic and bank-coethnic coincide and no information-incentive trade-off exists. The delegation coefficient flips sign: $\hat{\beta}_1 = +877.1$ (s.e. $= 59.0$) in coethnic cities versus -158.3 in misaligned cities (Panel C). The information-communication gap flips in the same way, from -24.6 to $+24.9$ (Panel D). When the trade-off disappears, the AI grants city-coethnic managers more authority, not less.

NPL mismatch. The AI predicts higher NPL for city-coethnic managers ($\hat{\beta}_1 = +0.77$, s.e. $= 0.12$), while the actual data produce a negative but imprecisely estimated coefficient ($\hat{\beta}_1 = -0.34$, s.e. $= 2.19$, $N = 650$; Panel C, scaled $\times 100$). In coethnic cities, the AI predicts *lower* NPL for city-coethnic managers ($\hat{\beta}_1 = -3.22$), so its positive prediction in misaligned cities is not a generic bias but a response to the structure of the trade-off. The sign disagreement likely reflects the model weighting the moral-hazard channel more heavily than the screening channel; we cannot distinguish these interpretations from the experiment alone.

Ethnicity choice. Unlike the organizational design outcomes, the AI's preferred manager ethnicity does not respond to conflict. The AI chooses a city-coethnic manager in 93.2% of cases regardless of conflict treatment ($\hat{\beta} = 0.008$, s.e. $= 0.018$ on the high-conflict indicator with branch and year fixed effects). In the actual data, conflict shifts manager assignment. The AI captures the organizational design response to conflict (delegation, lending) but not the assignment response, consistent with it overweighting the information advantage of city-coethnic candidates relative to the alignment concerns that drive real personnel choices.

K.9 Robustness Checks

We assess the robustness of the AI survey results along several dimensions suggested by the literature on LLMs as simulated economic agents (Argyle et al., 2023; Brand, Israeli and Ngwe, 2023; Horton, Filippas and Manning, 2023).

K.9.1 Model Sensitivity

Our main results use GPT-5-mini, a reasoning model that generates an internal chain of thought before producing answers. To check whether the findings depend on this architectural choice, we replicated the exercise using GPT-4o-mini, a non-reasoning model, with the prompt and experimental design held fixed.[3]
The non-reasoning model captures the first-order pattern: city-coethnic managers still score substantially higher on information acquisition ($+45$ points in GPT-4o-mini versus $+55$ in GPT-5-mini). It fails, however, on the variables that require joint reasoning about information and alignment. Information communication flips from -23 to $+8$, ethnic bias reverses from $+40$ to -4, delegation reverses from -158 to $+233$ thousand ETB, and expected NPL flips from $+0.8$ to -3.0 percentage points.
This is the same failure mode that the *minimal* prompt induces in GPT-5-mini (Section K.9.2): positive delegation, positive information communication, negligible or negative ethnic bias, and lower expected NPL. Whether one strips the agency structure from the *prompt* or uses a *model* that does not integrate information and alignment in the same judgment, the output defaults to a "local knowledge is uniformly good" heuristic—recognizing the information advantage of city-coethnic managers but not connecting it to moral hazard or tighter headquarters control. We therefore use GPT-5-mini for all reported results.

K.9.2 Prompt Sensitivity

A natural concern with AI survey experiments is that the model's responses may reflect the prompt rather than its latent knowledge. Our main specification uses a "subtle" prompt that provides the CEO with factual context about Ethiopian banking, including a description of the branch lending process: how managers acquire information about borrowers, communicate recommendations to headquarters, and make autonomous decisions below a delegation threshold. This context also describes how managers develop accountability relationships with local communities and with headquarters, noting that local ties create social obligations while headquarters ties create career accountability. While this framing avoids explicit mention of trade-offs, a skeptical reader might argue that describing these mechanisms primes the model to reproduce them.
To address this concern, we replicate the experiment using a "naive" prompt that provides only minimal context: ethnicity is described as "a demographic characteristic that varies across regions," and banks are described as serving "customers across different regions with varying ethnic compositions." Critically, the naive prompt retains the full lending process context, so any differences reflect the ethnicity framing rather than the institutional description.
Table K.4 reports the results. The core findings are remarkably stable across prompt versions. Panel A shows that city-coethnic managers score 53 points higher on information acquisition under the naive prompt

[3] The GPT-4o-mini replication used the *subtle* prompt on 98 of the 100 misaligned branches—196 of 200 branch-years—with the remaining 2 branches lost to API failures.

versus 55 under the subtle prompt, 21 points lower on information communication (versus -23), and 38 points higher on ethnic bias (versus 40). The information-alignment trade-off emerges with nearly identical magnitudes regardless of how ethnicity is framed.

Panel B confirms that conflict treatment effects are also robust. High conflict reduces delegation thresholds, increases safety concerns, and compresses lending volumes under both prompts. The conflict $\times$ city-coethnic interaction on lending volume—our key measure of how conflict differentially affects expectations about city-coethnic versus bank-coethnic managers—is -14 million ETB under the naive prompt and -15 under the subtle prompt.

The delegation level effect is also robust: city-coethnic managers receive -214 thousand ETB lower delegation under the naive prompt versus -158 under the subtle prompt, both highly significant ($p < 0.01$). The naive estimate is somewhat larger in magnitude, indicating that the minimal ethnicity context does not weaken the model's ability to translate the information-incentive trade-off into organizational design responses.

The role of institutional context. Both the subtle and naive prompts include a description of the branch lending process: how managers gather information about borrowers, communicate recommendations to headquarters, make autonomous decisions below a delegation threshold, and develop accountability relationships with local communities and with bank headquarters. A skeptical reader might argue that this description primes the model to reproduce the information-incentive trade-off. To test this, we run a "minimal" prompt that strips all mechanism framing from the lending process description, retaining only the bare logistical steps (assess applicants, recommend to headquarters, decide autonomously on small loans) without any mention of soft information, verification problems, favoritism pressures, or accountability relationships.

Table K.5 shows that the institutional context is doing essential work. Without the lending-process description, the information-acquisition advantage for city-coethnic managers survives but attenuates from $+55$ to $+38$ points: the model still recognizes their local-knowledge advantage. Three other variables, however, reverse sign. Information communication flips from -23 to $+20$; without the non-verifiability of soft information, the model treats local knowledge as equally useful for gathering and for transmitting. Ethnic bias flips from $+40$ to -4; without community pressure in the prompt, the model sees no reason to associate local embeddedness with biased lending. And delegation flips from -158 to $+346$ thousand ETB; the model interprets local knowledge as a competence signal that should be rewarded with greater autonomy.

The lending and NPL predictions under the minimal prompt are internally implausible. City-coethnic managers are expected to generate substantially more lending ($+60$ million ETB versus $+44$ under the subtle prompt) while simultaneously producing *lower* NPL rates (-3.0 percentage points versus $+0.8$). More lending with fewer defaults implies that the model sees no cost to the local information advantage. Under the full institutional context, the NPL sign reverses to marginally positive, reflecting that local ties create incentives to approve marginal loans.

The delegation comparison to the actual data is the punchline. The minimal prompt predicts that city-coethnic managers should receive *more* delegation ($+346$ thousand ETB), which directly contradicts the empirical estimate of $-1{,}518$ thousand ETB (Table K.3 Panel C). The full-context estimate (-158) recovers the correct sign. The stripped-context model gets the direction of organizational design wrong because it lacks the economic structure needed to translate an information advantage into a moral-hazard concern. That the full-context results align with the observed data while the stripped-context results do not is consistent with the agency-theoretic interpretation of the organizational patterns we document, rather than with a simple competence story.

K.9.3 Other Design Considerations

Temperature sensitivity. GPT-5-mini only accepts temperature 1.0, so the standard temperature-sensitivity check is not available for this model. The model-sensitivity analysis above partially substitutes by comparing architectures with different stochastic generation processes.

Question-order effects. The survey places perception scores and business outcomes first (Q1–Q14), mechanism weights second (Q15), and the manager ethnicity choice last (Q16–Q17). This order ensures that the final choice synthesizes prior analysis rather than anchoring subsequent scores.

Within-scenario variance. We do not run each scenario multiple times. Re-running each scenario k times would separate within-scenario measurement noise from systematic cross-scenario differences. The current design relies instead on cross-branch variation for statistical power. This is a limitation rather than a design choice: budget constraints preclude full k-fold replication at the present scale, and we note it as an avenue for extension.

Panel A: Manager Ethnicity Choice

	AI Survey	Actual Data	Coethnic Placebo
Share choosing city-coethnic	87.9%	33.7%	100.0%
Share choosing bank-coethnic	6.3%	53.7%	—
AI recommendation = actual hire (%)	33.7%		69.4%
Random baseline	25%		25%
N (branch-years)	190		98

Panel B: City-Coethnic Effect (Matched Data, z-Score Gap)

	AI	Actual	Coethnic Placebo (AI)
Delegation gap (city − comparison):			
2018	-0.014	-0.256	1.172
2022	-0.553	-0.450	1.373
NPL gap (city − comparison):			
2018	0.264	-0.386	-0.630
2022	0.422	-0.014	-1.223

Panel C: Regression Coefficients (β_1 on City-Coethnic)

	AI (Misaligned)	Actual (Misaligned)	AI (Coethnic)
Delegation	-158.3***	-1518.3**	877.1***
	(30.3)	(751.9)	(59.0)
NPL ($\times 100$)	0.77***	-0.34	-3.22***
	(0.12)	(2.19)	(0.11)
High conflict $\times$ city-coethnic (β_3):			
Delegation	-2.0	—	—
	(48.8)		
NPL	0.39*	—	—
	(0.21)		
N (delegation)	742	644	784
N (NPL)	742	650	784
Branch FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel D: Internal Mechanism Consistency (AI Only, Misaligned)

	Gap (city − bank)	Banks unanimous	Placebo gap
Info acquisition	54.7	13/13 positive	52.7***
	[5.9]		(0.6)
Info communication	-24.6	13/13 negative	24.9***
	[8.9]		(0.5)
Trade-off (both conditions)		13/13 banks	
Delegation	4.4	5/13 positive	877.1***
NPL	0.38	7/13 positive	-3.22***

Notes: Panels A–B compare AI predictions and actual survey data for a matched sample of 150 Ethiopian bank branches from the AI survey subsample. Panel C reports regression coefficients from the paper's main specification: AI regressions use the experimental design with demeaned high-conflict treatment and branch/year FE; actual-data regressions use the *full panel* (not the AI subsample) with branch and year FE. Delegation is inflation-adjusted (deflated to 2018 ETB) and winsorized at the 95th percentile within period $\times$ bank-city coethnicity cells, matching the paper's main specification. NPL in the actual data is in share form (0–1); coefficients are scaled $\times 100$ for comparability with the AI's percentage-point scale. Columns labeled "Misaligned" restrict to cities where bank and city have different dominant ethnicities (the paper's main sample); "Coethnic" restricts to cities where bank and city share ethnicity. Standard errors clustered at the branch level in parentheses. Panel D reports the AI's internal mechanism scores: the gap between city-coethnic and bank-coethnic managers on information acquisition (0–100) and communication (0–100), with bank-level unanimity counts. Standard deviations in brackets; standard errors from coethnic placebo regressions in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table K.3: External Validation: AI Survey vs Actual Data

Panel A: CEO Assessments and Mechanism Weights								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEO Assessments				Mechanism Weights			
	Info Acq.	Info Comm.	Ethnic Bias	Safety Concern	Info	Align	Safety	Other
City-coethnic	53.37***	-21.12***	38.37***	-28.36***	12.75***	-7.04***	-9.28***	3.57***
	(0.48)	(0.45)	(0.80)	(0.87)	(0.31)	(0.31)	(0.35)	(0.26)
High conflict	-5.74***	-0.89**	5.32***	31.87***	-4.07***	-4.18***	9.48***	-1.23***
	(0.46)	(0.41)	(1.26)	(1.12)	(0.50)	(0.45)	(0.53)	(0.26)
High conflict × City-coethnic	4.71***	-4.27***	-2.50*	-9.77***	0.97	3.76***	-3.37***	-1.36***
	(0.52)	(0.80)	(1.34)	(1.61)	(0.64)	(0.56)	(0.61)	(0.41)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	57.59	70.14	51.55	44.76	35.35	36.71	18.29	9.66
Observations	742	742	739	742	742	742	742	742
R^2	0.978	0.821	0.829	0.803	0.747	0.565	0.701	0.389

Panel B: Organizational Outcomes								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcomes				Lending (%)		NPL (%)	
	Deleg.	Wage Prem.	Exp. NPL	Lend Vol.	City-Coeth.	Bank-Coeth.	City-Coeth.	Bank-Coeth.
City-coethnic	-213.54***	-25.33***	0.74***	43.01***	0.29	-5.40***	1.71***	-2.32***
	(38.60)	(0.56)	(0.11)	(1.76)	(0.40)	(0.40)	(0.16)	(0.22)
High conflict	-237.89***	9.92***	2.19***	-16.21***	-0.59	0.95*	2.04***	2.84***
	(50.65)	(0.43)	(0.17)	(1.85)	(0.59)	(0.52)	(0.20)	(0.34)
High conflict × City-coethnic	48.12	-2.27**	0.55**	-14.09***	1.89**	-2.16***	1.31***	-1.58***
	(60.26)	(0.99)	(0.25)	(2.83)	(0.79)	(0.63)	(0.31)	(0.50)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	783.63	10.18	7.64	97.74	66.06	17.73	8.13	7.02
Observations	742	742	742	742	742	742	742	742
R^2	0.449	0.843	0.605	0.740	0.533	0.530	0.567	0.402

Notes: This table replicates Table 6 using a "naive" prompt that provides minimal context about the role of ethnicity in Ethiopian banking. The prompt describes ethnicity as "a demographic characteristic" without mentioning information networks, trust, or incentive trade-offs. The lending process context (information acquisition, communication to headquarters, autonomous decisions, and manager accountability relationships) is identical to the main specification. All other aspects of the experimental design—branch sample, conflict treatments, manager types, and survey questions—are unchanged. Sample: 98 misaligned branches (of 100 targeted; 2 branches lost due to API failures). Standard errors clustered at branch level in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table K.4: AI Survey: Prompt Robustness (Naive Prompt)

Panel A: CEO Assessments and Mechanism Weights								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEO Assessments				Mechanism Weights			
	Info Acq.	Info Comm.	Ethnic Bias	Safety Concern	Info	Align	Safety	Other
City-coethnic	38.30***	20.09***	-4.01***	-29.10***	8.98***	2.38***	-12.33***	0.98***
	(0.69)	(0.64)	(1.00)	(0.84)	(0.30)	(0.36)	(0.33)	(0.23)
High conflict	-11.36***	-11.08***	13.42***	27.21***	-5.11***	-6.74***	12.00***	-0.15
	(0.91)	(1.02)	(1.40)	(1.08)	(0.50)	(0.50)	(0.56)	(0.29)
High conflict × City-coethnic	5.86***	6.11***	-3.23*	-3.15*	2.15***	5.27***	-5.54***	-1.89***
	(1.14)	(1.19)	(1.81)	(1.83)	(0.68)	(0.53)	(0.63)	(0.40)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	60.60	67.81	38.88	47.24	35.80	34.43	20.90	8.87
Observations	741	742	727	742	742	742	742	742
R^2	0.876	0.679	0.337	0.783	0.642	0.401	0.770	0.190

Panel B: Organizational Outcomes								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcomes				Lending (%)		NPL (%)	
	Deleg.	Wage Prem.	Exp. NPL	Lend Vol.	City-Coeth.	Bank-Coeth.	City-Coeth.	Bank-Coeth.
City-coethnic	345.55***	-22.24***	-2.98***	60.04***	5.35***	-7.17***	-2.75***	-4.67***
	(33.04)	(0.44)	(0.14)	(2.13)	(0.48)	(0.49)	(0.14)	(0.27)
High conflict	-286.25***	9.21***	3.35***	-26.32***	-4.08***	4.06***	2.26***	6.37***
	(37.16)	(0.39)	(0.20)	(2.36)	(0.73)	(0.57)	(0.19)	(0.39)
High conflict × City-coethnic	40.95	0.93	-0.80***	-8.63**	2.78***	-2.81***	0.28	-3.31***
	(54.42)	(0.98)	(0.21)	(3.57)	(0.86)	(0.69)	(0.23)	(0.40)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	861.40	12.74	6.66	104.14	65.18	20.43	6.27	7.78
Observations	741	742	741	742	742	740	739	742
R^2	0.629	0.821	0.700	0.785	0.609	0.572	0.665	0.617

Notes: This table replicates Table 6 using a "minimal" prompt that strips all mechanism framing from the lending process description. The minimal prompt retains only the bare logistical steps (manager assesses applicants, recommends to headquarters, decides autonomously on small loans) without any mention of soft information, verification problems, favoritism pressures, or accountability relationships. The ethnicity context is identical to the naive prompt (Table K.4). Sign reversals on information communication, ethnic bias, delegation, and NPL indicate that the institutional context is necessary for the model to reason about the information-incentive trade-off rather than defaulting to a naive "local knowledge is always beneficial" heuristic. Sample: 98 misaligned branches. Standard errors clustered at branch level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table K.5: AI Survey: Institutional Context Ablation (Minimal Prompt)

Panel A: Manager Type Differences (Actual Conflict)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEO Assessments				Mechanism Weights			
	Info Acq.	Info Comm.	Ethnic Bias	Safety Concern	Info	Align	Safety	Other
City-coethnic	54.52***	-22.83***	39.87***	-27.80***	12.47***	-7.01***	-9.19***	3.73***
	(0.35)	(0.47)	(0.68)	(0.81)	(0.31)	(0.33)	(0.30)	(0.24)
City-coethnic × Year 2022	0.77	0.31	-1.07	1.76	0.38	-0.31	0.89	-0.95**
	(0.48)	(0.89)	(1.04)	(1.38)	(0.63)	(0.61)	(0.54)	(0.47)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	58.04	69.28	51.49	44.49	34.77	37.43	18.45	9.35
Observations	742	742	742	742	742	742	742	742
R^2	0.982	0.810	0.874	0.460	0.685	0.484	0.460	0.320

Panel B: Effect of Conflict (High vs Low)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcomes				Lending (%)		NPL (%)	
	Deleg.	Wage Prem.	Exp. NPL	Lend Vol.	City-Coeth.	Bank-Coeth.	City-Coeth.	Bank-Coeth.
City-coethnic	-158.21***	-25.73***	0.77***	44.30***	1.26***	-5.13***	1.91***	-2.69***
	(30.21)	(0.50)	(0.12)	(1.83)	(0.46)	(0.42)	(0.16)	(0.25)
City-coethnic × Year 2022	76.93	0.15	-0.24	4.63*	2.07***	-1.22*	-0.46	0.13
	(57.87)	(0.84)	(0.21)	(2.72)	(0.67)	(0.67)	(0.28)	(0.43)
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	704.85	9.73	7.77	94.08	65.88	17.80	8.38	6.83
Observations	742	742	742	742	742	742	742	742
R^2	0.410	0.778	0.386	0.677	0.499	0.501	0.420	0.305

Notes: This table reports the full set of AI-survey outcomes, extending Table 6. Panel A shows CEO assessments (columns 1–4) and the mechanism-weight allocation across information, alignment, safety, and other (columns 5–8). Panel B shows organizational outcomes (columns 1–4) and lending and NPL shares by customer ethnicity (columns 5–8). Regressors are an indicator for a city-coethnic manager and its interaction with a 2022-wave indicator, absorbing branch and year fixed effects. Sample restricted to branch-years in non-coethnic cities. Standard errors clustered at branch level in parentheses. Statistical significance is denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table K.6: AI Survey: Mechanism Weights and Lending by Manager Ethnicity

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