# Can Competition Reduce Corruption?

Muhammad Haseeb[*] Amen Jalal[†] Alexander Quispe [‡] Kate Vyborny[§¶]

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**Abstract:** Corruption remains a major obstacle to the delivery of public services in developing countries. We study whether competition between service delivery agents can mitigate corruption, leveraging exogenous changes to the market structure of agents responsible for delivering government cash transfers in Pakistan. A reform that increased the market power of these agents led to a 29.1 pp increase in the probability that a beneficiary had to pay an involuntary bribe to access the cash transfer. However, in areas with 1 standard deviation higher competition, this increase in bribe payments is almost completely eliminated. We rule out mechanisms other than competition that could drive these results, such as strategic entry, changes in market access, and differences in monitoring efforts or cash recipient characteristics.

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[*]University of Bristol
[†]London School of Economics
[‡]World Bank ID4D and SAR-GIL
[§]World Bank SAR-GIL
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# 1 Introduction

Developing countries allocate considerable resources to alleviating poverty, yet these efforts are often undermined by pervasive corruption and ineffective implementation. The efficiency and equity costs of corruption have been shown to far exceed the amounts originally misappropriated (Olken and Pande, 2012). Seminal theoretical work by Rose-Ackerman (1978) and Shleifer and Vishny (1993) suggests that introducing market competition in public service delivery could help reduce corruption. Public service providers supply a product – access to a government provided benefit or service – in exchange for a price – bribes – and may therefore respond to market incentives.

In the public sector, the effective price faced by beneficiaries often includes an illicit side payment that is typically neither posted nor credibly committed to. Beneficiaries, therefore, cannot easily compare prices across providers, and providers cannot publicly undercut one another. As a result, competition may have little effect on prices, unlike in private markets where posted prices enable comparison and prompt undercutting. Yet, empirical evidence on the effectiveness of competition in the public sector remains limited, largely due to difficulties in identifying exogenous variation in competition among public service providers. Addressing this gap is critical because market-driven incentives could offer an effective solution for combating corruption. This could potentially outperform more typical top-down approaches such as monitoring, audits, and penalties, which are themselves vulnerable to corruption.

This paper provides the first causal evidence on how increased competition among agents delivering a standardized public service influences bribe payments. Specifically, we study cash transfers - a widely used form of public assistance, with 1.9 billion beneficiaries worldwide (World Bank, 2015). We leverage a large natural experiment in Pakistan's flagship unconditional cash transfer program, the Benazir Income Support Programme (BISP), which exogenously altered the market structure of the agents responsible for delivering cash payments. Until 2016, beneficiaries could withdraw funds either from licensed payment agents – who could demand bribes to process withdrawals – or directly from ATMs using withdrawal-only debit cards. ATMs thus functioned as an outside option that could potentially discipline the agents' bribe-seeking behavior. In 2017, a government reform introduced biometric verification, requiring fingerprint authentication at the point of withdrawal. Because biometric authentication was only feasible at licensed payment agents during our study period, ATM access was effectively eliminated in some districts. As a result, the share of beneficiaries relying on payment agents rose sharply – from 42% to 69% – in 'treated' districts following the reform, which inadvertently increased the market power of agents and created a unique natural experiment.

Importantly, this setting allows us to isolate the effect of market structure from confounding changes in service quality. Cash transfers are a homogeneous good, agents are paid a flat fee by the government for each transaction, and they are legally prohibited from charging beneficiaries additional fees. Unlike in sectors such as health care, where competition may simultaneously affect both quality and bribes, our context offers a clean test of how competition influences the "price" of service delivery.

Our empirical framework leverages the biometrics reform alongside detailed panel survey data of cash transfer beneficiary households, and spatial data on all payment agents and ATMs nationwide. We use difference-in-differences and event-study approaches to compare households in districts where the new biometric technology requirement was rolled out early with those in districts where the reform was rolled out later, before and partway through the rollout. To examine the role of competition in shaping corruption, we analyze how baseline heterogeneity in competition among payment agents interacts with the reform. This baseline variation is driven in large part by targets set centrally by the government for the network of agents onboarded specifically for government cash transfer payments; as a result, baseline competition is uncorrelated with community characteristics such as population, accessibility or urbanicity.

We find that the near-exclusive reliance on payment agents induced by the reform in 'treated' areas increased corruption. At baseline, 19% of beneficiaries in our sample report paying a bribe to receive their payment. Beneficiaries in treated districts experienced a 29.1 pp increase in the likelihood of paying a bribe to access the cash transfer. The monetary value of these bribes rose by 168% relative to the pre-reform control mean. However, in areas where baseline competition between payment agents was 1 standard deviation higher, the increase in bribes after the reform was reduced by 23.7 percentage points. This highlights the mitigating role of competition.

Beyond bribes as side payments extorted to receive the transfer, qualitative reports suggest that payment agents sometimes capture the full amount of the transfer, for example by completing the transaction in the system for a beneficiary but telling her that there is no money in her account (Karandaaz, 2020). We find evidence that competition mitigates this form of corruption as well. Areas with greater baseline competition among payment agents saw an 18% increase in the amount of cash transfer beneficiaries report receiving, driven by an extensive margin increase in the likelihood of receiving any cash at all. This is consistent with a decrease in agent capture of the full transfer.

Importantly, we rule out the possibility that the observed effect of competition on bribes is driven by other factors potentially correlated with payment agent competition, such as beneficiary characteristics, local area attributes (e.g., bank access, population density, spatial compactness, or built area), or monitoring efforts by public officials. Finally, we rule out the possibility that these results are due to initial implementation issues associated with the new technology. We also show that results are not driven by differential entry or exit of payment agents in treated districts or changes in access to service providers.

Our results show that competition can help reduce corruption in the delivery of public services. An extensive empirical literature examines the impact of top-down approaches such as audits on corruption (Avis *et al.*, 2018; Olken, 2007; Zamboni and Litschig, 2018; Bobonis *et al.*, 2016; Tella and Schargrodsky, 2003; Lichand *et al.*, 2016; Lichand and Fernandes, 2019). The bottom-up approach of fostering competition between service providers is an important alternative to such top-down strategies. Theoretical groundwork suggesting the potential of competition to mitigate corruption was provided by Shleifer and Vishny (1993) and Rose-Ackerman (1978). However, empirical work testing how competition among alternative providers of a public service affects bribes in the field remains remarkably limited.[1] One branch of related literature has investigated how government service delivery structure affects corruption through mechanisms such as competition between *jurisdictions* to attract firms or residents choosing where to locate (Gadenne and Singhal, 2014; Fisman and Gatti,

[1] A number of studies have used laboratory experiments to examine the impact of competition among public officials on bribes, asking participants to play the role of public officials (Ryvkin and Serra, 2020; Drugov *et al.*, 2014).

2002; Fan *et al.*, 2009; Burgess *et al.*, 2012).[2] Two empirical studies most closely related to our work (Olken and Barron, 2009; Foltz and Li, 2023) examine market structure of highway checkpoints taking bribes from truck drivers. Olken and Barron (2009) exploit changes in the number of highway checkpoints on a single, unavoidable route in Indonesia, showing that when some checkpoints are removed, the remaining officials – who face no competition at their location – raise bribes. This setting represents a classic sequential holdup problem: drivers, once en route, have no opportunity to avoid or substitute away from officials. Foltz and Li (2023) study a context in which highway users in West Africa pass through a common segment prior to selecting one of two alternative corridors. An exogenous increase in travel costs on one branch shifts traffic to the other, raising bribe extraction by officials on the busier route, while lowering demands at the shared segment due to heightened price sensitivity. In both contexts, the ability to avoid or switch away from individual officials is limited, either because the route is fixed or because the choice is made only once at the outset of the journey. In contrast, we study variation in the level of competition among *alternative*, rather than sequential, agents. In areas with high competition, beneficiaries in the BISP program face multiple co-located payment agents, allowing them to freely choose among agents at each withdrawal with minimal switching costs. This setup eliminates the sequential holdup present in the other studies. As a result, we are able to observe how competition among agents shapes corruption in an environment that more closely mirrors a broader set of contexts – such as cash transfers, education, or health services – where users interact repeatedly with a range of providers and can actively respond to local market structure.

Our study also contributes to two further strands of literature. One strand investigates how market structure of the provision of financial services such as mobile money payments on the *private* market influences the costs to consumers (Annan, 2025; Brunnermeier *et al.*, 2025). Our study in contrast focuses on the impact on public services intended by the state to be delivered free of cost to beneficiaries, which is ex ante uncertain given potential frictions limiting beneficiaries' ability to comparison shop between providers. A second strand of literature examining the impacts of authentication infrastructure in developing countries (Jack and Suri, 2014; Field *et al.*, 2021; Giné *et al.*, 2012; Muralidharan *et al.*, 2016; Blu-

[2] A number of studies have also examined the market structure of *firms* and its relation to their decision to *pay* bribes (Ades and Di Tella, 1999; Bliss and Tella, 1997; Alexeev and Song, 2013).

menstock *et al.*, 2023). A recent paper by Muralidharan *et al.* (2023) highlights the costs associated with biometric verification technology in India, noting that some beneficiaries lost access to benefits due to the management of the system transition. Our paper complements their findings by showing that the impacts of new technologies can also be sensitive to the market structure of service delivery agents.

The rest of the paper is organized as follows: Section 2 outlines the context. Section 3 presents the data. Section 4 details the empirical strategy. Section 5 discusses the results, and Section 6 concludes.

# 2 Context and Intervention

The Benazir Income Support Programme (BISP) was launched in 2008 as Pakistan's signature social protection program, providing unconditional cash transfers to around 9 million of the country's poorest households. The program's targeting is based on a proxy means test using microdata from a nationwide poverty census conducted in 2010; this was first updated in 2020, after the period we study. During our study period, eligible recipients received quarterly installments of PKR 4,500 (equivalent to USD 42 at the time). The program has demonstrated significant success, with various studies highlighting its positive effects on recipient welfare (OPM, 2015, 2016; Ambler and Brauw, 2024). Nonetheless, challenges in reaching intended recipients, delivering the service efficiently, and preventing corruption of funds persisted. To address these issues, BISP has implemented several changes over the years, including updates to the targeting methods (Haseeb and Vyborny, 2022) and payment delivery mechanisms (OPM, 2015, 2016). Our analysis covers a period in which the targeting approach, list of beneficiaries and other aspects of program design stayed constant, while a significant reform was made to the payment delivery system.

## 2.1 Baseline Payment Delivery

Prior to the reform we study, BISP used a debit card-based system for distributing cash transfers. This system relied on specialized, limited mandate accounts which were designed solely for cash transfer withdrawals, and did not offer additional banking services such as savings or transfers between accounts. Recipients were issued debit cards linked to these accounts (shown in Figure A2), which they could use at any ATM or at designated "Points of Sale" run by licensed payment agents. These payment agents, typically mobile money shop owners, were contracted to facilitate BISP cash transfers as a supplementary service, earning a fixed commission paid by the government for each transaction processed. Crucially, it is illegal for them to charge any cash-out fee to beneficiaries. BISP partnered with various telecommunication providers and banks to manage the payment agents network, supplying necessary equipment and licenses to agents. To ensure compliance, both BISP district officers and the telecommunication providers monitored these agents via field inspections.

At baseline, the incidence of bribes was notably higher at payment agent locations than at ATMs. Specifically, only 8% of control group respondents using ATMs reported encountering demands for side payments at baseline, while this number is four times higher - 33% - for those who used payment agents. Thus at baseline the ATM represents an outside option for beneficiaries facing a demand for a bribe from a payment agent - potentially holding the frequency and amount of bribe demands in check.

However, reliance on debit cards posed challenges at both ATM and payment agent locations. Recipients frequently reported losing their cards, forgetting their PINs, or unauthorized withdrawals after their cards were stolen (OPM, 2016). To overcome these issues and ensure that funds were collected exclusively by the intended recipients, BISP initiated the development of a new payment system based on biometric authentication, moving away from debit cards.

## 2.2 Introduction of Biometric Verification

In 2017, BISP started transitioning to a biometric verification system (BVS). Under this system, payment agents were equipped with biometric readers to verify recipients' identities by scanning their fingerprints (see Figure A3). These were then validated in real time against the national biometric identity database. This process allowed agents to verify the recipient's identity against government records before releasing payments.

The reform was rolled out in a phased manner across districts, beginning in March 2017 (see Figure A1). Based on discussions with BISP, the sequence in which specific districts were transitioned was influenced by the readiness of local administrations and banks for the new system. Primarily, this depended on the speed with which sufficient payment agents were recruited and their licenses issued or renewed. To determine the timing of treatment implementation in each district, we rely on administrative records specifying the scheduled start date of biometric verification in that district. Anecdotally, we know that logistical challenges led to delays in some districts, but we treat the official start date as an intent-to-treat measure, with deviations from the schedule potentially attenuating our estimated effects. By the end of September 2018, approximately 91 out of 160 districts had been transitioned to the new system. For our analysis, we classify these early roll-out areas as the treated group, which we denote as "biometric districts," and compare them to areas where the reform was implemented after our study period, denoted as "non-biometric" districts.

## 2.3 Shift Towards Payment Agents

Once the switch to biometrics was executed in an area, cash withdrawals were managed exclusively by payment agents since ATMs lacked the necessary infrastructure for biometric authentication. Beneficiaries' accounts were transitioned to the new system based on their district of residence, so it was not possible for a beneficiary in a biometric district to cross district boundaries and use the non-biometric withdrawal system or vice versa. Consequently, beneficiaries in transitioned districts could no longer use ATMs for cash withdrawals, leading to a dramatic increase in the market power of payment agents.

The relative shock this implied for a given market was heterogeneous across space. In a given area, the density of payment points primarily depended on the existing payment agent network, which BISP and partner banks tapped into for meeting coverage targets in each sub-district. In areas with a high density of pre-existing payment agents, the impact of the shutdown of the option to withdraw from an ATM on agents' market power is limited. Conversely, in areas with many ATMs but only a single payment agent, this shift created a monopoly almost overnight. We explore the implications of this reform – which altered the market structure of payment agents – on corruption.

# 3 Data

## 3.1 Data sources

We use data from four key sources. First, we use three rounds (2014, 2016, and 2019) of nationwide household surveys conducted by Oxford Policy Management (OPM).[3] Households just above and just below the threshold for BISP eligibility were selected for the survey, as part of an existing study by OPM using a regression discontinuity design to study the overall impact of the BISP cash transfer. In Table A1, we show that attrition across survey waves is not systematically related with biometrics roll-out or our competition measure.

We focus our analysis on a balanced panel of BISP beneficiary households that are present in both the 2016 (last baseline) and 2019 (endline) rounds. If these panel households are additionally present in 2014 (first baseline), we include their 2014 outcomes in our analysis. We find that results are robust to using a fully balanced panel (in which only households present in all three waves are included).

The dataset includes information on beneficiaries' socio-economic characteristics (e.g., education and beneficiary age), as well as their experience of cash transfer withdrawal (e.g., payment method, amount withdrawn, amount paid in bribes, to whom the bribe was paid, and distance and cost of travel to withdrawal locations). The data also include village-level geo-coordinates.

Second, we geo-code administrative data on the universe of all payment points from 2015-2019, provided by BISP. This dataset includes information on ATMs and BISP-licensed payment agents nationwide, with corresponding details of their addresses, bank affiliations, and transaction volumes. We successfully geo-located 92% of all payment agents and ATMs in the data. The remaining payment points were mapped to the centroid of the smallest possible administrative unit they were found in (33% at the building/street level, 60% at the village level, 5% at the Union Council level and 0.7% at the tehsil i.e. subdistrict level). Figure A4 visually represents the geo-located payment points and panel survey villages.

[3] We do have access to an earlier round of data, collected in 2013, but we do not include it in our primary sample, both because it uses a different sampling approach, and because in 2013 BISP was piloting other payment methods besides the debit cards which represent the baseline status quo to which we compare the biometric payment system rollout.

Third, to confirm the first stage impact of the biometrics rollout, we use administrative data shared by BISP which records beneficiary-by-payment cycle observations on the use of biometric verification and the use of payment agents or ATMs.

Fourth, we also use information on monitoring visits from an administrative dataset provided by BISP covering December 2016 to January 2017, across all provinces of Pakistan. During this period, varying numbers of payment agents were visited by BISP officials across the country. We construct the share of payment agents visited in a given district during this time, and use that as our measure of monitoring intensity. This allows us to test for robustness of the competition results to accounting for monitoring intensity.

Finally, we leverage publicly available satellite and survey data to obtain regional characteristics of the districts in our study. We use Meta's High Resolution Population Density map from 2020 (Tiecke *et al.*), which contains information on the number of people living in each 100-meter grid cell. We use the Friction Surface Raster from 2018 (Weiss *et al.*, 2018), from the Malarian Atlas Projects, to obtain data on the time required to travel across a 1 km grid, expressed in hours per km. We use the Built Spaces Raster from 2018 (Pesaresi *et al.*, 2024) for land use information at the level of a 100-meter grid size. Finally, we use the Household Integrated Economic Survey of Pakistan 2014-15 to construct a district level measure of baseline bank access, using responses to a survey question on how frequently the respondent uses a bank facility.

## 3.2 Main Outcome Variables

In examining downstream impacts, our focus is on payment delivery outcomes. The primary variables of interest are the amount and incidence of side payments associated with cash transfer withdrawals. We use data from the OPM surveys, which directly ask intended BISP beneficiaries within the household about their payment experiences. Key survey questions include: "Have you (or your representative) ever had to pay money unwillingly to receive the transfer in the past year?" "How often are you (or your representative) required to pay any money to collect the BISP cash transfer in the last year?" and "What was the amount paid the most recent time you (or your representative) had to make such a payment?" These questions allow us to construct our two measures of bribes: (i) any bribes paid in the last 12 months, and (ii) the total amount of bribes paid in Pakistani Rupees in the last 12 months, calculated by scaling the most recent bribe amount by the frequency of payments. We also examine impacts on the total amount received by beneficiaries over the past 12 months, as reported in the survey.

We also use survey data on travel-related costs, including the time taken, distance traveled, and expenses incurred during respondents' most recent trip to collect the BISP cash transfer. We also construct four additional access-related outcomes using a combination of survey and administrative data. We compute the minimum distance to a payment point as the distance between the village centroid a household lives in, as per survey data, and the closest payment point to that centroid, as per BISP administrative data. Additionally, we construct measures of travel distance to the payment point used in the last withdrawal, as well cost of travel and time taken to travel to this payment point.

## 3.3 Summary Statistics

Table A2 presents summary statistics from two rounds of panel household surveys conducted at baseline, before the implementation of biometrics. The data show that biometric and non-biometric districts are comparable in observable characteristics at this stage. Cash transfers received over the past year are comparable between the two groups at baseline. The proportion of payment received and the likelihood of receiving any transfer, show no significant differences at this stage.

Travel metrics are also similar between the groups at baseline. Non-biometric districts have a mean travel time for the most recent withdrawal of 74 minutes, compared to 73 minutes in biometric districts. Travel costs average 142 PKR for non-biometric districts and 152 PKR for biometric districts. The minimum distances to payment points are 9.8 km for non-biometric and 7.6 km for biometric districts (p=0.23). These metrics confirm that, at baseline, the two groups are comparable across several dimensions.

Bribes paid in the last 12 months are similar between the groups, with non-biometric districts averaging 92 PKR and biometric districts 103 PKR (p=0.75). Although biometric districts have a slightly higher incidence of bribes (18% compared to 13% in non-biometric districts), this difference is not statistically significant (p=0.27). While the BISP program is exclusively targeted to poor households, the incidence of bribes falls disproportionately on the most disadvantaged among them: paying a bribe to collect the transfer is correlated with lower literacy, formal education and wealth (Table A4).

# 4 Empirical Strategy

## 4.1 Base specification

Using OPM panel data, we estimate the following difference-in-differences (DiD) specification:

$$Y_{idt} = \beta_1 treat_d \times post_t + \delta_d + \mu_t + \psi_p \times q + \epsilon_{idt} \tag{1}$$

where $Y_{idt}$ is an outcome variable for respondent $i$ in district $d$ in survey year $t$. We use three rounds of OPM surveys to estimate this equation: 2014 (first baseline), 2016 (second baseline), and 2019 (endline).$treat_d$ is an indicator for districts that implemented biometrics during 2017-2018 and *post* is an indicator for the 2019 round. The term $\delta_d$ represents district fixed effects, which account for time-invariant characteristics specific to each district. We also incorporate survey year fixed effects ($\mu_t$) to control for temporal changes. Additionally, we include province-specific time trends ($\psi_p \times q$) to capture any differential time trend across provinces.

The main coefficient of interest is $\beta_1$, which estimates the causal effect of the biometrics roll-out on the outcome $Y_{idt}$. The identification assumption requires that in the absence of biometrics roll-out, biometric and non-biometric districts would have exhibited parallel trends over time. Notably, this study avoids issues related to staggered designs since all districts that eventually received biometrics were untreated in both the base years.

Since all units were untreated at baseline, assessing pre-treatment trends is also more straightforward in this setting. We evaluate these trends by examining pre-2016 differences between treated and control districts using the event study specification outlined below:

$$Y_{ivdt} = \sum_{y=2014}^{2019} \gamma_y treat_d \times year_y + \delta_d + \mu_t + \psi_p \times q + \epsilon_{ivdt} \tag{2}$$

In this specification, we use 2016, the final survey round prior to biometrics implementation, as our base year. The remaining terms are analogous to those in Equation 1. In all specifications, we cluster standard errors at the district level, the unit of biometrics rollout. In Table A2, we show that at baseline, biometric and non-biometric districts were similar in observable characteristics. The pre-2016 estimates of $\gamma_y$ in equation 2 further test for parallel trends across these districts, prior to treatment. To ensure robustness, we conduct additional sensitivity analyses for pre-trends following the methodologies of Roth (2022) and Rambachan and Roth (2023) (reported in Figure A10 and discussed in Section 5.3)

## 4.2 Measuring Competition

As discussed in Section 2.3, the introduction of biometric verification removed the option of ATM withdrawals for cash transfers, potentially enhancing the market power of local payment agents. The coefficient $\beta_1$ in Equation 1 captures the overall effect of this policy change on payment delivery outcomes. However, this effect is likely to depend on the degree of competition among payment agents. Biometric verification may also influence delivery outcomes through channels other than changes in market power. To isolate the role of competition and account for alternative channels, we complement our main analysis by explicitly measuring competition and other relevant mechanisms.

We geo-code payment points using addresses from administrative records to construct a distance weighted measure of competition. Specifically, we count all potential payment points across the country that a household may access, and weight them by the inverse of their respective distances to the village centroid in which the household lives. This is similar to the market potential measure initially proposed by Harris (1954).[4] Formally, for a given village $i$, we compute the bilateral distance from village $i$ to each payment agent $j$ and then

[4]Some payment points are only geo-coded at the village level and may lie in the same village as the household, leading to zero distances and undefined inverse-distance weights. To address this, we impose a minimum distance threshold of 1 km, replacing all distances below this value (affecting 0.09% of the sample) with 1 km.

sum the inverse distances across $J$ payment agents:

$$Comp = \sum_{j=1}^{J} \frac{1}{Dist_{ij}} \tag{3}$$

To ensure that our measure of market competition is not influenced by the biometric reform itself, we construct it using administrative data on payment agent locations from one year prior to the rollout of biometric verification. For ease of interpretation, we divide this inverse-distance measure by its standard deviation. Figure A7 shows a strong positive correlation between baseline and endline market structure: a one standard deviation increase in baseline competition is associated with a 0.48 standard deviation increase in competition at endline (after controlling for district fixed effects and clustering errors at the district level)

To ensure the credibility of our competition measure, it is important to rule out confounding from other factors, particularly those related to bribe-seeking behavior. Three features of the institutional context help mitigate this concern. First, payment agents must be formally licensed by partner banks to operate as BISP cash-out points, and the issuance of these licenses is governed by district- and bank-specific targets set by BISP, limiting local discretion. Second, the baseline network of payment agents developed in parallel with the ATM infrastructure. Because the biometric reform abruptly disabled ATM access for BISP recipients, the structure of the pre-reform agent network is unlikely to reflect or anticipate post-reform opportunities for rent extraction. Third, variation in bank contracts across districts introduces quasi-arbitrary differences in which payment agents households can access. Each district is assigned a specific bank to handle BISP disbursements, and beneficiaries are generally limited to that bank's designated agents within the district. While cross-district access is permitted, it is only possible if the payment agent belongs to the same bank. This structure means that access is contingent on particular banks' presence rather than the broader network of payment points.

In Figure A5 and A6, we illustrate the variation of this measure across different locations. Appendix Table A5 shows that the baseline competition measure is not correlated with literacy level, location characteristics, market size, and monitoring efforts by BISP officials in these areas.

To examine how the effect of the biometric reform varies with competition among payment agents, we interact our baseline competition measure with the $treat_d \times post_t$ term in equation 1 as follows:

$$\begin{aligned} Y_{ivdt} = &\beta_1(treat_d \times post_t) + \beta_2(comp_v \times treat_d \times post_t) + \beta_3(comp_v \times post_t) \\ &+ \beta_4(comp_v \times treat_d) + \beta_5(comp_v) + \delta_d + \mu_t + \psi_p \times q + \epsilon_{ivdt} \end{aligned} \tag{4}$$

In this extended model, $comp_v$ is a village-level measure of competition and the other variables are the same as for Equation 1. The term $\beta_2(comp_v \times treat_d \times post_t)$ assesses how the effect of the biometric rollout varies with a 1 standard deviation increase in the level of baseline competition. Additionally, to analyze this relationship within an event study framework, we estimate equation 2 separately for two subgroups: those above and below median baseline competition level.

# 5 Results

In this section, we present results on the impacts of market competition between payment agents on corruption in the delivery of cash transfers. We begin by examining how the introduction of biometric verification affected its uptake and shifted recipients to using human agents instead of ATMs. Next, we study how the roll-out of biometric verification – which increased payment agents' market power by eliminating ATMs – affected cash transfer delivery (Equations 1 and 2). We then consider how these effects vary with the extent of baseline competition amongst payment agents.

## 5.1 First stage

Biometric verification disabled the use of ATMs for withdrawal of cash transfers. Instead, BISP beneficiaries had to rely on payment agents, who carried point-of-sale machines for verifying biometrics. Table A3 confirms that the roll-out of biometrics strongly predicts changes in payment withdrawal methods. At baseline, administrative microdata confirms that none of the recipients withdrew funding through biometric verification; at followup, recipients in treated districts were 70 pp more likely to withdraw through a biometric payment point (Column 1). As a result, reliance on payment agents rose by 26.7 pp from a baseline of 42 percent (Column 2).[5]

Since our measure of treatment relies on *intended* dates of biometric rollout, we present intent-to-treat effects in the following sections.

## 5.2 Impact on corruption

We present difference-in-differences estimates of Equation 1 in Panel A of Table 1. Column 1 shows that in districts where the reform had been implemented, there was a 29.1 pp (240%) increase in the probability that a cash transfer recipient had to involuntarily pay a bribe in the past year to withdraw their cash transfers. Column 2 shows that the amount paid in bribes in the past year increased by 168% (PKR 226) in districts that had adopted biometric verification, relative to districts that had not yet adopted it. The total amount that an average beneficiary paid in bribes (PKR 361) in districts with biometric verification amounts to 1.8% of the annual value of the cash transfer. While the overall amount for the average beneficiary appears modest as a fraction of the total transfer, two points are worth emphasising. First, among those who paid a bribe, the median amount per withdrawal was PKR 800, or approximately 16% of each payment installment. Second, these are intent-to-treat estimates based on a 71% compliance rate (Table A3), so the corresponding treatment-on-treated effects are proportionally larger. Moreover, Table A4 further examines the characteristics of beneficiaries most likely to report paying bribes. The results show that bribe payments are significantly more common among illiterate, less-educated, and poorer recipients. These findings suggest that leakages disproportionately affect the most vulnerable beneficiaries – those for whom even small diversions of funds can impose substantial financial strain.

[5] Due to incomplete reporting by the agent networks to BISP, these data have missing observations, which are empirically difficult to distinguish from a period in which a recipient did not withdraw. To mitigate this, for the first stage estimates we restrict the sample to those recipients who have at least one transaction observed at baseline, and pool together observations from all tranches for one recipient in one year, constructing variables for "used biometrics" and "used payment agent" in any tranche observed in that year. This approach with a subset of the sample allows us to confirm that the rollout dates are associated with a large increase in the probability of using biometrics and using a payment agent rather than an ATM. However, the unavailability of these data for some recipients limits the application of these data beyond the first stage analysis.

Figure 1a estimates the corresponding event study following Equation 2. The results confirm that biometric and non-biometric districts had similar pre-trends in their extensive and intensive margin prevalence of bribes, prior to the roll-out of biometric verification in those districts.[6]

We next examine to what extent pre-existing competition among payment agents might mitigate the increase in bribes triggered by the effective elimination of the outside option of ATM withdrawals. In areas with no baseline competition between payment agents, ATMs are the only outside option that cash transfer recipients have. Agents in such areas have the most to gain in market power when biometric verification shuts down ATMs. Panel B of Table 1 estimates Equation 4, showing how the effects of the transition to biometrics vary by levels of baseline competition between agents. Column 1 in Panel B of Table 1 shows that higher competition among payment agents is associated with a lower probability of bribe payments. Specifically, a one SD increase in baseline competition between payment agents almost completely eliminates the treatment-induced increase in bribes (a decrease of 23.8 pp, compared to the main treatment effect of 29.1 pp). In areas with sufficient competition between agents, the switch to biometrics did not lead to an increase in bribes - despite the fact that the outside option of the ATM was effectively eliminated for cash transfer beneficiaries.

Figure 1b presents event studies, estimated using Equation 2, but separately for areas with above- and below-median competition. These results support our earlier findings, showing that the increase in bribes is primarily concentrated in areas with relatively low baseline competition. Conversely, areas with above-median competition exhibited no significant change in side-payments following implementation of biometric verification.

The positive impact of competition on payment delivery is also reflected in the amounts beneficiaries receive. As shown in Columns 3 and 4 of Table 1, Panel A, biometric verification alone did not significantly affect the amounts received.[7] In contrast, Panel B shows that higher baseline competition is associated with larger amounts disbursed (Column 4), primarily through the extensive margin: beneficiaries in high-competition areas were more likely to receive at least part of their transfer following the reform (Column 3). The magnitude of the

[6] Following Roth (2022) and Rambachan and Roth (2023), Figure A10 shows that our results are unlikely to be influenced by pre-trends in the outcome variable.

[7] See Figure A8 for event studies.

effect – approximately 7.5% of the control group mean – is substantial. Since full capture of a cash transfer represents the most extreme form of leakage, these findings suggest that greater market competition reduces the likelihood of severe rent-seeking.[8] This pattern is further reinforced by event study evidence (Figure A8), which shows stronger improvements in high-competition areas relative to those with below-median competition.

Taken together, these findings suggest that competition among payment agents reduces leakage through two channels: by lowering the incidence of bribe payments and by decreasing the likelihood of full transfer capture. In addition to the impact on amounts directly reported as bribes by beneficiaries, the sizable increase in the share of beneficiaries receiving at least part of their transfer significantly amplifies the overall impact of competition in curbing leakages following the reform.

## 5.3 Robustness and Alternative Mechanisms

In this section, we examine a range of alternative mechanisms that could potentially account for our main findings and present evidence to rule each of them out. Table 2 tests whether our main findings could be explained by alternative household or district-level characteristics that correlate with baseline competition, and may co-vary with the treatment. We extend our baseline specification by including triple interactions between the biometric verification indicator, the post-reform period, and each potential confounding variable.

A potential alternative explanation for the increase in bribes is that the reporting of bribes, rather than the actual bribes, increased after the reform. In treated districts, the intended beneficiary now personally collects the funds and answers the survey, whereas previously, a representative may have collected the cash, and the beneficiary answering the survey might have been unaware of any bribes paid by the representative. Moreover, payment agents in treated districts may exploit the recipient's limited understanding of the new withdrawal process to demand bribes for facilitating the transaction. These factors may confound the estimated impact of competition if high-competition areas were also those where beneficiaries typically did not collect transfers personally before the reform. In Table 2, Panel A, Columns

[8] Prior process evaluations, including Karandaaz (2020), document various instances of full capture by payment agents.

2 and 3, we consider two proxies for the beneficiary's knowledge of bribe payments pre-reform, and their understanding of the withdrawal process: literacy and prior experience with cash withdrawal. In Column 2, we show that interacting the rollout with beneficiary literary status leaves our main coefficients of interest unchanged. In Column 5, we find a similar pattern for beneficiaries who were never present to collect cash at baseline, but were required to do so at endline. Together, these tests suggest that the increase in bribes is not driven by changes in reporting or other recipient characteristics, nor by a differential lack of understanding of the new process.

Another factor that may contribute to the rise in bribes may be insufficient monitoring in areas with biometric verification. Moreover, if areas with higher competition are more heavily monitored than areas with lower competition, the effects we attribute to competition may instead reflect the impact of higher monitoring on reduced bribe payment. While local BISP district teams are formally responsible for monitoring payment agents and ensuring compliance with protocols, their capacity to do so may vary across space, leading to uneven enforcement and higher bribe incidence in poorly monitored areas. To investigate this possibility, we interact the biometric reform with the baseline share of payment agents visited in the district (Table 2, Panel A, Column 3). We find that, after controlling for monitoring intensity, bribes remain 18.6 pp less likely in areas with 1 SD higher competition. This suggests that our estimated impact of competition on corruption is not driven by differences in monitoring capacity.

Another possible explanation for the observed increase in bribe payments is a mechanical shift in withdrawal channels following the reform. Specifically, by eliminating ATM access—which typically involved little to no rent-seeking—and directing beneficiaries to payment agents, the reform may have moved recipients from a low-bribe to a higher-bribe environment, thereby increasing the likelihood of reported bribe payments independent of any change in agent behavior. In this case, the observed increase in bribes would mainly come from individuals who switched from ATMs to payment agents, rather than from changes among those already using payment agents before the reform. If the likelihood of switching is correlated with baseline competition, our estimates of the effect of competition could partly reflect this mechanical change. We therefore include an interaction for whether the beneficiary used a payment agent at baseline in column 4 of Table 2. The results show that our main estimates are not explained by baseline use of payment agents.

We further test for the robustness of our competition effects to controlling for regional characteristics that may be correlated with higher competition. For instance, the presence of a more well-established banking infrastructure may be positively correlated with both payment agent competition and customer awareness of their rights, driving a negative relationship between bribes and competition. Similarly, areas that are more urban – higher population or population density – may have higher competition as well as lower bribes due to more financial literacy among recipients, or better state capacity for monitoring. In Table 2, Panel B, we consider whether local bank access (Column 1), population (Column 2), spatial compactness (time required to cross a polygon, Column 3), and built spaces (Column 4) explain the effects on bribes that we attribute to competition. We find that controlling for these potential confounders does not influence the coefficient on competition meaningfully. Column 8 demonstrates that the negative relationship between competition and bribes remains robust even when all the covariates discussed so far are accounted for together.

An additional concern is that the biometric verification reform may have systematically changed the spatial distribution of payment points, thereby affecting both access and the scope for bribe-seeking. This concern is partly mitigated by the fact that our competition measure is already constructed using the baseline distribution of payment agents. Nonetheless, we address the possibility directly in Table A6, where we test whether the reform led to any significant changes in beneficiary access to payment points. We find that the implementation of biometric verification did not affect access in biometric districts compared to non-biometric districts. This finding is consistent across multiple measures, including the distance to payment points, travel duration, travel distance and associated travel costs. Furthermore, Panel B of the same table shows no differential change in access for areas with higher baseline competition. These findings suggest that our results on bribes are not driven by changes in access to payment points.

In Table A7, we present further evidence that our results are not driven by strategic entry or exit in areas with varying levels of competition. The table reveals that the number of new entrants in biometric districts did not differ based on baseline competition levels (Column 1). Similarly, the number of exits showed no significant variation with respect to baseline competition (Column 2). This is consistent with the regulatory structure, where the opening of new payment points is partly governed by centrally determined targets rather than demand or agent incentive, limiting the scope for strategic entry or exit in response to local market conditions.

An alternative possibility is that the increase in bribes is driven primarily by short-term disruptions or learning challenges during the initial implementation of biometric verification. Since some districts adopted the technology earlier than others, we exploit this variation to assess whether the impacts diminish with longer exposure to the reform. Figure A9 shows corruption in districts where biometric technology has been in place for more than five tranches, versus districts where it has been in place for fewer than five tranches. We find no evidence that the impacts on bribes decay over time - if anything, the impacts are larger in areas where more payment tranches had taken place since the new system was implemented.

We also investigate whether the observed increase in bribes shown in Figure 1 could be linked to a violation of the parallel trend assumption. Figures A10 indicate that our findings are unlikely to be driven by pre-existing trends in the outcome variable. We apply the methodology proposed by Roth (2022) and Rambachan and Roth (2023), and find that at 70% power, the test rules out pre-treatment trend violations large enough to bias our post-treatment estimates.

Finally, we show that our results are not sensitive to the way in which we construct our panel. In our main results, we construct a balanced panel across the 2016 (last baseline) and 2019 (endline) survey waves, and further include any observations we may have on these households in 2014 (first baseline). In a robustness test, we limit our sample to only the households present in all three survey waves – i.e., a fully balanced panel. Tables A8 show that our results are stable to this alternative sample, and are not driven by the potentially different composition of households in the 2014 versus the 2016 and 2019 survey waves.

# 6 Conclusion

Our findings demonstrate that competition among payment agents in the distribution of government cash transfers has significant implications for corruption and the effectiveness of poverty alleviation programs. We find that the introduction of the biometric technology, which inadvertently increased the market power of payment point agents, led to a substantial rise in bribe payments. However, this effect was mitigated in areas with higher baseline competition among agents. Moreover, we show that this competition mechanism is not driven by other factors such as location characteristics, market size, or monitoring efforts.

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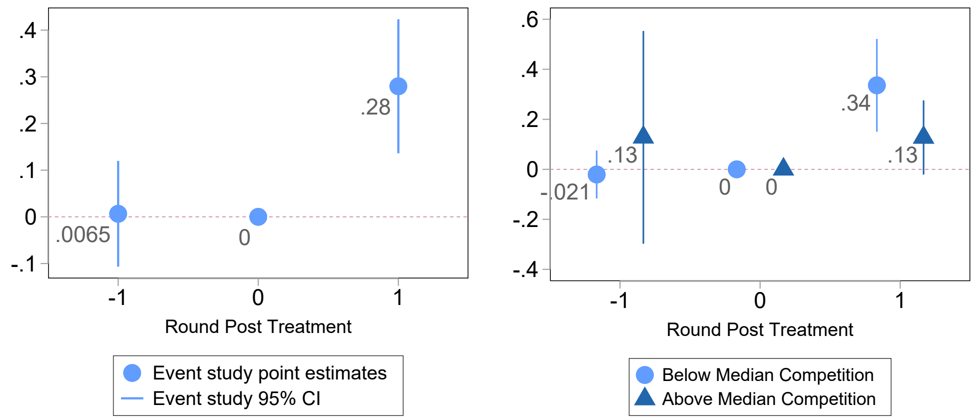
# Figures

**Figure 1:** Event Studies: Bribe Payments Increase in Biometric Districts




**(a)** Any bribes last 12 months **(b)** Any bribes by Competition Group

*Notes*: This figure presents event study plots. For details see sections 4 and 5. The sample consists of 1903 households. Data from the OPM Survey cover the time period 2014, 2016, and 2019. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents, divided by its standard deviation so that it has an SD of 1. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year (see section 4.2). "Any bribes" is a binary variable indicating if any bribes were made (1 if positive, 0 if zero). The variable "Any amount received last 12 months" is 1 if a positive amount was received. "Treated" districts are those that received the Biometric Verification System (BVS) in the earlier rollout (March 2017–September 2018).

# Tables

**Table 1:** Impact of Biometrics System on Bribes and Amount Received

| | Any Bribes last 12 months | Bribes (PKR) last 12 months | Any amount received last 12 months | Total amount (PKR) received last 12 months |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A. ***Difference in Differences*** | | | | |
| Biometric Verification District × Post | 0.291*** | 226.196*** | 0.004 | 546.606 |
| | (0.064) | (44.690) | (0.022) | (488.780) |
| Panel B. ***Triple Difference*** | | | | |
| Biometric Verification District × Post | 0.381*** | 273.902*** | -0.027 | -214.651 |
| | (0.087) | (61.736) | (0.029) | (755.117) |
| Biometric Verification District × Post × SD baseline competition | -0.238*** | -128.351 | 0.104* | 2370.462** |
| | (0.085) | (98.277) | (0.053) | (1064.752) |
| Observations | 4595 | 4595 | 4574 | 4574 |
| District FE | x | x | x | x |
| Time FE | x | x | x | x |
| Province Trend | x | x | x | x |
| Baseline mean Y in control group | 0.121 | 84.73 | 0.929 | 12956.1 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 1903 households. Data from the OPM Survey cover the time period 2014, 2016 and 2019. "Any Bribes" is a binary variable indicating if any bribes were made (1 if positive, 0 if zero). "Bribes PKR, last 12 months" is taken from the OPM survey and expressed in PKR. The variable "Any amount received last 12 months" is 1 if a positive amount was received. The total amount received was taken from the following questions in the OPM survey: "What was the total amount that you personally received in the last 12 months under your name? PKR". The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year (see section 4.2). "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018). Baseline mean for control group is the mean outcome in years 2014 and 2016 in districts not in the initial wave of implementation of biometric verification. The "post" is equals to one for the OPM survey round 2019, and 0 otherwise.

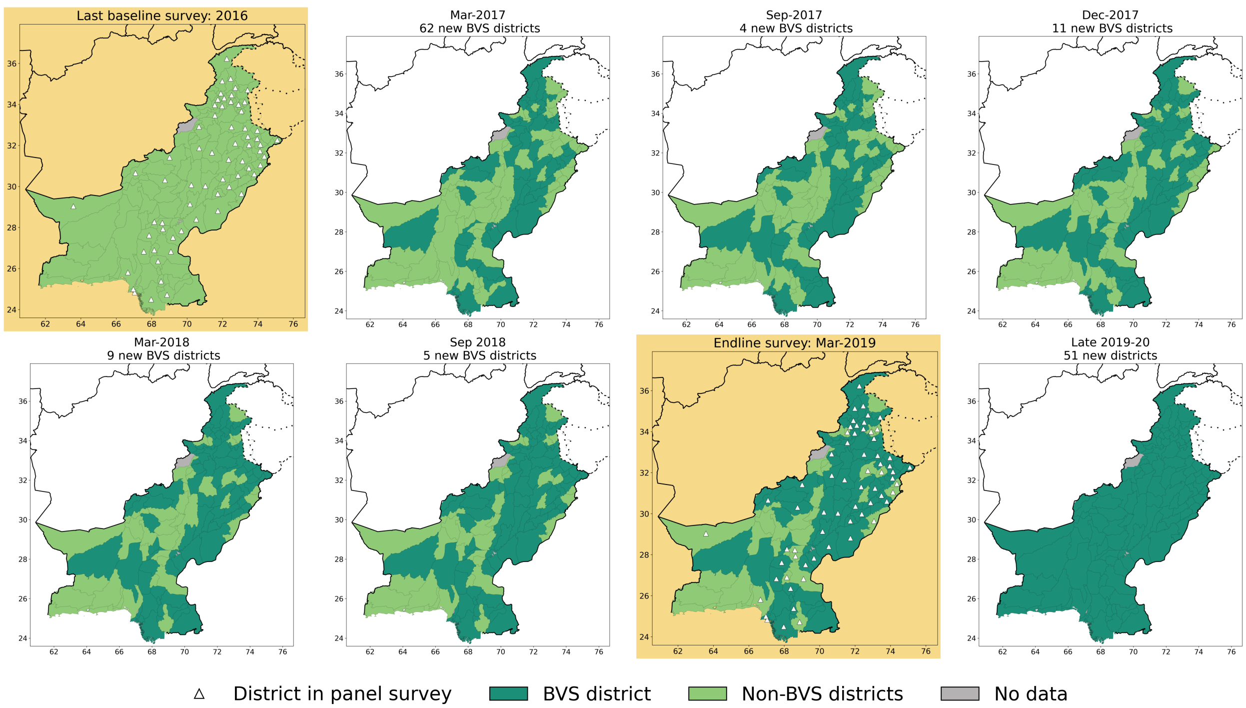
**Table 2:** Results not Driven by Other Potential Correlates of Baseline competition

| | None (1) | Literacy (2) | Never Personally collected cash BL (3) | Ever used Payment Agent BL (4) | Monitoring (5) |
|---|---|---|---|---|---|
| Panel A ***Any Bribes last 12 months*** | | | | | |
| Biometric Verification District × Post × SD baseline competition | -0.238*** | -0.223** | -0.243*** | -0.204** | -0.171* |
| | (0.085) | (0.090) | (0.082) | (0.082) | (0.086) |
| Observations | 4595 | 4583 | 4595 | 4509 | 3530 |
| Baseline Mean of Covariate | | 0.103 | 0.747 | 0.153 | 0.347 |
| Panel B ***Any amount received last 12 months*** | | | | | |
| Biometric Verification District × Post × SD baseline competition | 0.104* | 0.104** | 0.092* | 0.097** | 0.136** |
| | (0.053) | (0.052) | (0.051) | (0.044) | (0.050) |
| Observations | 4574 | 4568 | 4574 | 4525 | 3537 |
| Baseline Mean Control | | 0.103 | 0.747 | 0.153 | 0.347 |
| | Bank Access (6) | Population (7) | Crossing Time (8) | Built Spaces (9) | All Controls (10) |
| Panel C ***Any Bribes last 12 months*** | | | | | |
| Biometric Verification District × Post × SD baseline competition | -0.245*** | -0.218*** | -0.256*** | -0.185** | -0.298*** |
| | (0.089) | (0.079) | (0.083) | (0.080) | (0.084) |
| Observations | 4595 | 4595 | 4518 | 4595 | 3393 |
| Baseline Mean of Covariate | 0.726 | 10.75 | 0.102 | 0.491 | |
| Panel D ***Any amount received last 12 months*** | | | | | |
| Biometric Verification District × Post × SD baseline competition | 0.111** | 0.108** | 0.103** | 0.083* | 0.084** |
| | (0.054) | (0.052) | (0.046) | (0.043) | (0.038) |
| Observations | 4574 | 4574 | 4494 | 4574 | 3423 |
| Baseline Mean Control | 0.726 | 10.75 | 0.102 | 0.491 | |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Each column shows $\beta_1$ from the following specification: $Y_{idt} = \beta_1(\text{BVS}_d \times \text{Post}_t \times Comp_{idt}) + \beta_2(\text{BVS}_d \times \text{Post}_t \times Control_{idt}) + \gamma_t + \delta_d + \theta_{pt} + \epsilon_{idt}$ where we extend our main specification by adding the interaction of the biometric district indicator, post-reform period, and the variable in the column header. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 1903 households. Data from OPM Survey cover the time period 2014, 2016 and 2019. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year (see section 4.2). "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018). The "post" is equals to one for the OPM survey round 2019, and 0 otherwise. Column 2 controls for beneficiary literacy, specifically their ability to read, based on the question, "Can [HH member] read in any language with understanding?". Column 3 assesses the percentage of points of service visited within the district, using Monitoring and Evaluation Data from 2017. Column 4 controls for the use of Payment Agent at baseline. Column 5 controls for the presence of beneficiary at baseline. Column 6 controls for the percentage of bank access within the district. Column 7 incorporates the natural logarithm of the population in the union council. Column 8 measures the time required to traverse a 1 km grid, expressed in hours per km. Column 9 accounts for the percentage of built spaces. Finally, column 10 integrates all control variables.

# A Appendix Figures and Tables

**Figure A1:** Staggered Roll-out of Biometrics




*Notes*: The figure illustrates the staggered rollout of biometric verification across districts in Pakistan between 2016 and late 2019/early 2020. White triangles indicate the locations where data from the Oxford Policy Management (OPM) survey were collected. The OPM survey data correspond to the years 2014, 2016, and 2019. District boundaries are based on shapefiles obtained from Humanitarian Data Exchange for correct borders. The boundaries, colors, denominations and any other information shown on this map do not imply, on the part of the World Bank Group, any judgment on the legal status of any territory, or any endorsement or acceptance of such boundaries.

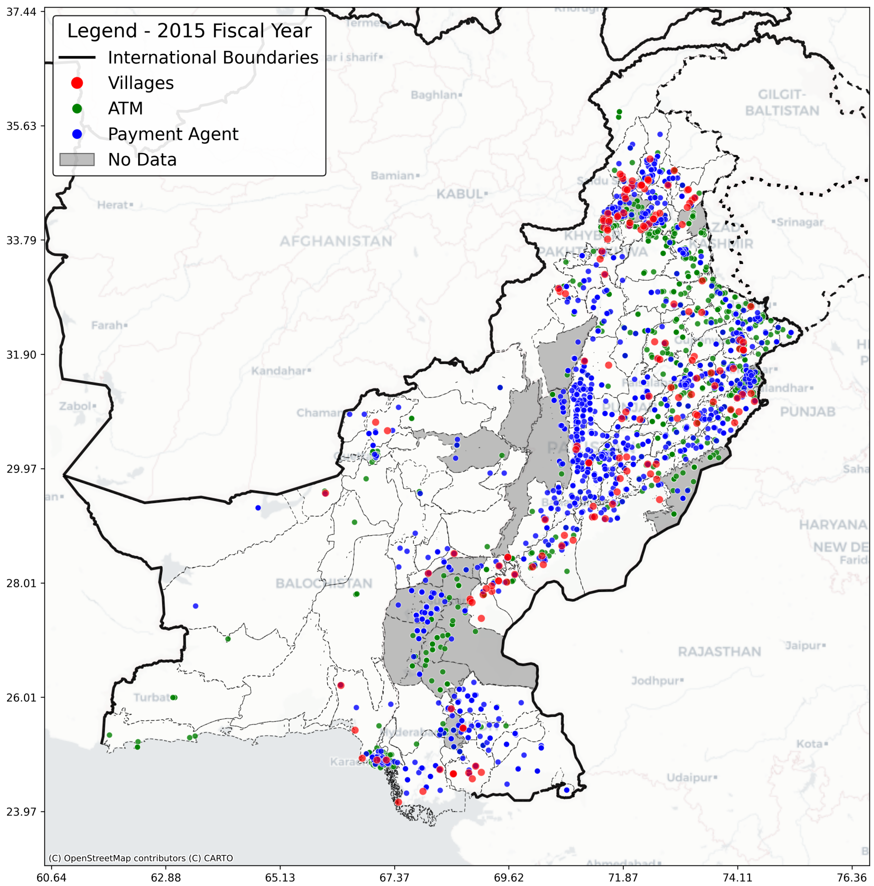
**Figure A2:** Debit card pre treatment [MH: do we need a source for these two figures?]

*Source*: Government of Pakistan - Benazir Income Support Program

**Figure A3:** Biometric verification post treatment

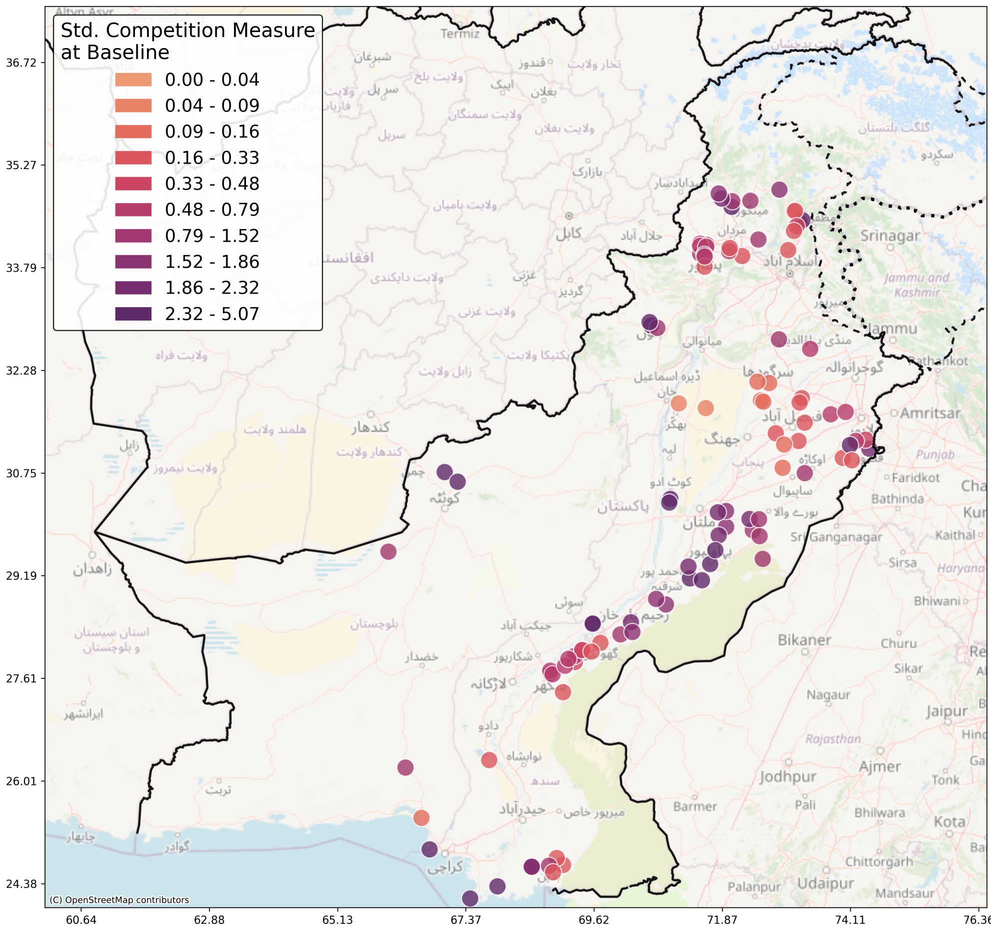
*Source*: The World Bank

**Figure A4:** Payment Points and Study Area



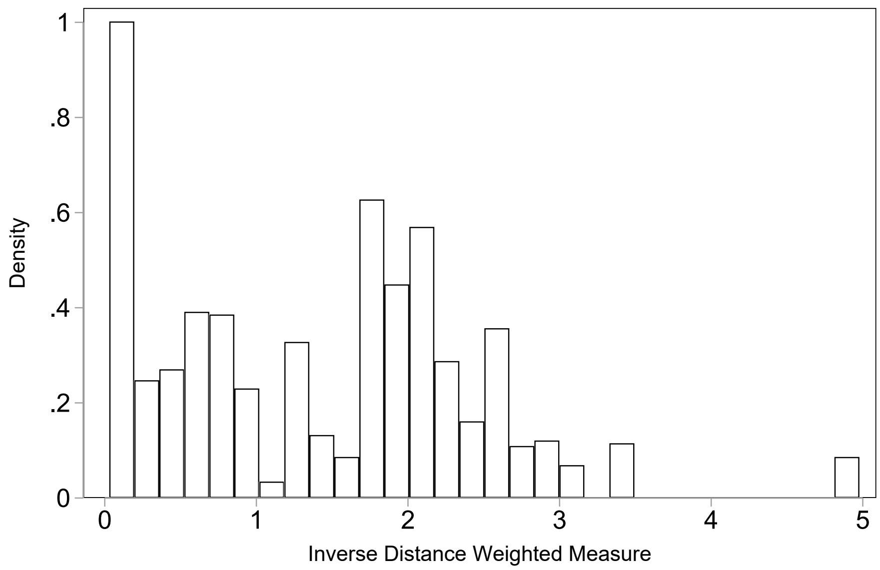

*Notes*: The map displays the distribution of sample villages, ATMs, and Payment Agents across the study area for the 2015 fiscal year. The gray areas represent districts excluded from the analysis due to missing information on payment points. HBL Bank operated in 15 of these districts without providing information about Payment Agents. Village coordinates were sourced from the 2016 OPM survey, and ATM and Payment Agents' locations from the 2015 Payment Point Data. The shapefile for these maps was obtained from the Humanitarian Data Exchange for accurate borders. The boundaries, colors, denominations and any other information shown on this map do not imply, on the part of the World Bank Group, any judgment on the legal status of any territory, or any endorsement or acceptance of such boundaries.

**Figure A5:** Competition Measure



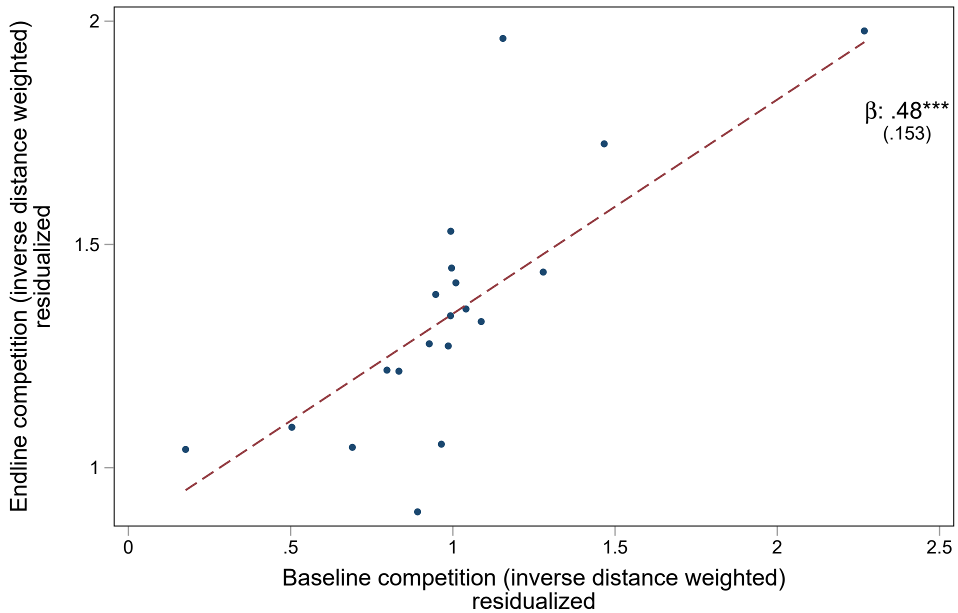

*Notes*: This map displays the Standardized Competition Measure for 163 villages in our sample. Villages in 15 districts where HBL Bank operates were excluded due to the lack of information on Payment Agents. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year. Village coordinates were sourced from the 2016 OPM survey, and ATM and Payment Agents' locations from the 2015 Payment Point Data. The shapefile for these maps was obtained from the Humanitarian Data Exchange for accurate borders. The boundaries, colors, denominations and any other information shown on this map do not imply, on the part of the World Bank Group, any judgment on the legal status of any territory, or any endorsement or acceptance of such boundaries.

**Figure A6:** Distribution of Baseline Competition



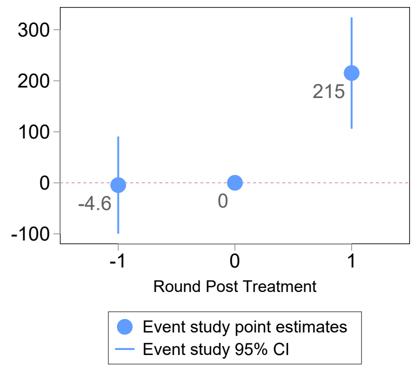

*Notes*: This figure displays the standardized baseline competition measure distribution for our 1903 Households in 2016. This measure represents the inverse distance weighted from each village to all Payment Agents, divided by its standard deviation so that it has an SD of 1. This variable was created using household village information from the OPM Survey 2016 and Payment Point Data from the 2015 fiscal year (see section 4.2). Households in 15 districts where HBL Bank operates were excluded due to the lack of information on Payment Agents. Village coordinates were sourced from the 2016 OPM survey, and ATM and Payment Agents' locations from the 2015 Payment Point Data.

**Figure A7:** Baseline Competition Strongly Predicts Endline Competition

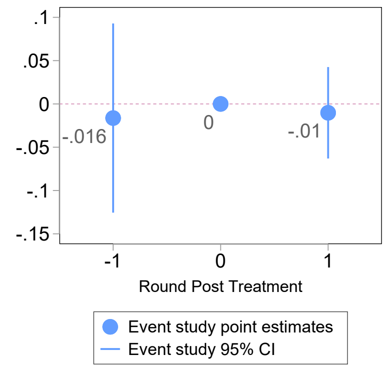



*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. The sample consists of 1903 households. Data from the OPM Survey covers the time period 2016 and 2019. The standardized baseline competition measure represents the inverse distance weighted from each village to all payment agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data one year prior to the launch of biometrics, and in the year following the intervention. The figure displays residualized values: both baseline and endline competition measures are regressed on district fixed effects, and the residuals are plotted. The dashed line represents the best linear fit through these residualized values, with the slope coefficient $\beta = 0.48$ indicating the relationship between baseline and endline competition.

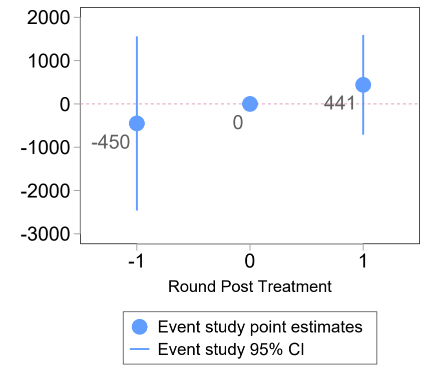
**Figure A8:** Additional event studies



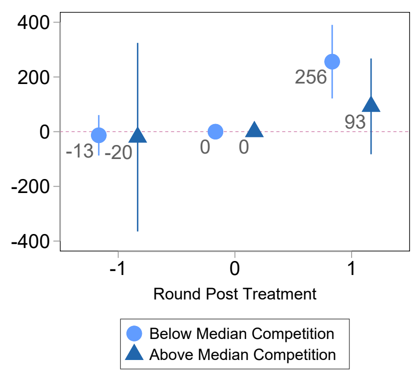

**(a)** Bribes (PKR) last 12 months



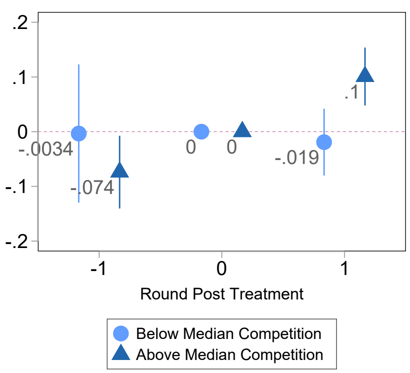

**(b)** Any amount received last 12 months



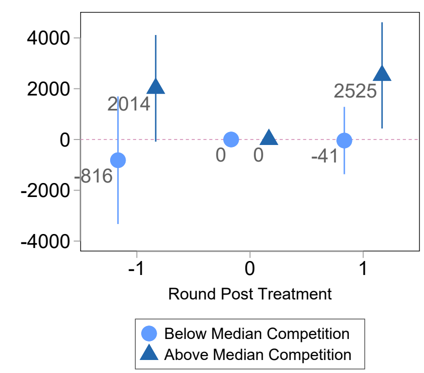

**(c)** Total amount (PKR) received last 12 months




**(d)** Bribes (PKR) last 12 months



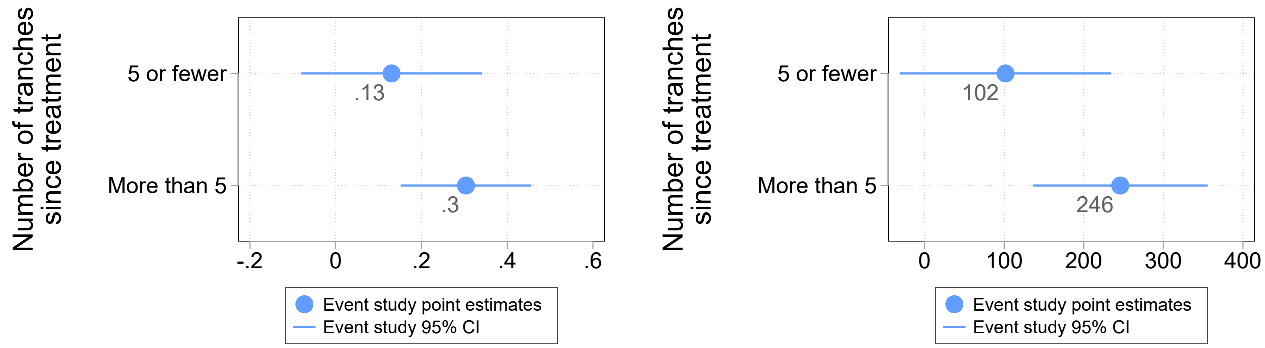

**(e)** Any amount received last 12 months




**(f)** Total amount (PKR) received last 12 months

*Notes*: This figure presents event study plots by competition groups. For details see section 4 and 5. The sample consists of 1903 households. Data from the OPM Survey cover the time period 2014, 2016 and 2019. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year (see section 4.2). We divide the sample into above-median and below-median competition groups using pre-reform data for this analysis. "Any Bribes" is a binary variable indicating if any bribes were made (1 if positive, 0 if zero). "Amount paid in bribes in last 12 months" is expressed in Pakistani Rupees (PKR). "Treated" districts are those that adopted the Biometric Verification System (BVS) during the initial implementation wave (March 2017-September 2018).

**Figure A9:** Results Not Driven by Initial Challenges: Bribes

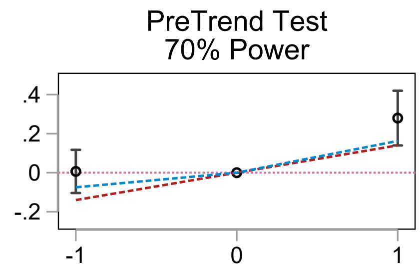



**(a)** Any Bribes last 12 months

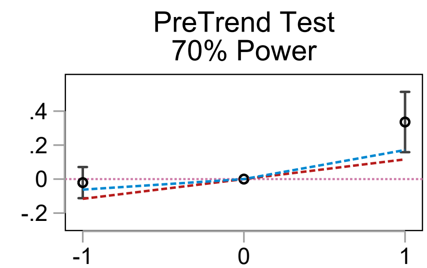
**(b)** Bribes (PKR), last 12 months

*Notes*: This figure presents estimates for two subgroups: districts where BVS was active for more than 5 tranches, and those where it was not. The sample consists of 1903 households. The figures plot $\beta_1$ after estimating the following regression: $Y_{idt} = \beta_1(\text{BVS}_i \times \text{Post}_t \times \text{BVS Group}_g) + \beta_2(\text{BVS}_i \times \text{Post}_t) + \beta_3(\text{Post}_t \times \text{BVS Group}_g) + \beta_4(\text{BVS}_i \times \text{BVS Group}_g) + \delta_d + \mu_t + \psi_{pt} + \varepsilon_{idt}$. BVS Group is Groups of district by number of tranches since BVS. Data from the OPM Survey cover the time periods 2014, 2016, and 2019. "Any bribes" is a binary variable indicating if any bribes were made (1 if positive, 0 if zero). "Amount paid in bribes in last 12 months" is expressed in Pakistani Rupees (PKR). "Treated" districts are those that adopted the Biometric Verification System (BVS) during the initial implementation wave (March 2017-September 2018).

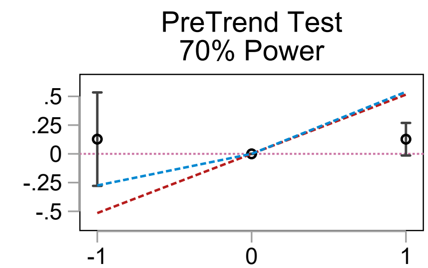
**Figure A10:** Pretrend Analysis



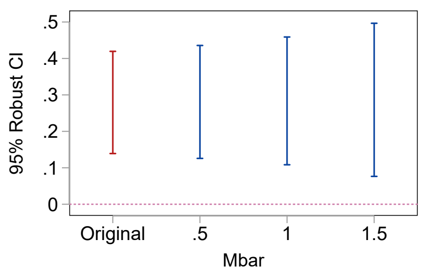

**(a)** Any Bribes last 12 months



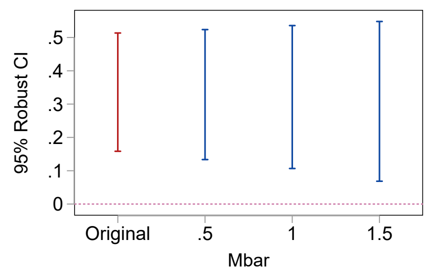

**(b)** Any Bribes last 12 months - below median competition



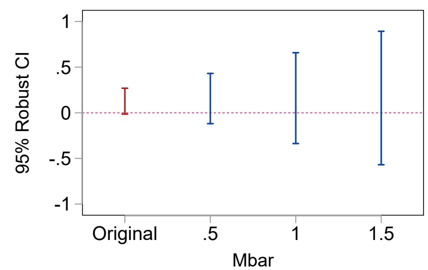

**(c)** Any Bribes last 12 months - above median competition




**(d)** Any Bribes last 12 months




**(e)** Any Bribes last 12 months - below median competition




**(f)** Any Bribes last 12 months - above median competition

*Notes*: This figure presents a pre-trend analysis for our key outcome variable an indicator for any bribes paid in the last 12 months. Panels (a) - (c) show pre-trend tests based on Roth (2022). Estimated coefficients are plotted alongside confidence intervals arising from potential violations of parallel trends that could be detected at 70% power. Panel (a) shows the full sample, Panel (b) shows the subsample with low baseline competition, and Panel (c) the subsample with high baseline competition. Panels (d) - (f) implement the sensitivity analysis proposed in Rambachan and Roth (2023); each line corresponds to an estimate of the difference-in-differences treatment effect allowing for successively larger violations of the parallel trends assumption, up to a 1.5 times larger violation of parallel trends than the largest pre-treatment violation. Panel (d) shows the full sample, Panel (e) shows the subsample with low baseline competition, and Panel (f) the subsample with high baseline competition. The sample consists of 1903 households covered in the OPM survey in three rounds: 2014, 2016 and 2019.

**Table A1:** Attrition

| | household responded in round t | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Biometric Verification District=1 × Post=1 | 0.096 | 0.094 | 0.052 | 0.056 |
| | (0.069) | (0.088) | (0.065) | (0.103) |
| Biometric Verification District=1 × Post=1 × SD baseline competition | | -0.114 | | -0.359 |
| | | (0.623) | | (0.322) |
| Observations | 6730 | 6730 | 5244 | 5244 |
| District FE | x | x | x | x |
| Time FE | x | x | x | x |
| Province Trend | x | x | x | x |
| Control group mean at endline | 0.493 | 0.493 | 0.561 | 0.561 |
| Panel relative to: | Present in 2016 | Present in 2016 | Present in 2014 and 2016 | Present in 2014 and 2016 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. In columns 1 and 2, we use a dataset that contains 3365 households that appeared in 2016. Columns 3 and 4 use a sample of 1748 households that appeared in 2014 and 2016. The main outcome measures whether the household is present in period $t$. Data from the OPM Survey covers the time period 2014, 2016, and 2019 "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018). The "post" is equals to one for the OPM survey round 2019, and 0 otherwise.

**Table A2:** Descriptive Statistics at Baseline

| | Non Biometric Verification Mean (SD) | Biometric Verification Mean (SD) | T-test(p-value) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Bribes (PKR), last 12 months | 92.48 | 103.34 | 0.75 |
| | (262.68) | (256.45) | |
| Any Bribes last 12 months | 0.13 | 0.18 | 0.27 |
| | (0.34) | (0.39) | |
| Total amount (PKR) received last 12 months | 13968.56 | 13853.06 | 0.85 |
| | (4941.74) | (4762.16) | |
| Proportion of payment received last 12 months | 0.75 | 0.75 | 0.91 |
| | (0.26) | (0.26) | |
| Any amount received last 12 months | 0.93 | 0.94 | 0.77 |
| | (0.26) | (0.24) | |
| Round-trip travel time × attempts for last withdrawal (minutes) | 74.17 | 72.60 | 0.85 |
| | (78.58) | (77.14) | |
| Round-trip travel distance × attempts for last withdrawal (km) | 37.30 | 34.74 | 0.69 |
| | (47.58) | (47.77) | |
| Minimum Distance to Payment Agent | 16.82 | 13.83 | 0.53 |
| | (16.36) | (14.03) | |
| Num. Obs | 369 | 1534 | 1903 |
| Num. Clusters | 10 | 39 | 49 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. All estimates include survey year fixed effects. The sample consists of 1903 households. Data from the OPM Survey cover the periods 2014 and 2016. 1'Any Bribes last 12 months" is a binary variable indicating if any bribes were made (1 if positive, 0 if zero). The total amount received was based on: "What was the total amount that you personally received in the last 12 months under your name? PKR". The proportion of the amount received was calculated by dividing the total amount received by 18000 PKR, the annual total from quarterly BISP transfers of 4500 PKR. "Any amount received last 12 months" is 1 if a positive amount was received. Travel Time, Travel Distance, and Travel Cost data were obtained from the OPM survey. Minimum Distance to payment agents (PP) and Point of Sales Agents (payment agents) were constructed using Payment Point Data from the 2015 fiscal year and household geo-coordinates given in the OPM survey.

**Table A3:** First stage: Transition to Biometrics

| | BVS Used | Payment Agent Used |
|---|---|---|
| | (1) | (2) |
| Biometric Verification District × Post | 0.707*** | 0.267*** |
| | (0.150) | (0.094) |
| Observations | 2065 | 2056 |
| District FE | x | x |
| Time FE | x | x |
| Province Trend | x | x |
| Baseline mean Y in control group | 0 | 0.421 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample includes 1,037 households from the MIS in 2016 and 2019 (2 tranches in 2016, 3 in 2019). This is the subset of OPM households that have any transaction observed at baseline. A variable equals 1 if the household used a payment agent or BVS in any tranche of a given year. "BVS Used" and "Payment Agent Used" are derived from MIS. Households with no transactions in 2016 tranches are excluded. "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018). The "post" is equals to one for the OPM survey round 2019, and 0 otherwise.

**Table A4:** Correlates of Bribes at Baseline

| | Any Bribes last 12 months | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Beneficiary can read | -0.052*** | | | | 0.019 |
| | (0.016) | | | | (0.043) |
| Beneficiary ever attended school | | -0.075*** | | | -0.090** |
| | | (0.020) | | | (0.044) |
| Age | | | -0.000 | | -0.001 |
| | | | (0.001) | | (0.001) |
| Proxy means test - wealth measure (SD) | | | | -0.031*** | -0.029*** |
| | | | | (0.010) | (0.010) |
| Observations | 1799 | 1738 | 1743 | 1805 | 1737 |
| $R^2$ | 0.046 | 0.047 | 0.043 | 0.050 | 0.053 |
| Province FE | x | x | x | x | x |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 1903 households. Data from the OPM Survey cover the time period 2016. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year. "Any Bribes" is a binary variable indicating if any bribes were made (1 if positive, 0 if zero). The standardized wealth measure is the Benazir Income Support Programme proxy means test poverty score, constructed from household characteristics collected by the National Socio-Economic Registry household survey.

**Table A5:** Correlates of Competition Measure

| | SD baseline competition | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Beneficiary can read | -0.000 | | | | | | | | 0.006 |
| | (0.086) | | | | | | | | (0.066) |
| Bank use % in District | | 0.812 | | | | | | | 0.785 |
| | | (0.706) | | | | | | | (0.628) |
| Log Population in Union Council | | | 0.218 | | | | | | 0.195 |
| | | | (0.155) | | | | | | (0.151) |
| Time to cross 1km grid in hr/km | | | | 0.223 | | | | | 0.020 |
| | | | | (0.878) | | | | | (0.669) |
| % of area built spaces | | | | | 2.473 | | | | 1.549 |
| | | | | | (3.158) | | | | (3.421) |
| % Payment Agent visited in District | | | | | | -0.389 | | | 0.021 |
| | | | | | | (0.611) | | | (0.395) |
| Used Payment Agent at baseline | | | | | | | 0.898*** | | 0.923*** |
| | | | | | | | (0.156) | | (0.142) |
| Never Personally collected cash baseline | | | | | | | | -0.143 | -0.071 |
| | | | | | | | | (0.104) | (0.095) |
| Observations | 1897 | 1903 | 1903 | 1872 | 1903 | 1470 | 1860 | 1903 | 1409 |
| $R^2$ | 0.072 | 0.095 | 0.093 | 0.085 | 0.080 | 0.055 | 0.256 | 0.075 | 0.268 |
| Adjusted $R^2$ | 0.070 | 0.093 | 0.091 | 0.083 | 0.078 | 0.052 | 0.254 | 0.073 | 0.262 |
| Province FE | x | x | x | x | x | x | x | x | x |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 1903 households. Data from the OPM Survey cover the time period 2016. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year. Column 1 uses beneficiary literacy, specifically their ability to read, based on the question, "Can [HH member] read in any language with understanding?" Column 2 considers the percentage of bank access within the district using data from the 2015-16 Household Integrated Economic Survey (HIES), specifically, we used the question "How often do you use the facility of a bank?" Column 3 considers the natural logarithm of the population in the union council, created using the spatial distribution of population Raster in 2020. Column 4 uses the time required to traverse a 1 km grid, expressed in hours per kilometer, utilizing the friction surface from the Malaria Atlas Project database in 2018. Column 5 uses the percentage of built spaces at the council level, derived from raster data from the Global Human Settlement Layer in 2018. Column 6 considers the percentage of points of service visited within the district, using Monitoring and Evaluation Data from 2017. Column 7 uses the use of Payment Agent at baseline. Column 8 uses if the person never personally collected cash at baseline. Finally, Column 9 integrates all these variables.

**Table A6:** Impact of Biometrics System on Access to Payment Point

| | Log Min. Dist. Payment Agent | Log Travel Time (min) x N. trips | Log Travel Dist (km) x N. trips | Travel Cost (PKR) x N. trips |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A. ***Difference in Differences*** | | | | |
| Biometric Verification District × Post | -0.254 | -0.088 | -0.448 | -35.063* |
| | (0.323) | (0.186) | (0.359) | (20.015) |
| Panel B. ***Triple Difference*** | | | | |
| Biometric Verification District × Post | -0.432 | 0.121 | -0.447 | -56.444* |
| | (0.465) | (0.274) | (0.482) | (29.708) |
| Biometric Verification District × Post × SD baseline competition | -1.080 | -0.518 | -0.556 | 17.518 |
| | (0.944) | (0.517) | (0.532) | (61.744) |
| Observations | 3780 | 4356 | 4286 | 4372 |
| District FE | x | x | x | x |
| Time FE | x | x | x | x |
| Province Trend | x | x | x | x |
| Baseline mean Y in control group | 2.193 | 3.790 | 2.778 | 157.0 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 1903 households. Data from OPM Survey cover the time period 2014, 2016 and 2019. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year (see section 4.2). "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018). Travel Time, Travel Distance, and Travel Cost data were obtained from the OPM survey. The first two variables are in logs, and the Travel cost variable was winsorized at the 95th percentile. Minimum Distance to payment points (PP) and Point of Sales Agents (payment agents) were constructed using Payment Point Data from the 2015 fiscal year and household geo-coordinates given in the OPM. Baseline mean for control group is the mean outcome in years 2014 and 2016 in districts not in the initial wave of implementation of biometric verification. The "post" is equals to one for the OPM survey round 2019, and 0 otherwise.

**Table A7:** Differential Entry and Exit

| | Number of Payment Agents | Number of new Payment Agent Endline | Number of Payment Agent exits Endline |
|---|---|---|---|
| | (1) | (2) | (3) |
| Biometric Verification District × SD baseline competition | 4.264 | 0.612 | -2.334 |
| | (3.198) | (3.289) | (2.588) |
| Observations | 1903 | 1903 | 1903 |
| $R^2$ | 0.768 | 0.767 | 0.904 |
| District FE | x | x | x |
| Mean Outcome | 16.29 | 16.18 | 1.030 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 1903 households The sample consists of 1903 households. Data from OPM Survey cover the time period 2019. Column 1 measures the number of Payment Agents available to a user. Column 2 for the number of new payment agents in 2019. Column 3 measures the number of payment agents that were in 2016 but are not anymore in 2019. All three variables were adjusted by their proximity. We use inverse distance weighting, where each agent's contribution is weighted by the inverse of its distance (1/distance). This means closer agents receive higher weights in the local competition measure, while agents farther away contribute proportionally less. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year. "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018).

**Table A8:** Impact of Biometrics System on Bribes and Amount Received - strongly balanced panel

| | Any Bribes last 12 months | Bribes (PKR) last 12 months | Any amount received last 12 months | Total amount (PKR) received last 12 months |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A. ***Difference in Differences*** | | | | |
| Biometric Verification District × Post | 0.325*** | 262.851*** | -0.006 | 745.857 |
| | (0.077) | (53.337) | (0.027) | (740.389) |
| Panel B. ***Triple Difference*** | | | | |
| Biometric Verification District × Post | 0.389*** | 292.835*** | -0.035 | -177.233 |
| | (0.099) | (76.415) | (0.035) | (1018.536) |
| Biometric Verification District × Post × SD baseline competition | -0.227** | -79.198 | 0.094* | 2815.270** |
| | (0.091) | (92.751) | (0.048) | (1167.856) |
| Observations | 2808 | 2808 | 2891 | 2891 |
| District FE | x | x | x | x |
| Time FE | x | x | x | x |
| Province Trend | x | x | x | x |
| Baseline mean Y in control group | 0.117 | 81.99 | 0.932 | 12644.0 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 978 households. Data is a balanced panel from the OPM Survey covering the time period 2014, 2016, and 2019. "Any Bribes" is a binary variable indicating if any bribes were made (1 if positive, 0 if zero). "Bribes PKR, last 12 months" is taken from the OPM survey and expressed in PKR. The variable "Any amount received last 12 months" is 1 if a positive amount was received. The total amount received was taken from the following questions in the OPM survey: "What was the total amount that you personally received in the last 12 months under your name? PKR". The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year (see section 4.2). "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018). Baseline mean for control group is the mean outcome in years 2014 and 2016 in districts not in the initial wave of implementation of biometric verification. The "post" is equals to one for the OPM survey round 2019, and 0 otherwise.

**Table A9:** Impact of Biometrics System on Distribution of Bribe Amounts

| | Any Bribes | Bribes larger than 400 PKR | Bribes larger than 800 PKR | Bribes larger than 1200 PKR |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A. ***Difference in Differences*** | | | | |
| Biometric Verification District × Post | 0.278*** | 0.278*** | 0.196*** | 0.062* |
| | (0.069) | (0.071) | (0.045) | (0.034) |
| Panel B. ***Triple Difference*** | | | | |
| Biometric Verification District × Post | 0.381*** | 0.368*** | 0.201*** | 0.085** |
| | (0.087) | (0.090) | (0.060) | (0.034) |
| Biometric Verification District × Post × SD baseline competition | -0.238*** | -0.209** | 0.002 | -0.052 |
| | (0.085) | (0.085) | (0.106) | (0.119) |
| Observations | 4595 | 4595 | 4595 | 4595 |
| District FE | x | x | x | x |
| Time FE | x | x | x | x |
| Province Trend | x | x | x | x |
| Baseline mean Y in control group | 0.121 | 0.108 | 0.0692 | 0.0212 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 1903 households. Data from the OPM Survey cover the time period 2014, 2016 and 2019. Column (1) reports an indicator variable equal to 1 if any bribe was reported, and zero otherwise Column (2) reports an indicator variable equal to 1 if any bribe larger than 400 was reported, and zero otherwise Column (3) reports an indicator variable equal to 1 if any bribe larger than 800 was reported, and zero otherwise Column (4) reports an indicator variable equal to 1 if any bribe larger than 1200 was reported, and zero otherwise The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year (see section 4.2). "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018). Baseline mean for control group is the mean outcome in years 2014 and 2016 in districts not in the initial wave of implementation of biometric verification. The "post" is equals to one for the OPM survey round 2019, and 0 otherwise.

**Table A10:** Impact of Biometrics System on Distribution of Amount Received

| | Any amount received in 12m | Amount larger than 9000 | Amount larger than 13000 | Amount larger than 18000 |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A. ***Difference in Differences*** | | | | |
| Biometric Verification District × Post | -0.005 | 0.036 | 0.070 | 0.034 |
| | (0.022) | (0.027) | (0.067) | (0.054) |
| Panel B. ***Triple Difference*** | | | | |
| Biometric Verification District × Post | -0.027 | 0.016 | 0.084 | -0.063 |
| | (0.029) | (0.044) | (0.088) | (0.065) |
| Biometric Verification District × Post × SD baseline competition | 0.104* | 0.100 | -0.046 | 0.173 |
| | (0.053) | (0.069) | (0.122) | (0.141) |
| Observations | 4574 | 4574 | 4574 | 4574 |
| District FE | x | x | x | x |
| Time FE | x | x | x | x |
| Province Trend | x | x | x | x |
| Baseline Mean Outcome | 0.929 | 0.870 | 0.714 | 0.259 |

*Notes*: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors clustered at the district level are reported in parentheses. The sample consists of 1903 households. Data from OPM Survey cover the time period 2014, 2016 and 2019. The total amount received was taken from the following questions in the OPM survey: "What was the total amount that you personally received in the last 12 months under your name? PKR". Column (1) reports an indicator variable equal to 1 if any amount was received within 12 months, and zero otherwise Column (2) reports an indicator variable equal to 1 if any amount larger than 9000 was received, and zero otherwise Column (3) reports an indicator variable equal to 1 if any amount larger than 13000 was received, and zero otherwise Column (4) reports an indicator variable equal to 1 if any amount larger than 18000 was received, and zero otherwise. The standardized baseline competition measure represents the inverse distance weighted from each village to all Payment Agents in Pakistan. This variable was created using household village information from the OPM Survey and Payment Point Data from the 2015 fiscal year (see section 4.2). "Biometric Verification District" equals 1 for those districts that were included in the initial implementation wave of the biometric verification system (BVS) (March 2017-September 2018). The "post" is equals to one for the OPM survey round 2019, and 0 otherwise.