Digital Footprints and Policing: The Socioeconomic Impacts of Mobile Payment Reform on China's Sex Industry

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Abstract

This paper examines how China's 2016 Real-name Reform—requiring ID verification for mobile payments and authorizing police use of this data—enhanced law enforcement in the sex industry. Using a continuous difference-in-differences design comparing prefectures with varying pre-reform mobile payment adoption levels, we find increased sex-related arrests, especially in private locations, with harsher penalties after the reform. However, the enhanced enforcement efficiency had mixed socioeconomic consequences: decreased infection rate for sexually transmitted diseases but increased sexual violence against women, higher divorce rates due to infidelity, and more domestic violence. Effects were amplified by local sex imbalances and police force size. Our findings contribute to understanding how technology-driven enforcement efficiency affects illegal markets and generates unintended social consequences.

Keywords: police enforcement, mobile payment, sex industry, sexual violence, public health
JEL codes: I18, J40, K42

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1 Introduction

The sex industry, one of the oldest in human history, has long been a subject of controversial policy debates. While existing research focuses on formal legal reforms (Cunningham and Shah, 2020), less attention has addressed how changes in law enforcement efficiency affect sex industry dynamics and broader socioeconomic outcomes. However, recent advancements in technology, such as the adoption of DNA databases for solving crimes and the use of IT systems to optimize patrolling strategies, have significantly transformed the cost-efficiency and effectiveness of law enforcement (Doleac, 2017; Mastrobuoni, 2020). This paper contributes a novel perspective by investigating how enhanced police enforcement efficiency through mobile payment information has reshaped China's sex industry, generating unintended consequences for sexual violence, public health, and other important socioeconomic outcomes.

China offers an ideal setting for this analysis. First, despite its illegality since the regime's founding, China hosts one of the world's largest sex industries—with UNAIDS estimating 4.5 million sex workers by 2006[1]—where participants face penalties ranging from fines to detention. Second, China leads globally in mobile payment adoption—boasting 911 million out of 1.75 billion global accounts by 2022 (PCAC, 2023; Raithatha and Storchi, 2024)—facilitating a highly digitalized illegal sex industry.[2] The introduction of the real-name reform for mobile payments in July 2016, originally intended to enhance financial security and payment transparency, inadvertently increased police enforcement efficiency by mandating ID verification and explicitly authorizing law enforcement to access digital transaction data for criminal investigations. This significantly reduced the costs of tracking and verifying illegal sex transactions. We leverage this real-name reform as a natural experiment to identify the causal impact of enhanced policy enforcement efficiency.

Our analysis begins with the construction of a comprehensive dataset on Chinese law enforcement activities as our dependent variables. Illegal behaviors in China can result in sanctions from two distinct institutions. For acts below the criminal threshold, police impose administrative penalties, which are publicly disclosed on

[1]Report by aidsdatahub.org, "SEX WORK & HIV CHINA" https://www.aidsdatahub.org/sites/default/files/resource/sex-work-hiv-china.pdf.

[2]See Lianhe Zaobao's article: "China's Sex Industry Uses 'Over-the-Wall Ladder' but Can't Escape the Eye of Big Data." https://www.zaobao.com/news/china/story20240721-3918655.

their official websites. We systematically collected these records from *Pkulaw.com* to create the *China Administrative Penalty (CAP)*. Conversely, when violations constitute crimes, cases proceed to court trials, with resulting verdicts published on *China Judgements Online (CJO)* after 2003. By integrating data from both sources, we obtain a holistic view of police enforcement in the sex industry. Additionally, we applied identical methodology to gather records related to sexual violence, human trafficking for tests on unintended consequences, as well as theft and robbery for robustness checks. Our dataset spans 2014-2019, covering crucial periods before and after the implementation of the 2016 real-name reform.

We employ a continuous difference-in-differences empirical design to assess the impact of the real-name reform, which interacts the proxy for intent-to-treat exposure—using prefectural intensity of mobile payment adoption—with the timing of the real-name reform in 2016. To measure mobile payment adoption, we employ the Digital Financial Inclusion Index of China (DFIIC), developed through collaboration between Peking University and Ant Group utilizing billions of payment records from *Alipay*.

Our initial analysis examines whether mobile payment technology has strengthened enforcement against the sex industry. We find significantly increased arrests in prefectures more exposed to the real-name reform. In addition, direct evidence shows that the proportion of mobile payment-based arrests rose substantially in high-exposure prefectures, supporting our contention that digital payment surveillance has dramatically reduced tracking and verification costs. To exclude alternative explanations related to general police capacity changes, we conduct placebo tests using theft and robbery arrest data, finding no significant effects. Our results remain consistent across three robustness checks: (i) alternative mobile payment adoption measurements, including binary treatment indicators and varied DFIIC intensity metrics; (ii) modified sample specifications excluding key cities like Dongguan—the center of sex industry in China, and Hangzhou or Shenzhen—the headquarters of two main mobile payment platforms, *Alipay* and *Wechat Pay*; and (iii) single-source analyses using either CAP or CJO datasets independently. These findings collectively demonstrate that mobile payment technology has substantively enhanced enforcement capacity within China's sex industry.

We then investigate the broader implications of the real-name reform for sex industry dynamics. First, regarding enhanced enforcement efficiency, we observe increased arrested cases transacted at private locations in prefectures with greater reform exposure. Before the reform, tracing transactions in private spaces posed significant challenges; afterward, digital payment footprints facilitated detection. Additionally, since sentencing for sex transactions depends on the economic return involved, mobile payment records provide authorities with more precise transaction value estimates, improving sentencing accuracy and efficiency. Indeed, we find offenders in high-exposure regions facing steeper fines and longer detention periods post-reform. Finally, we confirm industry contraction following the reform, evidenced by rising sex service prices documented in penalty records—a classic market response to supply reduction under sustained demand.

Next, we assess impacts on broader socioeconomic outcomes. First, prefectures more affected by the reform experienced significant increases in sexual violence against women—spanning both milder harassment and violent rape—aligning with previous findings on criminalization and decriminalization effects (Bisschop et al., 2017; Cunningham and Shah, 2018). Second, our analysis reveals enhanced enforcement efficiency significantly correlates with reduced sexually transmitted infection (STI) rates, evidenced by declining HIV and syphilis incidence, likely reflecting more targeted enforcement against higher-risk services in sex industry. Third, we demonstrate that prefectures with higher mobile payment adoption show increased divorce rates attributed to marital infidelity, elevated domestic violence incidents, but no significant changes in human trafficking patterns.

Finally, we perform two heterogeneity analyses. First, we examine how pre-reform male sex ratios—a proxy for sexual service demand (Edlund et al., 2013)—mediate reform effects. Our findings show that higher male sex ratios amplify both enforcement intensity against the sex industry and sexual violence increases. Second, we revisit the established negative relationship between police intensity and crime (Owens and Ba, 2021; Di Tella and Schargrodsky, 2004). Using the pre-reform number of police recruitment to proxy for the police intensity, the result indicates that a significant interacted effect of police intensity with the reform on various outcomes.

This paper contributes to three strands of literature. First, we advance the ongoing debate on sex industry regulation (Cunningham and Shah, 2020). While critics advocate prohibition based on morality and human rights concerns (Farley, 2004, 2005), proponents suggest regulated markets could reduce violence against women and STI transmission. Existing research has examined how formal legal reforms—criminalization or decriminalization of sex industry—affects sex violence, human trafficking, and disease spread (Cunningham and Shah, 2018; Berlin et al., 2019; Cameron et al., 2021; Ciacci, 2024). Our study extends this literature by investigating how technology-driven enforcement efficiency changes affect the crackdowns of sex industry, their effect on industry dynamics, and broader unintended social consequences. We also provide novel findings about policing and China's sex industry, complementing work by He and Peng (2022) on police complicity in organized prostitution; our focus is on reforms that increased enforcement efficiency.

Second, we speak to the growing research on technology's transformation of law enforcement. Studies have shown that DNA databases reduce crime rates (Doleac, 2017; Anker et al., 2021), information technology improves crime clearance rates (Mastrobuoni, 2020), and autocratic governments leverage AI to suppress social unrest (Beraja et al., 2023). More broadly on governance, Axbard and Deng (2024) demonstrated how air pollution monitors enhanced enforcement and reduced pollution. Our work provides causal evidence on how mobile payment information affects police enforcement in China's sex industry, highlighting both the indirect social costs and benefits of enhanced enforcement efficiency.

Finally, we contribute to digital economics literature (Goldfarb and Tucker, 2019), particularly regarding government utilization of digital platform data for governance. Research shows digital technologies reduce transaction costs, affecting price discrimination, inducing personalized advertising, and shaping reputation systems (Ba and Pavlou, 2002; Athey and Gans, 2010; Fudenberg and Villas-Boas, 2012; Suri, 2017). Recent studies suggest mobile payments also lower tracking and verification costs (Goldfarb and Tucker, 2019), making them valuable tools for policing digitally transacted crimes. Our findings reveal the political consequences of mobile payment technology—enhancing law enforcement in illegal industries and strengthening social control—while contributing to digital privacy discussions by demonstrating how real-name reform enables authorities to combat illegal activities more effectively, albeit with significant social costs.

The remainder of this paper is structured as follows. In Section 2, we introduce China's digitalized sex industry and the real-name reform for mobile payments. Section 3 describes our data sources and empirical strategies. Section 4 presents the main findings on the effects of real-name reform on police enforcement in the sex industry. Section 5 explores the indirect effects of the reform on a series of outcomes, including sexual violence, public health, and other outcomes. In Section 6, we examine the heterogeneous effects of the male sex ratio and police intensity. Finally, Section 7 provides conclusions and discusses the implications of our findings.

2 Background

The sex industry is illegal in China. According to the *Criminal Law* and *Public Security Administration Punishments Law*, individuals involved in the sex industry face legal penalties, as detailed in Appendix Table B.1. Despite its illegal status, this long-standing industry persists in various forms. This section provides an overview of the institutional context surrounding this issue in China. First, we explain the rationale for focusing on China's digitalized sex industry. Then, we discuss the implementation of the real-name reform for mobile payments, which served as an exogenous shock that enhanced police enforcement.

2.1 Sex Industry in the Digital Age

China's digitalized sex industry provides a compelling context for this study due to three key factors: the widespread adoption of mobile payments, the resulting digitalization of the traditional sex industry, and the incentives for enhanced police enforcement.

First, mobile payment technologies have seen extensive adoption across China (PCAC, 2023). By 2022, there were 911 million mobile payment users holding 6.4 billion accounts — equivalent to 64.5% of the total population.[3] In the same year, mobile payment companies processed 982.79 billion transactions, with a cumulative value of 317.33 trillion yuan. On average, people used mobile payments three times a day, with a mean transaction value of 322 yuan. According to the *Mobile Payment User Usage Survey 2022*, approximately 84% of mobile payment users engaged with the service daily. Furthermore, mobile payments were dominated by small transactions, with around 90% of individual transactions under 500 yuan.

[3] All statistics in this section are sourced from PCAC (2023): the China Payment Industry Report 2023.

Second, the traditional sex industry in China has rapidly digitalized, driven by the adoption of mobile payments. China is widely recognized as hosting one of the largest sex markets globally, involving an estimated 4.5 million sex workers according to UNAIDS.[4] The convenience and suitability of mobile payments for small transactions have made it a primary method of payment in the sex industry. According to a sex worker interviewed, requesting cash payments has become nearly impossible in modern China.[5] To navigate payment restrictions, she registered five WeChat accounts and alternated their use across different transactions.

Third, the digitalization of the sex industry has made it a focal point for police crackdowns. Previously, law enforcement efforts against prostitution were primarily campaign-based. A prominent example is the 2014 crackdown on Dongguan City — often referred to as China's "Sin City" — which was orchestrated under the leadership of Guangdong's provincial secretary, Chunhua Hu.[6] With advancements in technology, Chinese law enforcement has increasingly adopted digital tools to enhance their surveillance and enforce social control. As a result, the digitalized sex industry has become a primary target, allowing authorities to showcase their enforcement efficiency.

In summary, China's digitalized sex industry provides an ideal context for studying the intersection of mobile payment technology and police enforcement. However, to establish causality, it is essential to address the challenges of endogeneity and anticipation effects arising from the enhanced enforcement capabilities enabled by mobile payment technology. We address these challenges by using a natural experiment: the real-name reform for mobile payments.

2.2 Real-Name Reform for Mobile Payment

The real-name reform for mobile payments was introduced by China's central bank in July 2016. The regulation, titled *Administrative Measures for the Online Payment Business of Non-Banking Payment Institutions*, required all users of non-banking mobile payment platforms to verify their identity, ensuring real-name usage during

[4]Report by aidsdatahub.org, "SEX WORK & HIV CHINA" `https://www.aidsdatahub.org/sites/default/files/resource/sex-work-hiv-china.pdf`.

[5]See Lianhe Zaobao's article: "China's Sex Industry Uses 'Over-the-Wall Ladder' but Can't Escape the Eye of Big Data." https://www.zaobao.com/news/china/story20240721-3918655.

[6]See CNN's report: "Sex trade goes underground in China's 'sin city'." https://edition.cnn.com/2015/05/25/asia/china-sin-city/index.html.

transactions.[7] Although the primary objective of the reform was to improve financial security and transparency, it also unintentionally reduced tracking and verification costs, thus bolstering police enforcement against illegal activities by facilitating easier access to verified payment records.[8] Thus, this reform serves as an ideal natural experiment for this study.

In the context of China's digitalized sex industry, the reform significantly enhanced police capabilities to monitor transactions and trace responsible parties through money trails. Prior to the reform, tracing payments made through mobile platforms required law enforcement to submit formal requests to payment companies. These requests often necessitated approval from higher government authorities, adding significant layers of complexity and extending the time required for investigations. Post-reform, law enforcement can quickly identify payers using readily accessible payment records linked to verified identities, thereby substantially lowering the cost and effort of tracking and verification. Even if a sex worker deletes payment records from personal devices, the police can easily recover this information to continue investigations. We argue that this enhanced traceability, enabled by the reform, has allowed the police to more effectively identify and arrest sex workers, their organizers, and clients, thereby disrupting the digitalized sex industry and producing a range of consequential impacts.

A potential concern is that individuals involved in the sex industry might rationally respond to increased police enforcement by substituting alternative payment methods, such as cash. However, we present several lines of evidence suggesting that this substitution effect is minimal. First, most sex transactions are spontaneous, which reduces the likelihood of participants carrying sufficient cash, leaving mobile payments as the predominant transaction method. Anecdotal evidence supports this claim, highlighting that mobile payments are nearly ubiquitous in such contexts.[9] Second, our dataset includes specific cases linked to mobile payment records, allowing us to conduct formal tests to evaluate this issue. Our analysis reveals an increasing share of arrests involving mobile payment records during the study period. Finally, while experienced participants may indeed shift to

[7] Link: https://www.pkulaw.com.

[8] As stated in the policy, its purposes are "preventing payment risks and protecting the parties' lawful rights and interests".

[9] See Lianhe Zaobao's report: "China's Sex Industry Uses 'Over-the-Wall Ladder' but Can't Escape the Eye of Big Data." https://www.zaobao.com/news/china/story20240721-3918655.

cash transactions, such cases would merely attenuate the observed impact of the reform without undermining the validity of our findings.

3 Data and Empirical Strategy

In this paper, we construct a comprehensive dataset of police enforcement by merging two data sources: the *China Administrative Penalty* and *China Judgement Online* Databases. This dataset provides detailed information on arrests for illegal activities, including offenses related to the sex industry, sexual violence and others. A detailed description of the dataset is provided in Section 3.1. In Section 3.2, we present our measures of mobile payment adoption, with a particular focus on the Digital Financial Inclusion Index of China, which serves as an indicator to capture regional exposure to the real-name reform. Furthermore, in Section 3.3, we complement the dataset with various sources to construct the main sample and provide summary statistics. Lastly, Section 3.4 outlines our empirical strategies.

3.1 Police Enforcement

In China, when illegal activities occur, responsible parties may face penalties from one of two distinct authorities. If the activity does not meet the threshold for a criminal offense, administrative penalties are imposed directly by government authorities, with records disclosed on official websites. These records comprise the *China Administrative Penalty* (CAP) dataset, compiled and maintained by www.pkulaw.com. The CAP dataset includes over 31 million administrative penalty records from both central and local governments in China. We collect all penalty records from CAP and provide an overview in Appendix A.1. Each record contains the following information: title, date, region, issuing authority, names of responsible parties, facts, punishments, and legal basis.

Conversely, when an illegal activity constitutes a crime, government authorities refer the case to trial, where courts determine the punishment. The resulting verdicts are documented and published on *China Judgements Online* (CJO), an official platform established by the Supreme People's Court in 2013 to promote judicial transparency. All courts in China are required to disclose their verdicts on this platform, which now contains over 140 million verdicts. Liu et al. (2022) provides a comprehensive introduction to this dataset. Each verdict includes detailed information such as title, date, region, court, names of plaintiffs and defendants, facts, trial process, results, legal basis, and names of judges.

To construct a comprehensive dataset on police enforcement, we merged the CAP and CJO databases. From these sources, we extracted 225,439 records related to the sex industry, 58,276 records of sexual violence, 121,174 records of domestic violence, 2,630 records of human trafficking, 1,115,679 records of theft, and 88,445 records of robbery for the period 2014 to 2019. A key limitation of the dataset is the incomplete and selective disclosure of records by police and courts. Nevertheless, we believe this dataset represents the most comprehensive collection of illegal activity records available in China to date. In the following sections, we detail the construction of our measurements, with a primary focus on records related to police enforcement in the sex industry. Arrest-level summary statistics are presented in Appendix Table A.1, while prefecture-level summary statistics are provided in Panel A of Table 1.

First, we extracted the number of arrests from each record. In the CAP data, each record corresponds to a single arrest, whereas in the CJO data, each record may involve multiple offenders, identified using defendant information. We then aggregated the total number of arrests at the prefecture-year level and normalized it by population per 100,000 people. On average, the number of arrests related to the sex industry was 3.22 per 100,000 people. Based on the reasons for punishment, we classified each arrest into three categories: sex organizer, sex worker, and sex buyer. We also calculated the number of arrests in each category per 100,000 people.

Second, we computed the share of arrests made using mobile payment records. Both the CAP and CJO datasets contain information about the facts and evidence of each case. Ideally, we identified cases involving mobile payment records using keywords such as "mobile payment," "payment records," "Alipay," or "WeChat Pay." For records lacking explicit mention, we determined whether the offender was arrested at the crime scene. The share of arrests involving mobile payment records was calculated by dividing the number of such arrests by the total number of arrests involving either mobile payments or on-site apprehensions. On average, approximately 18.95% of arrests are made using mobile payment records.

Third, we calculated the share of arrests occurring in private crime scenes. Using a similar method, we labeled crime scenes as private if the sex business took place in homes or rented residential locations. Public crime scenes were defined as locations where police patrols are likely, such as clubs and massage parlors. We then calculated the share of arrests in private locations by dividing the number of private-location arrests by the total number of arrests in private or public locations. On average, 21.52% of sex industry-related arrests occurred in private locations.

Fourth, we extracted data on the type and severity of punishments. Offenders involved in the sex industry could face one or more of four types of punishment: warnings, fines, confiscation of illegal gains, or detention. Detention was the most common penalty, applied in 85% of cases, followed by fines, issued in 32.6% of cases. The severity of the punishments varied, with the prefecture-level average fine being 18,646 CNY and the average detention lasting 534 days. Notably, the punishments in the CAP dataset are generally less severe than those in the CJO dataset.

Finally, we extracted information on the price of sex services from case details. This information is critical for quantifying the reform's impact on the sex industry. We found that the prefecture-level average price for sex services in arrested cases was 433 CNY. However, since this price reflects only the arrested sample, caution is required when making inferences about the broader market.

3.2 Mobile Payment Adoption

Due to the absence of temporal variation in the implementation of the real-name reform across regions, it is crucial to develop a metric to quantify the intensity of exposure to the reform. Ideally, a comprehensive measure that accounts for the adoption of all mobile payment applications would be most suitable; however, such data is challenging to acquire. Fortunately, a suitable proxy is available in the form of the *Digital Financial Inclusion Index of China* (DFIIC). The DFIIC is compiled by the Institute of Digital Finance at Peking University in collaboration with Ant Group, the largest digital financial company in China (Guo et al., 2020). Drawing on billions of payment records from Alipay, a leading mobile payment platform operated by Ant Group, the index provides province-level, prefecture-level, and county-level measures of mobile payment adoption in China from 2011 to 2018.

The DFIIC comprises three dimensions and 33 variables, which are listed in Appendix Table A.2. Given the small transaction sizes characteristic of the sex industry, we focus specifically on the measurement of mobile payment coverage breadth. This measure is constructed using three variables: the number of Alipay accounts per 10,000 individuals, the share of users linking a bank account to their Alipay account, and the number of bank accounts per Alipay account. For our baseline measure of exposure, we used the coverage breadth index from 2015, corresponding to the year preceding the reform. While the other two dimensions — usage depth and digitalization level — are excluded from our primary exposure measure, we include the total DFIIC index as an alternative measure in robustness checks. It is important to note that the index is calculated using 2011 as the base year, which means that its values represent percentage changes relative to this baseline, and the index may exceed 100 for years after 2011. Detailed definitions and the index's processing methodology can be found in Guo et al. (2020).

Panel B of Table 1 provides summary statistics for the different measures of mobile payment adoption at the prefecture level. The average value of our primary exposure measure, the coverage breadth index, is 165.54. The highest exposure levels, 242.9 and 238.4, are observed in Shenzhen and Hangzhou, respectively — cities that also serve as headquarters for WeChat Pay and Alipay. When combining the usage depth and digitalization level dimensions, the average total DFIIC index is 172.3. The pattern of the total DFIIC index closely mirrors that of the coverage breadth index, as the latter carries significant weight in its calculation.

3.3 Main Sample and Summary Statistics

We supplemented our analysis with additional data from various sources. First, we incorporated provincial-level incidence of STIs from the Center for Disease Control (CDC), covering AIDS, HIV, gonorrhea, and syphilis. Second, we extracted divorce cases from the CJO database and identified whether the reasons for divorce included marital infidelity. Third, we included variables such as population, GDP, fiscal revenue, and fiscal expenditure from the *China City Statistical Yearbook*. Finally, we introduced two additional variables to explore heterogeneous effects: the male sex ratio, calculated from China's 2015 census data, to capture variations in demand for sexual services, and data on police recruitment extracted from the OffCN Education Technology website to measure the intensity of police presence.

Our main sample consists of 1,710 observations in 285 prefectures from 2014 to 2019. We excluded the four municipalities directly under central government jurisdiction, as these are classified as province-level divisions and are omitted when controlling for province-by-year fixed effects. Furthermore, approximately 40 prefectures, primarily in western and central regions, are excluded due to missing data. The sample period begins in 2014, as the CJO and CAP datasets were well-established by that year, and ends in 2019 to mitigate the potential confounding effects of the COVID-19 pandemic. Table 1 provides prefecture-level summary statistics, including the number of observations, means, and standard deviations for each variable. Summary statistics for provincial-level public health data are presented in Appendix Table A.3.

To illustrate the motivation behind our study, Figure 1 presents descriptive patterns. Panel A compares the trends in arrests for sex business associated with mobile payment records across prefectures with high and low mobile payment adoption. We observe that prefectures with higher mobile payment adoption experience a substantial increase in arrests linked to mobile payment records following the real-name reform. Additionally, Figure A.6 illustrates that the average prefecture-level share of arrests with mobile payment records increased from 2.7% in 2014 to 50.1% in 2019. Panel B of Figure 1 highlights the positive association between the number of arrests for sex business and sexual violence. Furthermore, Figure 2 depicts the spatial distributions of arrests for sex business and sexual violence, while Figure A.7 illustrates the adoption of mobile payments. Notably, arrests for both sex business and sexual violence are concentrated in Guangdong and Zhejiang Provinces, which are also major hubs for mobile payment adoption in China. These graphical patterns align with our intuitive expectations. To establish causal effects, we outline our identification strategy in the subsequent section.

3.4 Empirical Strategy

Our main estimation strategy employs a continuous difference-in-differences (DiD) approach. Unlike the standard DiD method, our approach uses a continuous treatment variable — mobile payment adoption — to account for varying levels of exposure to the reform's intensity. To ensure robustness, we also test the results using a binary treatment variable as a complementary specification. Since the real-name reform was implemented in July 2016, we define the post-treatment period as beginning after 2016.

The main equation is:

$$Y_{ct} = \beta \cdot MPA_c \cdot Post_t + X_{ct} \cdot \gamma + \theta_c + \lambda_t + \epsilon_{ct} \tag{1}$$

where c and t indicate prefectures and years, respectively. Our main sample comprises 285 prefectures, covering the period from 2014 to 2019. The treatment intensity, MPA_c, is defined as the prefecture-level mobile payment adoption in 2015,[10] capturing the level of exposure to the reform. To reflect the reform shock, we define $Post_t$ as a binary indicator variable that equals one for years after 2016. The outcome variable of interest, Y_{ct}, represents the number of arrests for various illegal activities, including sex business, sexual violence and others. We incorporate prefecture fixed effects θ_c to control for time-invariant factors specific to each prefecture and province-by-year fixed effects λ_t to account for time-varying confounders at the province level. Additionally, we control for prefecture-by-year economic characteristics X_{ct}, including GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefecture level.

The coefficient of interest in the main equation is β, which captures the effect of exposure to the real-name reform on the outcomes of interest. For β to be interpreted causally, the key identifying assumption is that the outcomes of prefectures with varying levels of treatment intensity would have followed parallel trends prior to the implementation of the real-name reform. To evaluate the validity of this parallel trends assumption, we employ an event study specification to estimate the dynamic effects of the reform.

$$Y_{ct} = \sum_{t=2014}^{2019} \beta_t \cdot MPA_c \cdot I_t + X_{ct} \cdot \gamma + \theta_c + \lambda_t + \epsilon_{ct} \tag{2}$$

All variables are defined as in the main equation, except β_t, which is a vector of coefficients for each year from 2014 to 2019. We take 2016, the year when the real-name reform began, as the reference year. Therefore, our point estimates can be interpreted as the relative changes compared to the base year. We expect the coefficients before 2016 to remain constant, while those after 2016 should change significantly. If this holds true, we can conclude that the pre-trend assumption is valid, and the estimated effect is statistically significant.

Furthermore, we use a triple-differences approach to explore the heterogeneous effects of the real-name reform. Specifically, factors such as male sex ratio and police recruitment may amplify or modify the reform's impact. To analyze these dynamics, we estimate the following equation:

$$Y_{ct} = \beta_1 \cdot MPA_c \cdot Post_t + \beta_2 \cdot Z_c \cdot Post_t + \beta_3 \cdot MPA_c \cdot Z_c \cdot Post_t + X_{ct} \cdot \gamma + \theta_c + \lambda_t + \epsilon_{ct} \tag{3}$$

[10] Measured by the Digital Financial Coverage Breadth Index.

Based on Equation (1), we incorporate an triple-interaction term $MPA_c \cdot Z_c \cdot Post_t$ to capture the heterogeneity with respect to the indicator variable Z_c. For instance, let Z_c refer to male sex ratio. In this case, the coefficient β_1 describes the effect of the real-name reform for prefectures with a lower male sex ratio, while the sum of coefficients $\beta_1 + \beta_3$ quantifies the effect for prefectures with a higher sex ratio. The coefficient of the triple interaction term, β_3, captures the differential impact of the real-name reform between prefectures with varying levels of male sex ratio.

4 Impacts of the Real-Name Reform on the Sex Industry

We aim to examine how mobile payment technology, driven by the real-name reform, impacts the sex industry. Cunningham and Shah (2020) provide a comprehensive summary of the effects of various regulations — such as criminalization, decriminalization, and licensing — and internet technology on the sex industry. Our study contributes to this literature by offering a novel perspective on mobile payment technology, which is utilized by both the sex industry and law enforcement. We hypothesize that mobile payment technology enhances police enforcement by reducing the costs of tracking and verification in the sex industry. Specifically, we expect it to increase the number of arrests related to the sex industry, as well as improve the efficiency of police enforcement. Consequently, we anticipate a contraction in the sex market, reflected by higher prices for sex services. The increased costs and risks associated with enhanced police enforcement likely raise barriers to entry in the market.

This section analyzes the effects of the real-name reform for mobile payments on police enforcement in the sex industry. Section 4.1 presents evidence that the real-name reform has strengthened police enforcement through mobile payment records. Section 4.2 demonstrates improved efficiency in police enforcement. Finally, Section 4.3 examines the contraction of the sex market resulting from the reform.

4.1 Impact on Police Enforcement in the Sex Industry

We first examine the effect of the real-name reform on police enforcement in the sex industry. Table 2 reports the results from estimating the main specification in Equation (1). All regressions include prefecture and province-by-year fixed effects to account for confounding factors.

The results for the number of arrests for sex business per 100,000 people are reported in columns (1)-(2) of Table 2. In Column (1), the estimate suggests that a one-standard-deviation (25.45) increase in mobile payment adoption leads to an average increase of 5.09 arrests per 100,000 people. We control for time-varying prefecture-level characteristics in Column (2), including GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. The estimate in Column (2) slightly decreases to 4.86. Compared to the pre-reform mean during 2014–2016, this result implies a substantial 466% increase in arrests for sex-related activities if mobile payment adoption increases by one standard deviation.

To evaluate the pre-trend assumption, we estimate the event study model in Equation (2), and visualize the β_t coefficients in Figure 3. The results reveal a flat pre-trend before the reform, followed by a significant increase in arrests afterward, which persists and grows for three years post-reform. Consistent results for different participants in the sex industry, such as sex organizers, workers, and clients, are presented in Appendix Table B.2.

We argue that mobile payment technology plays a critical role in enhancing police enforcement. Columns (3)–(4) of Table 2 provide evidence of the effect of the real-name reform on the share of arrests involving mobile payment records. We find that prefectures with higher mobile payment adoption experienced a higher share of arrests linked to mobile payment records after the real-name reform. Although smaller in magnitude compared to total arrests, this likely represents a lower-bound estimate, as only 30.1% of cases covering the detailed information for identification.

To establish causality, we address alternative explanations. One concern is that the observed effects could be driven by a general increase in police transparency or capabilities coinciding with the reform. If this were the case, we would expect similar patterns in arrests for other illegal activities. To test this, we conduct two placebo tests using arrests for theft and robbery per 100,000 people as dependent variables. The results, reported in columns (5)–(6) of Table 2, show no statistically significant effects for theft or robbery arrests. These findings mitigate concerns about alternative mechanisms and bolster the validity of our explanation.

We conduct several robustness checks, categorized into three types: alternative measurements of mobile payment adoption, alternative sample specifications, and alternative datasets. The first set includes (i) using a binary treatment as a proxy for mobile payment adoption and (ii) using total DFIIC intensity as an alternative measure. The second set involves (i) excluding Dongguan City, known as the "Sin City" of China, and (ii) excluding Hangzhou and Shenzhen, the headquarters of Alipay and WeChat Pay, respectively. The third set uses (i) only the CAP dataset and (ii) only the CJO dataset. Table 3 summarizes the robustness results. Panel A shows that the effect on the number of arrests remains robust across all specifications, while Panel B demonstrates that the effect on the share of arrests involving mobile payment records is robust in most cases, except when only the CAP dataset is used, likely due to fewer observations.

4.2 Impact on Efficiency of Police Enforcement

Next, we investigate whether the real-name reform improves police enforcement efficiency, as mobile payment technology significantly reduces tracking and verification costs and provides stronger evidence. We propose two measures to evaluate enforcement efficiency in the sex industry. First, mobile payment technology facilitates the identification of sex trade occurring in private locations, which should result in a higher share of arrests tied to private crime scenes. Second, we hypothesize mobile payment records provide stronger evidence for arrests and lead to more severe penalties, such as more fines and longer detention days.

Table 4 presents the results from estimating Equation (1). Columns (1)–(2) report findings for the share of arrests involving private crime scenes. We observe a significant increase in arrests tied to private locations after the reform. Columns (3)–(6) indicate that higher mobile payment adoption results in more fines and longer detention. We also examine extensive margin effects on different types of punishments. The results in Appendix Table B.6 indicate no statistically significant effects on the share of various punishments. These findings indicate that the real-name reform enhances enforcement efficiency in the sex industry by reducing the costs associated with tracking and identifying offenders and providing stronger evidence through mobile payment technology.

4.3 Impact on Size of the Sex Industry

Finally, we examine whether the real-name reform has affected the size of the sex industry. Given that both the cost and risk of participating in the sex market have increased, we hypothesize that the industry would contract. However, comprehensive transaction data on the sex industry in China are unavailable. As a proxy, we use the price of sex services, which we expect to rise if the market contracts. Using data extracted from legal verdicts, we analyze changes in the price of sex services. Table 5 shows that prefectures with higher mobile payment adoption are associated with higher price of sex services. These findings suggest that the real-name reform has contributed to a contraction in the sex market in China.

5 Impacts of the Real-Name Reform on Sexual Violence, Public Health, and Other Outcomes

We have provided evidence that the real-name reform enhances police enforcement and reduces the size of the sex industry, effectively functioning as a mechanism akin to criminalization. Existing literature has established a link between the criminalization or decriminalization of the sex industry and various indirect outcomes, including sexual violence, public health, and other outcomes (Cunningham and Shah, 2020). This evidence suggests that increased law enforcement targeting the sex industry may indirectly influence sexual violence and related outcomes. In this section, we analyze these indirect effects, presenting the impact of the real-name reform on sexual violence in Section 5.1, public health in Section 5.2, and other outcomes in Section 5.3.

5.1 Impact on Sexual Violence

The relationship between the size of the sex industry and sexual violence remains a key issue in discussions on regulating the sex industry. Some case studies and qualitative interviews argue that the growth of the sex industry increases sexual violence, as prostitution is often associated with various forms of violence against women (Farley, 2004, 2005). In contrast, recent empirical studies suggest a negative correlation between the sex industry and sexual violence. For instance, Bisschop et al. (2017) find that legal street prostitution zones in the Netherlands reduce reported cases of sexual abuse and rape. Similarly, Cunningham and Shah (2018) demonstrate that decriminalizing sex work reduces reported rape offenses in Rhode Island. Moreover, Gao and Petrova (2022) and Ciacci (2024) both find that banning the purchase of sex increases the cases of rape.

In this subsection, we investigate the impact of the real-name reform on the incidence of sexual violence. Given the difficulty of directly observing such violence, we use the number of arrests for sexual violence as a proxy. Using the specification in Equation (1), we present the results in Table 6. Columns (1)–(2) report the effects of mobile payment adoption on arrests for sexual violence per 100,000 people. The estimate in Column (1) indicates that a one-standard-deviation (25.45) increase in mobile payment adoption leads to an average increase of 0.31 arrests per 100,000 people. Including control variables in Column (2) slightly decreases the effect to 0.28. Relative to the baseline mean from 2014 to 2016, this corresponds to a 81.4% increase in arrests with a one-standard-deviation increase in adoption.

To assess the pre-trend assumption, we estimate Equation (2) and plot the β_t for sexual violence arrests in Figure 4. The results show no pre-existing trend between prefectures with different levels of mobile payment adoption prior to 2016. However, after the reform, prefectures with higher exposure to mobile payment adoption exhibited a significant increase in sex violence arrests compared to others.

We further disaggregate sexual violence into milder sexual harassment and more violent rape. Columns (3)–(4) of Table 6 show that a one-standard-deviation increase in mobile payment adoption leads to a 301% increase in arrests for sexual harassment per 100,000 people, regardless of the inclusion of control variables. Columns (5)–(6) reveal a 30.3% increase in arrests for rape per 100,000 people with the same increase in mobile payment adoption. To benchmark these findings, we compare them with existing literature on criminalization or decriminalization. For example, Cunningham and Shah (2018) report a 30% decrease in reported rape offenses following the decriminalization of indoor prostitution in the U.S., while Ciacci (2024) find that banning the purchase of sex in Sweden increases reported rapes by 44%–62%. Although direct comparison is difficult, our findings suggest that variations in law enforcement play a significant role in socioeconomic outcomes in China. Robustness checks presented in Appendix Table B.8-Table B.10 show consistent results in nearly all specifications.

The observed increase in sexual violence following the contraction of the sex industry raises critical questions about the underlying mechanisms. One possible explanation is that contraction exacerbates the risks for sex workers by reducing investments in security equipment, discouraging reporting to law enforcement, or increasing opportunities for police corruption (Brents and Hausbeck, 2005; Church et al., 2001; Levitt and Venkatesh, 2007). However, our dataset contains limited records of sexual violence targeting sex workers. To investigate this, we split the sample into incidents involving sexual violence against sex workers and others, with the results presented in Appendix Table B.11. The findings show statistically significant effects only for incidents involving others, not sex workers, ruling out this mechanism. Another possible explanation is the reallocation of police resources or the increase in enforcement capabilities (Draca et al., 2011; Adda et al., 2014). However, the results of the placebo test in Table 2 do not support this hypothesis. Finally, prostitution may act as a substitute for sexual violence (Posner, 1994). When the risks and costs of purchasing sex increase due to enhanced enforcement, marginal sex buyers may resort to violence against women. This substitution effect remains the most plausible explanation.

5.2 Impact on Public Health

Next, we examine the impact of the real-name reform on public health, particularly with respect to sexually transmitted infections (STIs). Theoretically, the contraction of the sex industry could affect STI transmission through opposing mechanisms. On one hand, a reduced scale of the sex industry could lower the overall infection rate by decreasing the volume of the sex business. On the other hand, contraction could also lead to reduced condom use and riskier sexual behaviors, increasing STI transmission. Empirical studies support both perspectives. For instance, Gertler and Shah (2011) find that increased enforcement of licensing regulations in the street-based sex sector significantly reduces STI prevalence, while similar enforcement in the brothel sector increases the likelihood of infection among sex workers. Additionally, Cunningham and Shah (2018) report that decriminalizing indoor prostitution reduces female gonorrhea incidence by over 40%, whereas Cameron et al. (2021) show that criminalization increases STIs among female sex workers by 58%, as measured through biological tests, due to decreased access to and use of condoms.

Due to the unavailability of prefecture-level STI data in China, we rely on province-level data to provide suggestive evidence. Our analysis follows a specification similar to Equation (1), including province and year fixed effects, with standard errors clustered at the provincial level. The findings, summarized in Table 7, indicate that mobile payment adoption is negatively associated with the incidence of

HIV and syphilis per 100,000 people. However, the result is not significant for gonorrhea. A possible explanation for these negative correlations is that riskier sexual behavior tends to be more concealed. As a result, increased police enforcement of the sex industry, enabled by mobile payment records, may disproportionately target higher-risk sexual behaviors, leading to a general decrease in STI transmission.

5.3 Impact on Other Social-economic Outcomes

Finally, we examine the effects of the real-name reform on other outcomes, including divorce due to marital infidelity, domestic violence, and human trafficking. First, enhanced police enforcement exposes previously anonymous participants, which might lead to higher divorce rates due to revealed marital infidelity. Columns (1)–(2) of Table 8 show that prefectures with higher mobile payment adoption experienced higher divorce due to marital infidelity. Event study graphs in Panel A of Figure 5 confirm a flat pre-trend and a significant increase post-reform. These results hold across various robustness checks, as detailed in Appendix Table B.12.

Second, we explore the impact on domestic violence. The unmet demand for sex services resulting from the market contraction can not only increase sexual violence but also domestic violence (Berlin et al., 2019). Columns (3)–(4) of Table 8 indicate a significant increase in domestic violence after the reform. The event study graphs in Panel B of Figure 5 verify the pre-trend assumption, while robustness checks in Appendix Table B.13 further support this finding.

Third, we investigate the effects on human trafficking. Theoretical literature suggests that the legalization of the sex industry exerts two contradictory effects on trafficking: while it may reduce trafficking by improving regulation and oversight, it may also increase demand, thereby incentivizing trafficking (Cho et al., 2013). Lee and Persson (2022) argue that current policies are largely ineffective in combating human trafficking. They propose that a hybrid approach that combines elements of the Dutch and Swedish models may yield better outcomes. Cross-country studies further suggest that a legalized sex industry is associated with higher reported inflows of trafficking (Jakobsson and Kotsadam, 2013; Cho et al., 2013). Our results, presented in columns (5)–(6) of Table 8, find no statistically significant effect of the real-name reform on trafficking arrests. This insignificance may result from two potential explanations. First, as suggested in the theoretical literature, the positive and negative effects of the contraction of the sex industry might offset each other, resulting in no observable net effect. Second, the insignificance could be attributed to data limitations, particularly challenges in identifying and arresting traffickers.

6 Heterogeneous Effects

This section examines the heterogeneous effects of the real-name reform on police enforcement within the sex industry, sexual violence, and other indirect outcomes. Two primary dimensions of heterogeneity are explored. First, in Section 6.1, we consider the role of male sex ratio in accounting for the rise in crime (Edlund et al., 2013), where a higher male sex ratio corresponds to a higher demand for sexual services. Second, in Section 6.2, we explore variations in law enforcement intensity driven by differing local government incentives to increase policing and surveillance (Beraja et al., 2023).

6.1 Heterogeneity in Male Sex Ratio

The male sex ratio has been identified as a significant factor contributing to the rise in crime in China (Edlund et al., 2013). A higher male sex ratio corresponds to a higher demand for sexual services. This section evaluates how prefectures with higher male sex ratios exhibit distinct outcomes when police enforcement in the sex industry is intensified. Specifically, we hypothesize that higher male sex ratios lead to more arrests related to the sex industry, higher incidences of sexual violence, and other associated outcomes. To test this hypothesis, we define the male sex ratio using census data from 2015, measuring the ratio of males aged 16 to 60 within each prefecture. Prefectures with a male sex ratio above the median are classified as having a ”high male sex ratio”.

Using a triple-differences estimation approach, we estimate Equation (3) and present the results in columns (1)-(4) of Table 9. Column (1) reports the number of arrests related to the sex industry. Prefectures with a higher male sex ratio experienced a significantly greater increase in enforcement. Columns (2)-(4) focus on arrests related to sexual violence, revealing a higher incidence of such crimes in prefectures with higher male sex ratios. While a similar pattern was observed for arrests related to sexual harassment, no significant effects were found for arrests related to rape. Lastly, columns (1)-(3) of Appendix Table B.14 report results for other social outcomes, including divorce due to marital infidelity, domestic violence, and human trafficking, which were not statistically significant. Collectively, the findings suggest that a higher male sex ratio amplifies the increase in arrests related to the sex industry and sexual violence but does not significantly affect other outcomes.

6.2 Heterogeneity in Police Intensity

The intensity of policing is another critical factor influencing enforcement outcomes. Extensive research has demonstrated a negative relationship between crime rates and police presence (Owens and Ba, 2021; Di Tella and Schargrodsky, 2004). It is thus plausible that the effects of the real-name reform interact with police intensity, amplifying enforcement outcomes in regions with higher policing levels. Due to the unavailability of data on the total number of police officers in China, we use police recruitment data from OffCN Education Technology to measure police intensity. Newly recruited officers are categorized into ”field jobs”, which involve direct crime prevention, and ”office jobs”. Our analysis focuses on the cumulative number of field officers hired prior to the real-name reform. Police intensity is measured as the ratio of field officers to the population, with prefectures above the median classified as having ”high police intensity”.

The results of our triple-differences estimation are presented in columns (5)-(8) of Table 9. Column (5) reports the number of arrests for the sex industry, showing that prefectures with higher police intensity experienced significantly larger increases in enforcement. Columns (6)-(8) present results for arrests related to sexual violence, revealing a similar pattern. As with the male sex ratio analysis, the results for sexual harassment were significant, while those for rape were not. Columns (4)-(6) of Appendix Table B.14 examine broader social outcomes, including divorce due to marital infidelity, domestic violence, and human trafficking, which were found to be insignificant. Overall, these findings underscore the role of police intensity in amplifying the effects of the real-name reform, particularly regarding enforcement in the sex industry and sexual violence.

7 Conclusions

Mobile payment technology has empowered police enforcement in China by reducing tracking and verification costs. Using the real-name reform for mobile payment platforms as an exogenous shock, this paper examines the impact of mobile payments on police enforcement within China's digitalized sex industry and its unintended consequences.

This paper compiles the most comprehensive dataset on police enforcement in China. Our analysis shows that the real-name reform led to an increase in arrests related to the sex industry, a larger share of arrests involving mobile payment records, and improvements in the efficiency of police enforcement. Additionally, we observed a rise in the price of sex services, reflecting the increased costs and risks of entering the sex industry. As the contraction of the sex industry left more unmet demand for sexual services, the reform inadvertently contributed to a rise in sexual violence, including sexual harassment and rape. Moreover, we found suggestive evidence of a decrease in the incidence of STIs, such as HIV and syphilis. We also found that the reform led to higher divorce rates due to marital infidelity and increased domestic violence, although it had no significant effects on human trafficking. Finally, we observed that factors such as the male sex ratio and police intensity played a significant role in amplifying the reform's effects on both police enforcement in the sex industry and sexual violence.

Our findings have important implications for police enforcement strategies. Although a growing body of literature has explored the positive role of technology in enhancing police capabilities, this paper not only reinforces this perspective but also highlights the unintended consequences of intensified enforcement in the sex industry. Furthermore, the study underscores the significant role of enforcement capacity in shaping socio-economic outcomes, even without legislative changes. This study does not take a position on how the sex industry should be regulated. Policymakers must determine how best to design optimal policies within the constraints of real enforcement capabilities, considering the potential trade-offs between legitimacy, efficiency, and social costs from various perspectives.

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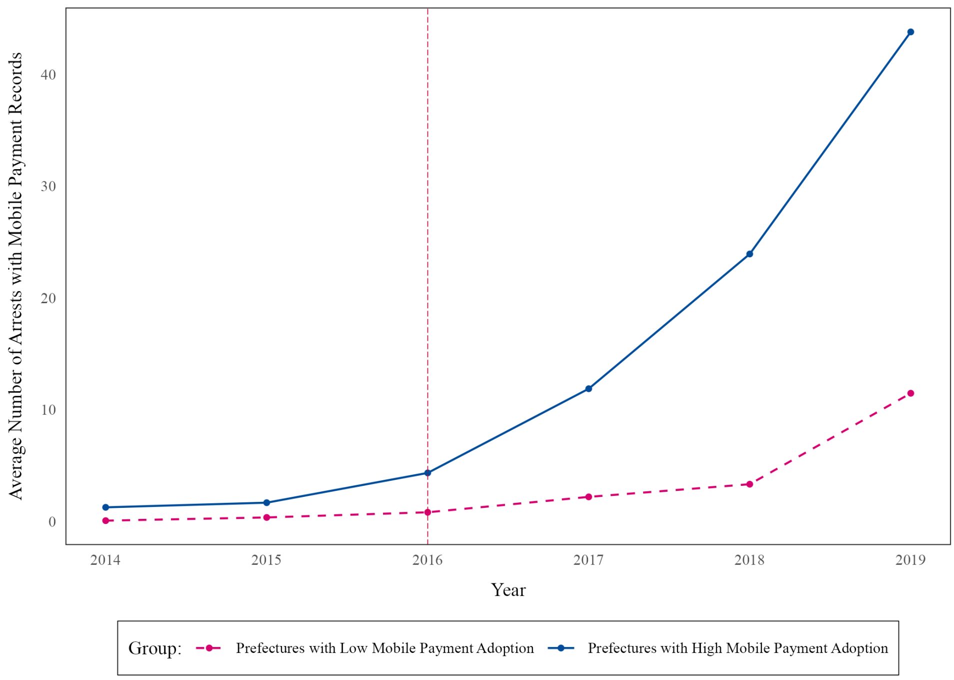
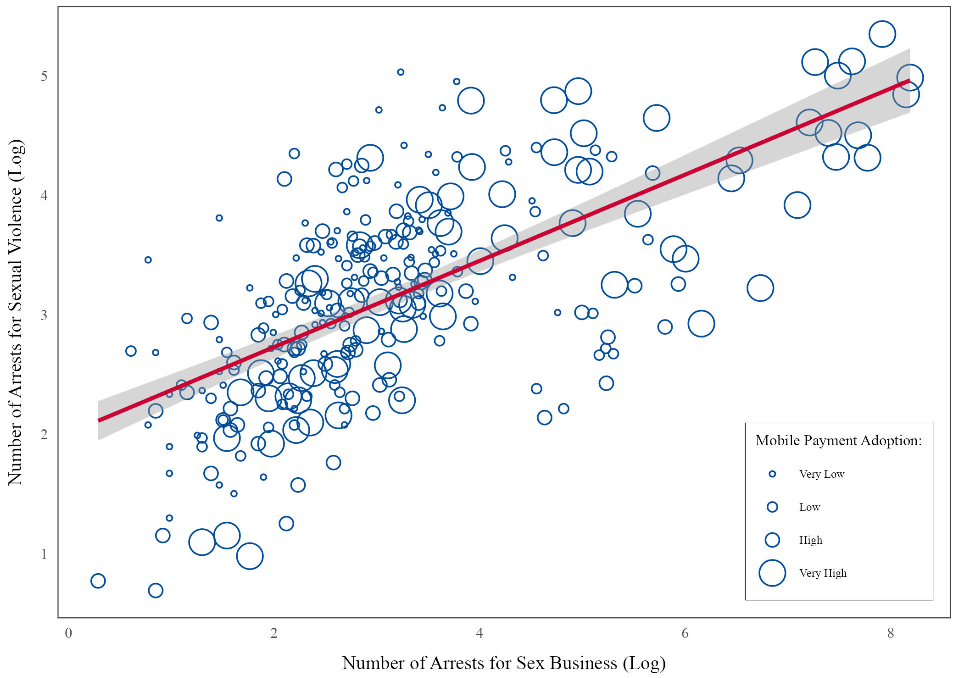


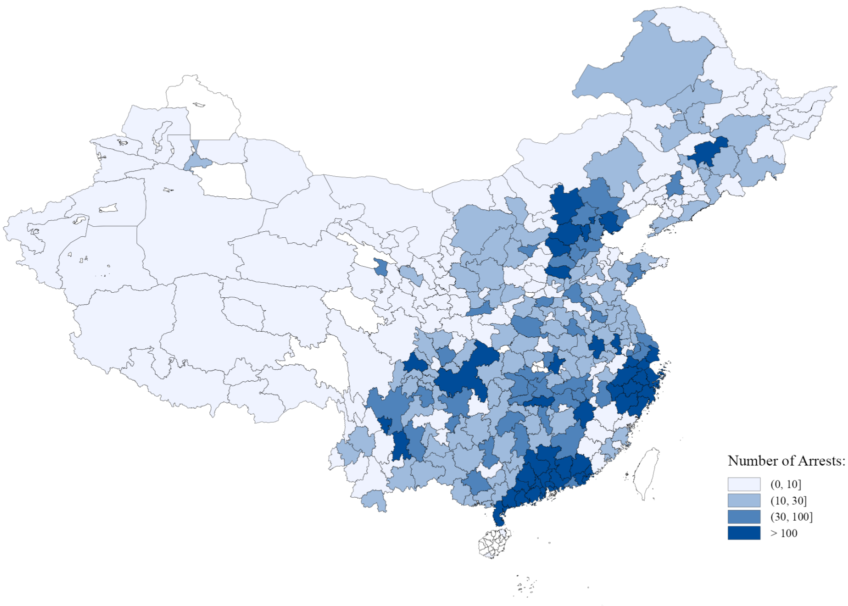
Panel A: Trends in Arrests for Sex Business with Mobile Payment Records



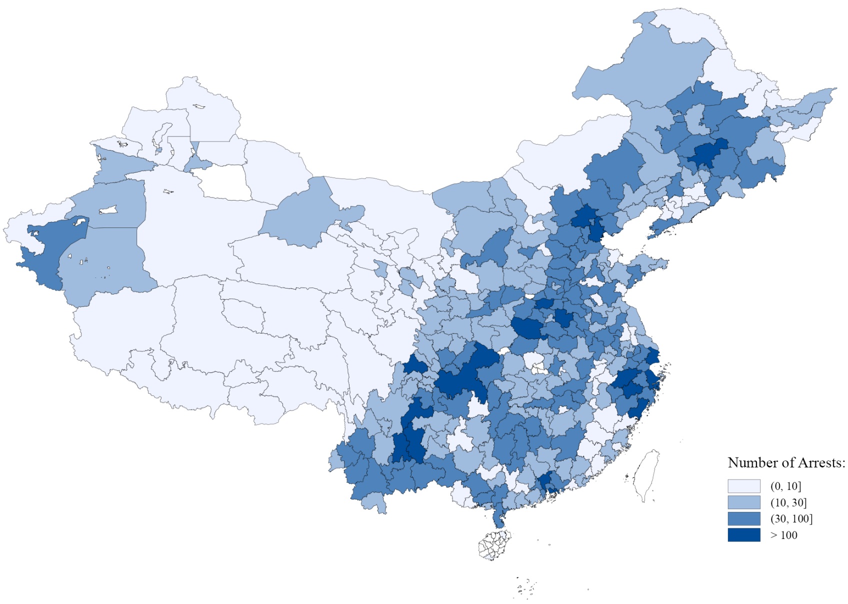
Panel B: Correlation between Arrests for Sex Business and Sexual Violence

Figure 1: Descriptive Patterns for Main Variables

Notes: The data on the sex industry and sexual violence is sourced from the police enforcement dataset, which integrates the CAP and CJO datasets. The measurements of mobile payment adoption are derived from DFIIC.



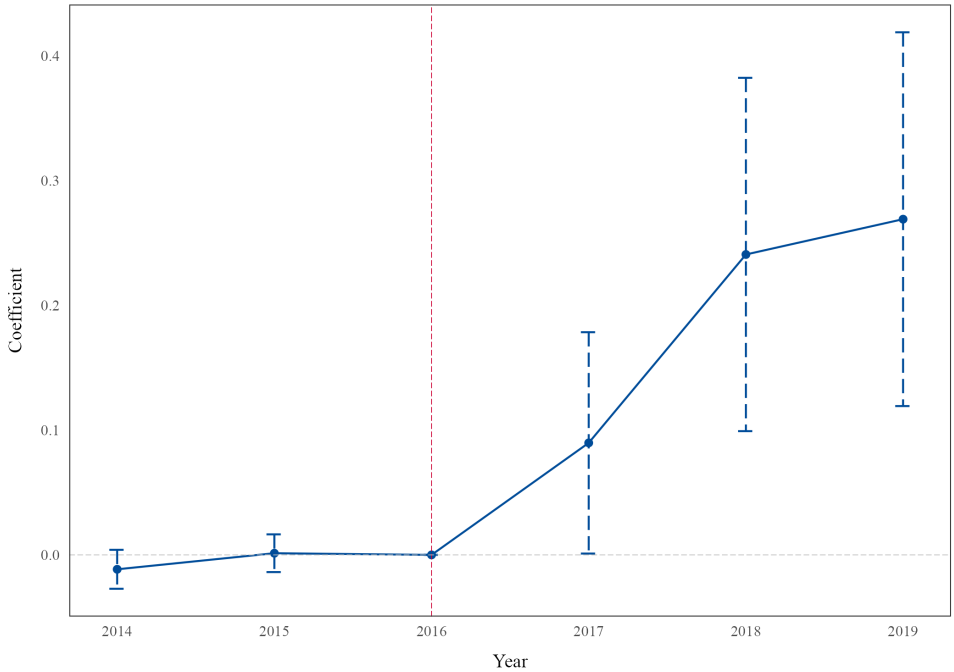
Panel A: Average Number of Arrests for Sex Business per Year



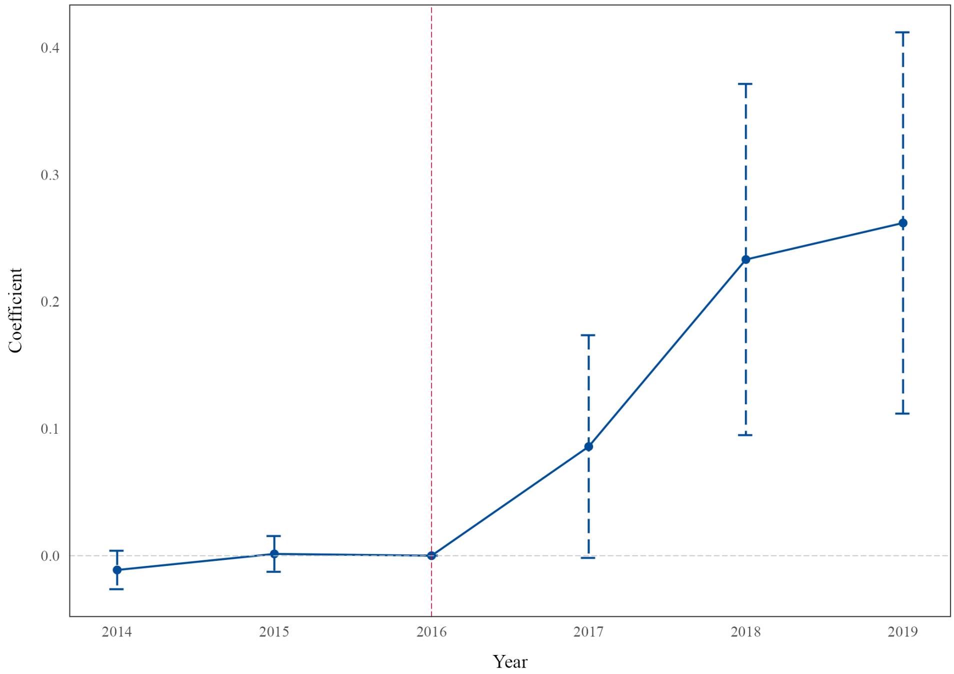
Panel B: Average Number of Arrests for Sexual Violence per Year

Figure 2: Spatial Distribution of Sex Business and Sex Violence Across Prefectures

Notes: The data on the sex industry and sexual violence is sourced from the police enforcement dataset, which integrates the CAP and CJO datasets.

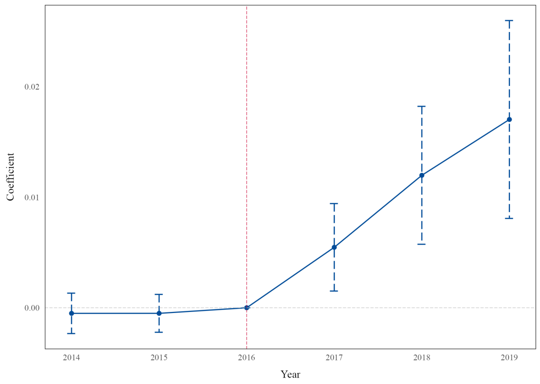


Panel A: Baseline

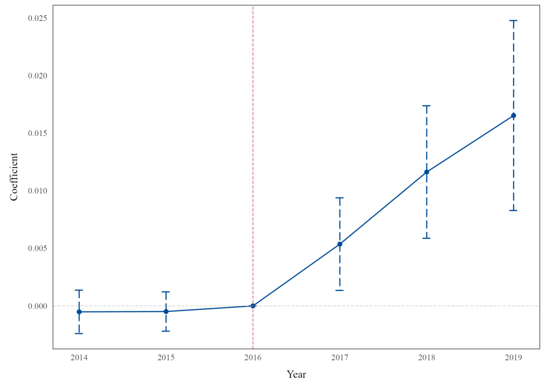


Panel B: Plus Controls

Figure 3: Event Studies for Number of Arrests for Sex Business

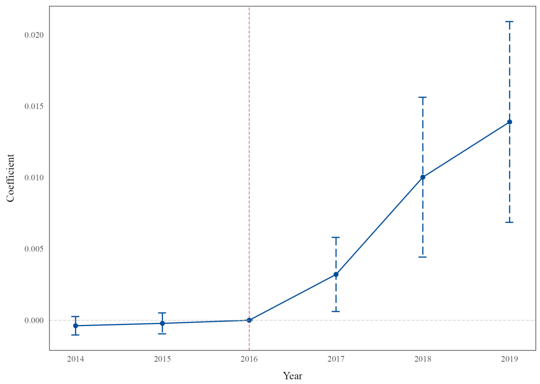


(a) Baseline

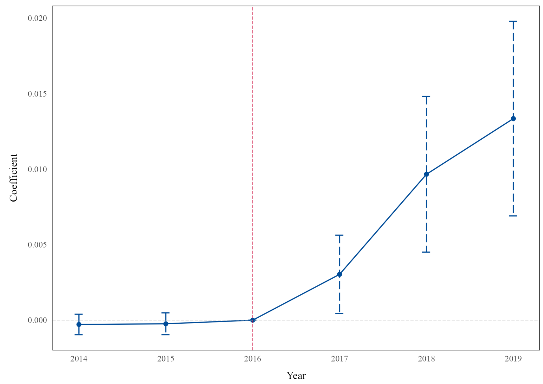


(b) Plus Controls

Panel A: Sexual Violence

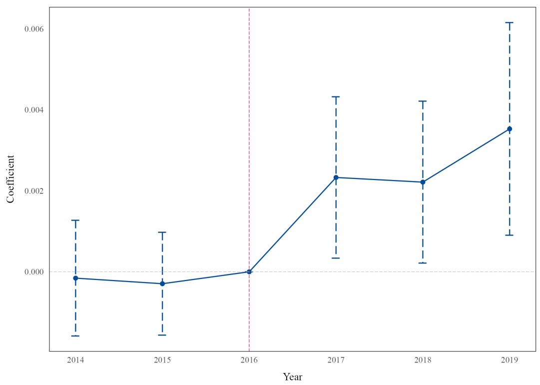


(a) Baseline

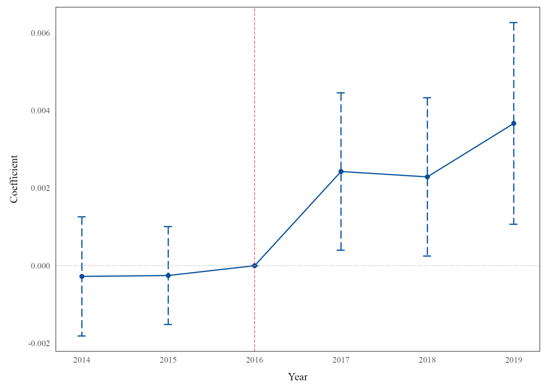


(b) Plus Controls

Panel B: Sexual Harassment



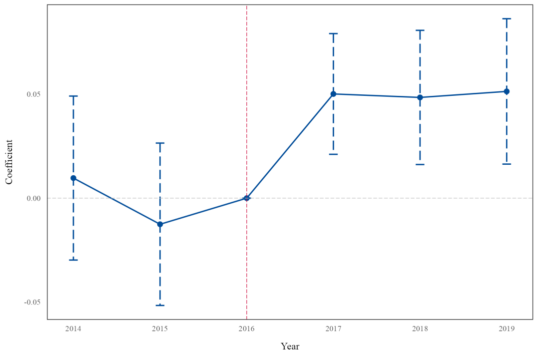
(a) Baseline



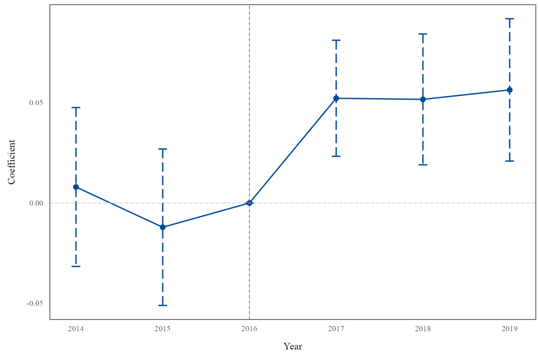
(b) Plus Controls

Panel C: Rape

Figure 4: Event Studies for Number of Arrests for Sexual Violence

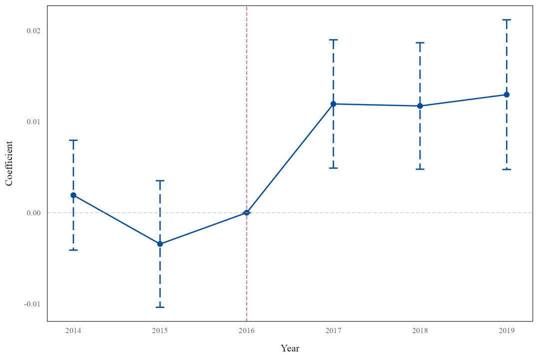


(a) Baseline

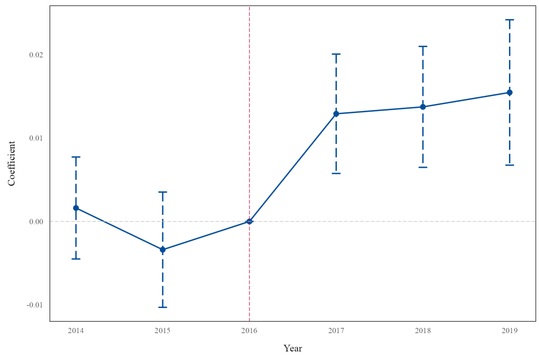


(b) Plus Controls

Panel A: Divorce due to Marital Infidelity



(a) Baseline



(b) Plus Controls

Panel B: Domestic Violence

Figure 5: Event Studies for Other Socio-economic Outcomes

Table 1: Summary Statistics

	Mean	S.D.	Obs
Panel A. Dependent Variables			
Sex business arrests per 100,000	3.22	14.56	1,710
Share of arrests with mobile payment records (%)	18.95	27.37	1,497
Share of arrests with private crime scenes (%)	21.52	22.80	1,544
Average amount of fines (CNY)	18,646	71,795	1,541
Average days of detention	534	377	1,542
Average price of sex services	433	464	1,239
Sexual violence arrests per 100,000	0.77	0.93	1,710
Sexual harassment arrests per 100,000	0.23	0.53	1,710
Rape arrests per 100,000	0.48	0.51	1,710
Divorce cases due to marital infidelity per 100,000	6.33	8.02	1,710
Domestic violence cases per 100,000	1.56	2.27	1,710
Human trafficking arrests per 100,000	0.05	0.12	1,710
Theft arrests per 100,000	13.23	13.01	1,710
Robbery arrests per 100,000	1.10	1.54	1,710
Panel B. Mobile Payment Adoption			
Total DFIIC index	172.34	18.15	1,710
Coverage breadth index	165.54	25.45	1,710
Usage depth index	145.48	21.76	1,710
Digitalization level index	243.59	13.97	1,710
Panel C. Prefecture-Level Characteristics			
Population (100,000)	43.15	25.97	1,710
GDP per capita	55,155	32,261	1,710
Fiscal revenue per capita	5,145	6,505	1,710
Fiscal expenditure per capita	10,533	8,718	1,710
Male sex ratio	1.05	0.05	1,710
Police recruitment per 100,000	5.78	8.67	1,710

Notes: This table reports summary statistics for key variables. Panel A provides the summary statistics for dependent variables. Panel B presents the summary statistics for mobile payment adoption. Panel C reports the summary statistics for prefecture-level characteristics.

Table 2: Real-Name Reform and Police Enforcement in Sex Industry

	Police Enforcement in Sex Industry				Placebo Tests	
	Number of Arrests for Sex Business Per 100,000		Share of Arrests with Mobile Payment Records (%)		Number of Arrests Theft Per 100,000	Number of Arrests Robbery Per 100,000
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption × Post	0.200***	0.191***	0.088**	0.083**	0.030	-0.005
	(0.060)	(0.060)	(0.041)	(0.042)	(0.021)	(0.003)
Observations	1,710	1,710	1,086	1,086	1,710	1,710
R-squared	0.772	0.774	0.717	0.717	0.930	0.922
Pre-Shock Mean Y	1.043	1.043	4.160	4.160	12.327	1.205
Control Vars	No	Yes	No	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of the real-name reform on police enforcement in the sex industry and placebo tests. Columns (1)-(2) focus on the effect on the number of arrests for sex business per 100,000. Columns (3)-(4) examine the effect on the share of arrests involving mobile payment records. Columns (5)-(6) report the results of placebo tests, using the number of arrests for theft or robbery per 100,000 as outcomes. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table 3: Real-Name Reform and Police Enforcement in Sex Industry: Robustness Checks

	Alternative Adoptions		Alternative Samples		Alternative Datasets	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen	Only CAP Dataset	Only CJO Dataset
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent - Number of Arrests for Sex Business Per 100,000						
Mobile Payment Adoption (Binary)	3.596**					
× Post	(1.577)					
Mobile Payment Adoption (Total)		0.252***				
× Post		(0.078)				
Mobile Payment Adoption			0.154***	0.186***	0.184***	0.007**
× Post			(0.052)	(0.066)	(0.061)	(0.004)
Observations	1,710	1,710	1,704	1,698	1,710	1,710
R-squared	0.759	0.770	0.794	0.766	0.759	0.784
Pre-Shock Mean Y	1.043	1.043	1.019	0.960	0.617	0.425

Panel B: Dependent - Share of Arrests with Mobile Payment Records (%)						
Mobile Payment Adoption (Binary)	5.009**					
× Post	(2.362)					
Mobile Payment Adoption (Total)		0.107*				
× Post		(0.064)				
Mobile Payment Adoption			0.086**	0.081*	-0.012	0.076*
× Post			(0.042)	(0.044)	(0.079)	(0.044)
Observations	1,086	1,086	1,080	1,074	186	1,062
R-squared	0.718	0.717	0.717	0.716	0.769	0.741
Pre-Shock Mean Y	4.160	4.160	4.102	4.119	1.245	4.510
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the results of the real-name reform on police enforcement in the sex industry. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Columns (5)-(6) use alternative datasets, using only CAP dataset or only CJO dataset. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table 4: Real-Name Reform and Efficiency of Police Enforcement in Sex Industry

	Share of Private Crime Scenes (%)		Amount of Fine (CNY)		Days of Detention	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption	0.169***	0.176***	88.626*	86.870*	1.618***	1.610***
× Post	(0.049)	(0.048)	(45.329)	(47.002)	(0.573)	(0.579)
Observations	1,200	1,200	1,092	1,092	1,206	1,206
R-squared	0.402	0.404	0.489	0.491	0.577	0.578
Pre-Shock Mean Y	21.519	21.519	10844	10844	550	550
Control Vars	No	Yes	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of the real-name reform on the efficiency of police enforcement in the sex industry. Columns (1)-(2) focus on the effect on the share of arrests with private crime scenes. Columns (3)-(4) examine the effect on the the amount of fines (CNY). Columns (5)-(6) explores the effect on the days of detention. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table 5: Real-Name Reform and Prices of Sex Services

	Prices of Sex Services	
	(1)	(2)
Mobile Payment Adoption	1.169*	1.268**
× Post	(0.639)	(0.634)
Observations	1,149	1,149
R-squared	0.458	0.459
Pre-Shock Mean Y	311	311
Control Vars	No	Yes
City FE	Yes	Yes
Prov-Year FE	Yes	Yes

Notes: This table reports the results of the real-name reform on the prices of sex services. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table 6: Real-Name Reform and Sexual Violence

	Number of Arrests for Sexual Violence Per 100,000					
	Total		Sexual Harassment		Rape	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption × Post	0.012***	0.011***	0.009***	0.009***	0.003***	0.003***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	1,710	1,710	1,710	1,710	1,710	1,710
R-squared	0.789	0.790	0.722	0.725	0.797	0.797
Pre-Shock Mean Y	0.344	0.344	0.076	0.076	0.252	0.252
Control Vars	No	Yes	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of real-name reform on the number of arrests for sexual violence. Columns (1)-(2) focus on the effect on the total number of arrests for sexual violence per 100,000. Columns (3)-(4) examine the effect on the number of arrests for sexual harassment per 100,000. Columns (5)-(6) reports the effect on the number of arrests for rape per 100,000. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table 7: Real-Name Reform and the Incidence of Sexually Transmitted Infections

	HIV	Gnorrhea	Syphilis
	(1)	(2)	(3)
Mobile Payment Adoption	-0.016**	-0.010	-0.111***
× Post	(0.006)	(0.033)	(0.021)
Observations	155	186	186
R-squared	0.955	0.930	0.956
Pre-Shock Mean Y	6.357	7.546	34.941
Control Vars	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table reports the results of the real-name reform on the incidence of sexually transmitted infections per 100,000. Column (1) focuses on the effect on the incidence of HIV per 100,000. Columns (2)-(3) examine the effect on the incidence of gnorrhea and syphilis per 100,000, respectively. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the province level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table 8: Real-Name Reform and Other Socio-economic Outcomes

	Number of Cases Per 100,000					
	Divorce due to Marital Infidelity		Domestic Violence		Human Trafficking	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption	0.034**	0.036**	0.012***	0.014***	0.0003	0.0004
× Post	(0.016)	(0.016)	(0.004)	(0.004)	(0.0002)	(0.0002)
Observations	1,710	1,710	1,710	1,710	1,710	1,710
R-squared	0.841	0.841	0.857	0.859	0.464	0.464
Pre-Shock Mean Y	11.486	11.486	2.768	2.768	0.0475	0.0475
Control Vars	No	Yes	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of the real-name reform on other socio-economic outcomes. Columns (1)-(2) focus on the effect on the number of cases for divorce due to marital infidelity per 100,000. Columns (3)-(4) examine the effect on the number of cases for domestic violence per 100,000. Columns (5)-(6) show the effect on the number of arrests for human trafficking per 100,000. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table 9: Heterogeneity on Male Sex Ratio and Police Recruitment

	Number of Arrests Per 100,000							
	Sex Business	Sexual Violence	Sexual Harassment	Rape	Sex Business	Sexual Violence	Sexual Harassment	Rape
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile Payment Adoption	0.271***	0.013***	0.010***	0.003				
× Post × Male Sex Ratio	(0.088)	(0.004)	(0.003)	(0.002)				
Mobile Payment Adoption					0.373***	0.011**	0.012***	-0.000
× Post × Police Recruitment					(0.104)	(0.005)	(0.004)	(0.002)
Observations	1,710	1,710	1,710	1,710	1,710	1,710	1,710	1,710
R-squared	0.790	0.799	0.741	0.799	0.793	0.794	0.740	0.798
Pre-Shock Mean Y	1.043	0.344	0.076	0.252	1.043	0.344	0.076	0.252
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of heterogeneity on male sex ratio and police recruitment. Columns (1)-(4) provides results for heterogeneity on male sex ratio. Columns (5)-(8) presents results for heterogeneity on police recruitment. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

A Data Appendix

A.1 China Administrative Penalty Database

Under China's Administrative Penalty Law, an administrative penalty is defined as an action by which an administrative authority imposes a sanction — either by restricting rights or imposing additional obligations — on individuals, legal entities, or organizations that have violated administrative regulations, in accordance with the law. The China Administrative Penalty (CAP) Database, compiled by www.pkulaw.com, encompasses over 30 million records of administrative penalties issued by central and local governments across China from 2000 to 2022. In this appendix, we provide a comprehensive summary of the database, along with basic descriptive statistics. Figure A.1 presents screenshots illustrating the database structure.

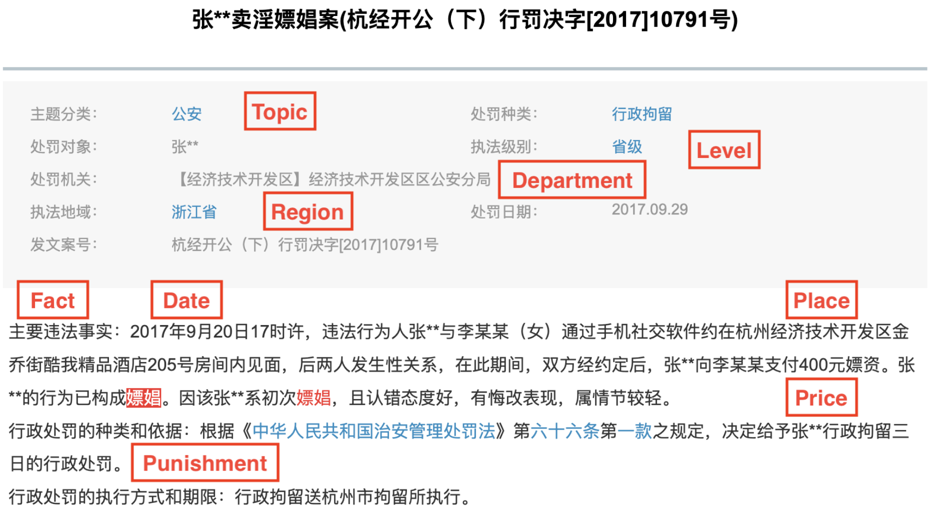
First, the number of administrative penalty records has surged since 2014, peaking in 2019 before declining. As illustrated in Panel A of Figure A.2, the initial years of the database show only a few thousand records per year. However, after 2014, this figure rose sharply, reaching a peak of 5.5 million in 2019, before declining to 3.5 million by 2022. Two primary factors explain this rising and then declining trend. First, state capacity expanded alongside China's economic growth, with the government investing significantly in enacting laws, regulations, and enhancing enforcement authorities. The uneven spatial distribution shown in Panel B of Figure A.2 also reflects the influence of economic growth and state capacity: the number of records in eastern regions is markedly higher than in western regions, a pattern consistent with regional economic disparities. Second, government agencies were mandated to publicize administrative penalty records following transparency policies introduced prior to 2014. However, this shift towards transparency began to reverse after 2020, likely influenced by the COVID-19 pandemic and a general decrease in transparency measures.

Second, local governments account for a higher proportion of administrative penalties, with significant variations across administrative levels. As shown in Panel A of Figure A.3, the total number of administrative penalty records rises substantially at lower administrative levels, largely due to the greater number of administrative units at these levels. For instance, county-level governments issued nearly 20 million records, comprising 69% of the total. However, as shown in Panel B of Figure A.3, provincial-level records are, on average, the highest, followed by those at the prefectural and central levels, with county-level records being the lowest per unit. Between 2000 and 2022, each provincial government issued approximately 36,000 administrative penalties, while each prefectural government issued about 23,000. Provincial and prefectural governments are particularly active in exercising administrative penalty authority, reflecting their extensive regulatory responsibilities and reach within local governance structures.

Third, a diverse array of government departments holds the authority to impose administrative penalties across various sectors. In total, 93 different types of government agencies issue administrative penalty records. Panel A of Figure A.4 highlights the top 20 departments with the highest number of penalty records, while Panel B categorizes these records by subject area. The data show that public security-related penalties, primarily issued by the police, are by far the most prevalent, totaling over 13 million records and comprising 45.6% of all penalties. Following public security, market regulation and transportation represent the next largest categories, accounting for 19% and 12% of penalty records, respectively. Departments overseeing fiscal and taxation matters, as well as land and urban development, also represent significant shares, making up 7% and 6% of the total penalties, respectively.

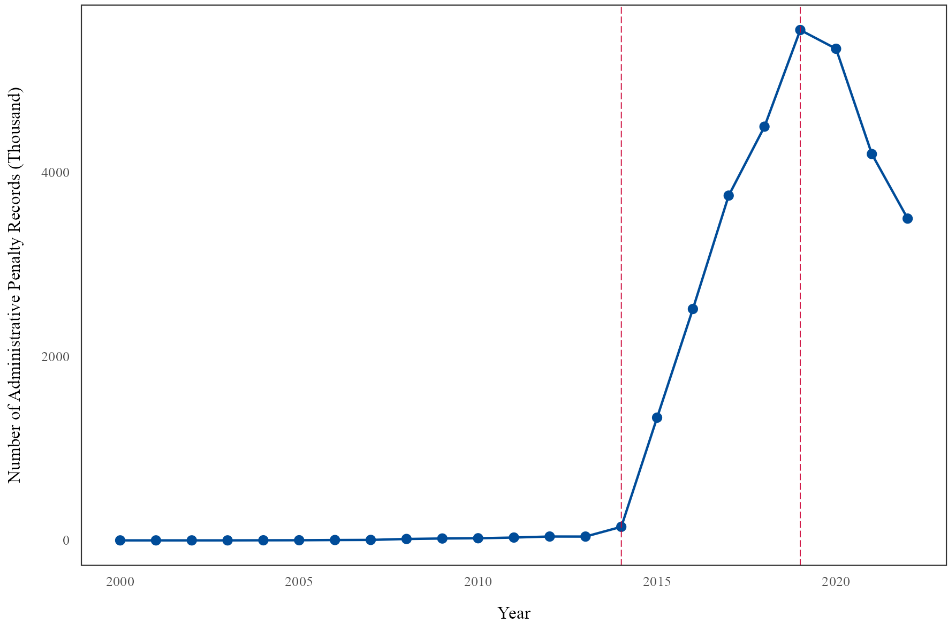
Finally, various types of punishments serve different roles in addressing violations by different subjects. As shown in Panel A of Figure A.5, fines and confiscations are the most frequently imposed penalties, comprising over 20 million records and accounting for 57% of all cases. This is followed by suspensions of licenses or production, and detention, which represent 16% and 7% of penalties, respectively. It is important to note that authorities may apply multiple types of penalties simultaneously to address specific violations comprehensively. Panel B of Figure A.5 indicates a nearly balanced distribution of administrative penalties imposed on individuals versus legal entities.

Panel A: An Screenshot of the Website

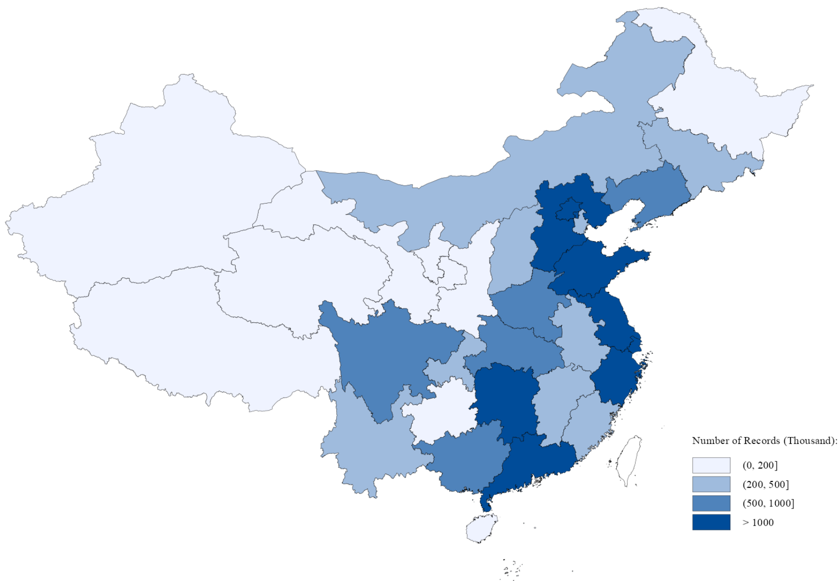


Panel B: An Example of Sex Business

Figure A.1: Screenshots of the China Administrative Penalty Database

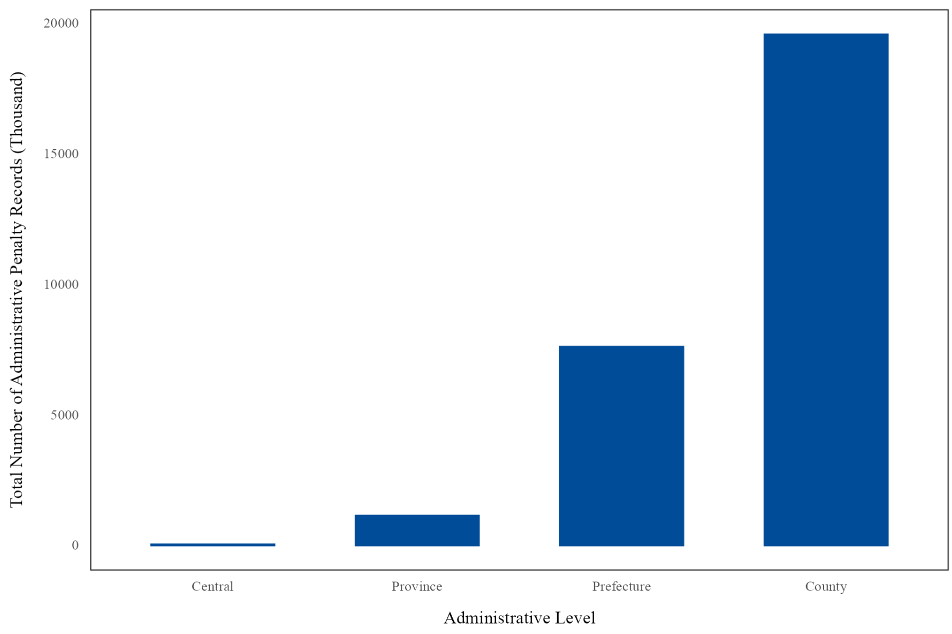


Panel A: Temporal Distribution from 2000 to 2022

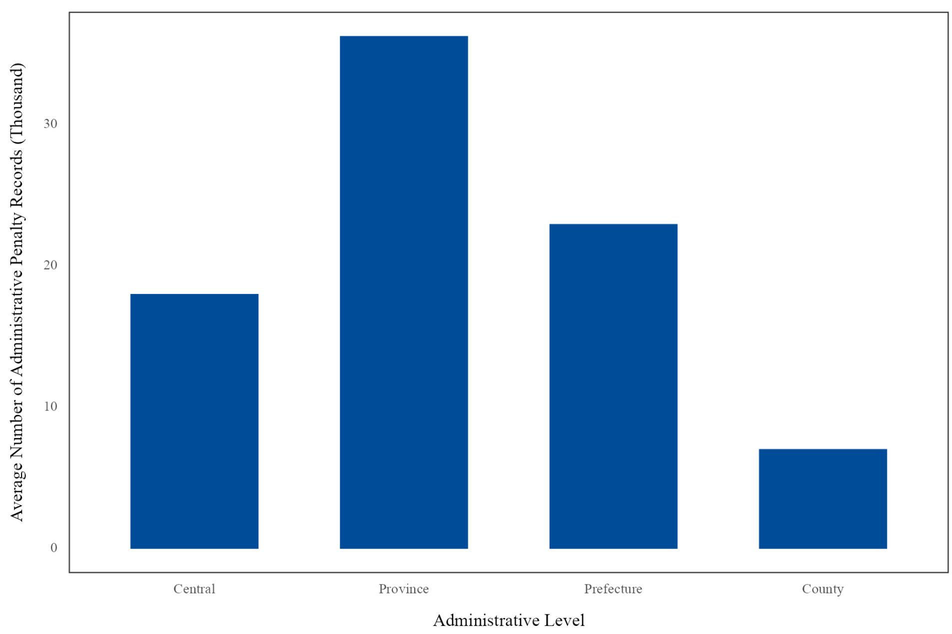


Panel B: Spatial Distribution Across Provinces, Summed from 2000 to 2022

Figure A.2: Temporal and Spatial Distribution of Administrative Penalty Records

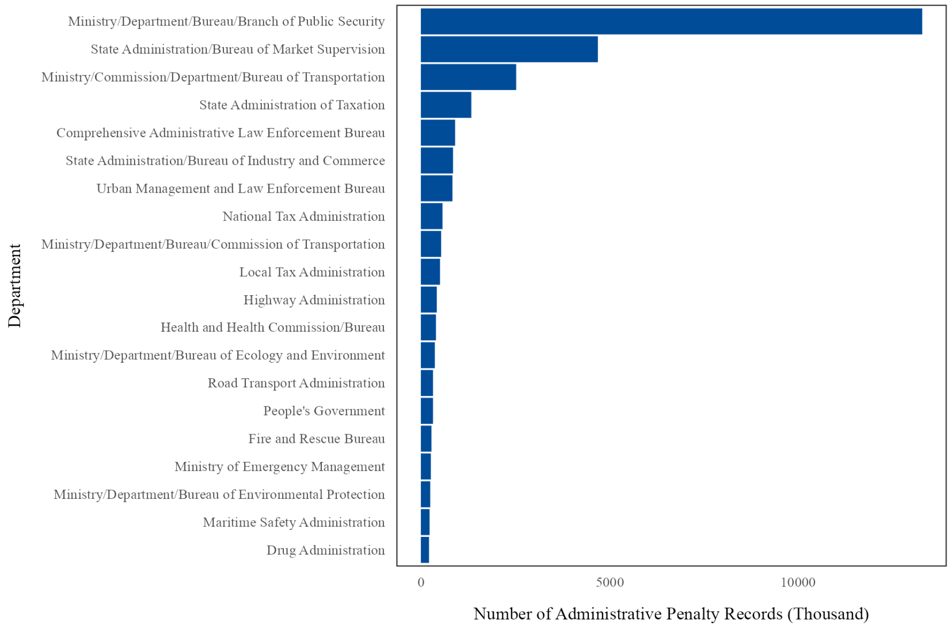


Panel A: Total Number Across Regions in Each Administrative Level

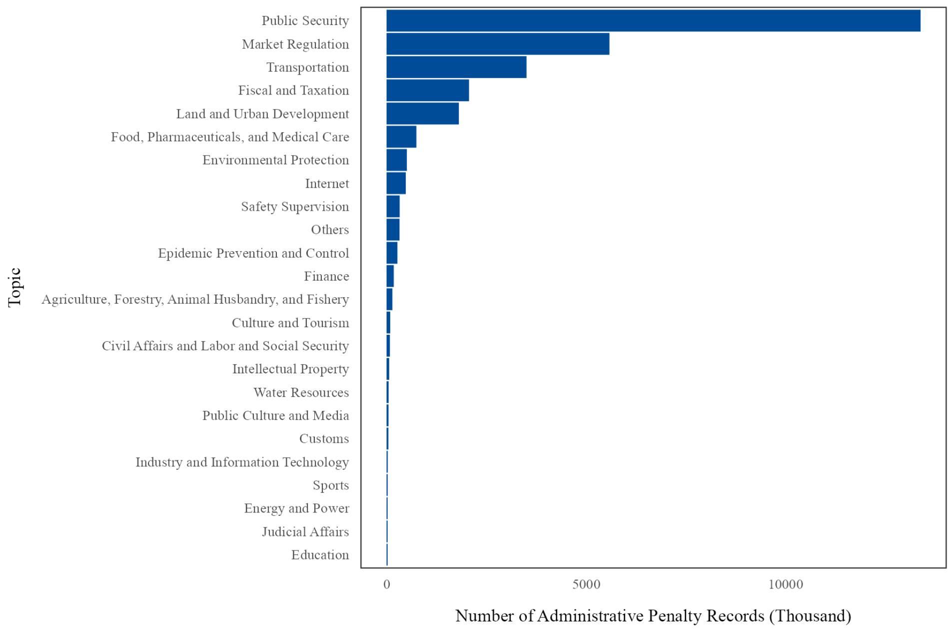


Panel B: Average Number Across Regions in Each Administrative Level

Figure A.3: Number of Administrative Penalty Records by Administrative Level, Summed from 2000 to 2022

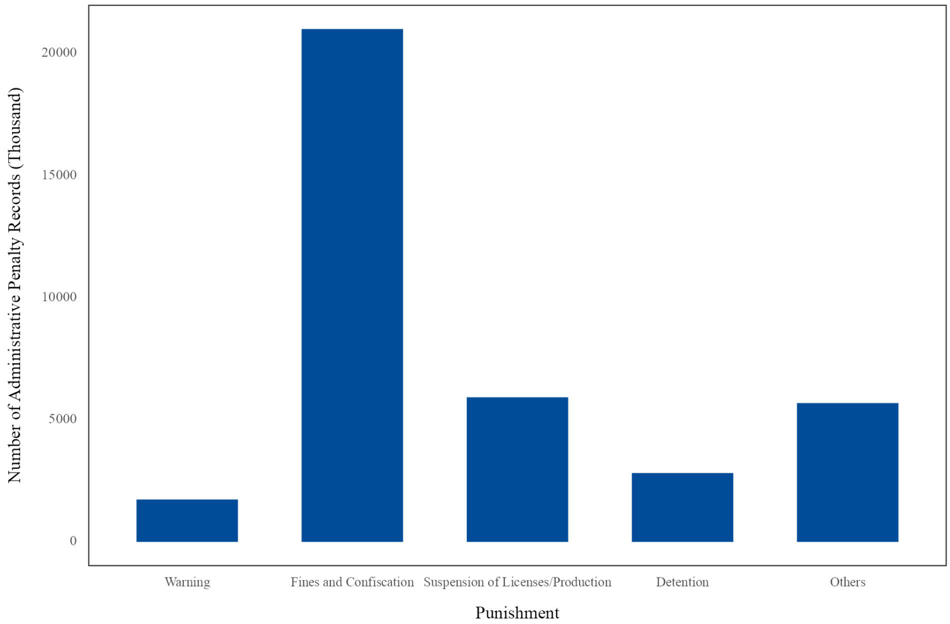


Panel A: Number of Administrative Penalty Records by Department (Top 20)

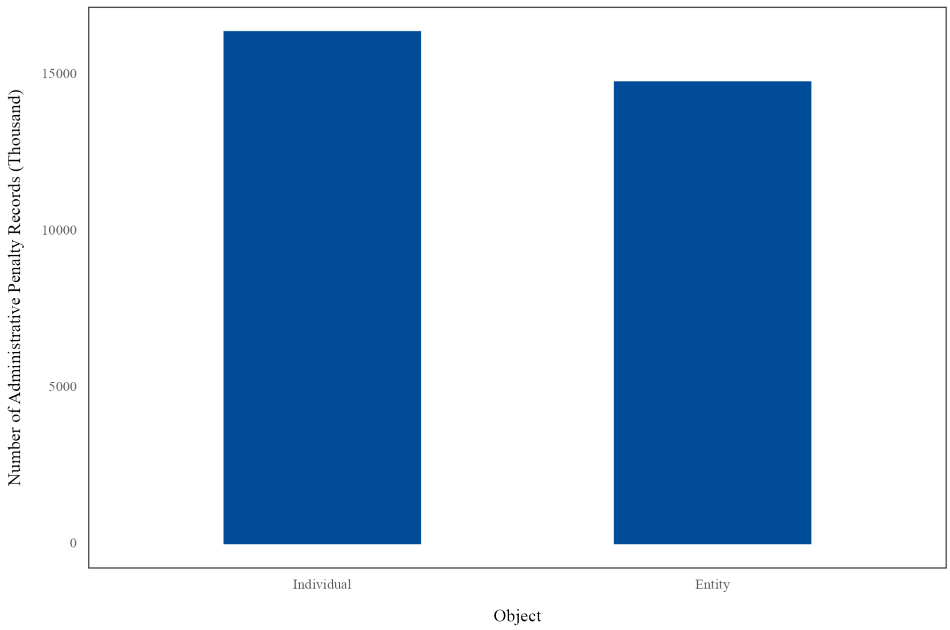


Panel B: Number of Administrative Penalty Records by Topic

Figure A.4: Number of Administrative Penalty Records by Department and Topic, Summed from 2000 to 2022



Panel A: Number of Administrative Penalty Records by Punishment



Panel B: Number of Administrative Penalty Records by Object

Figure A.5: Number of Administrative Penalty Records by Punishment and Object, Summed from 2000 to 2022

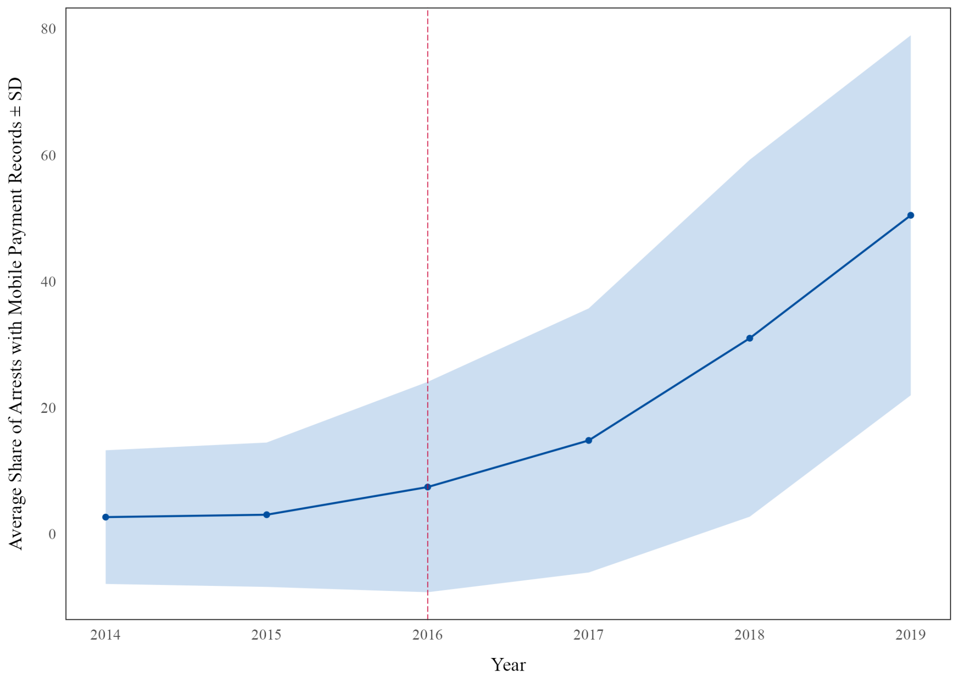
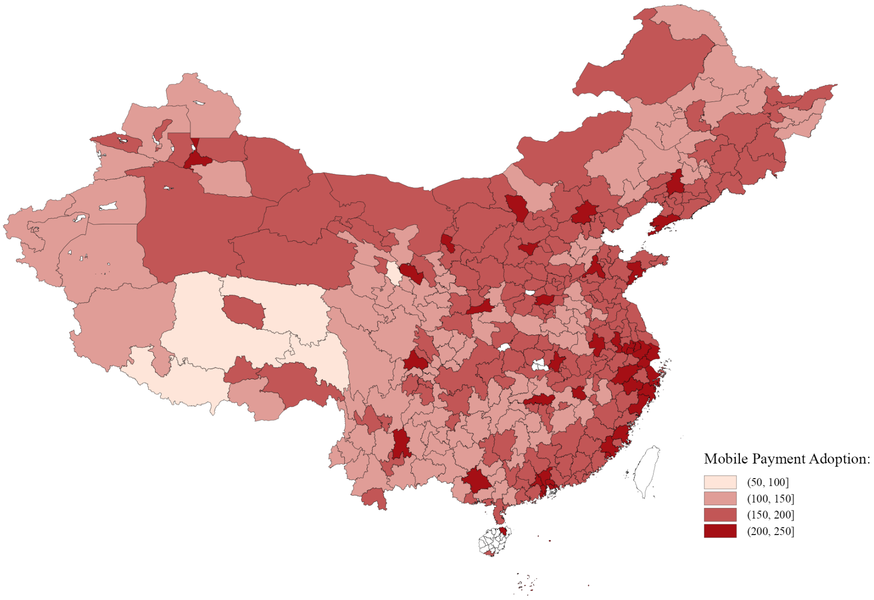
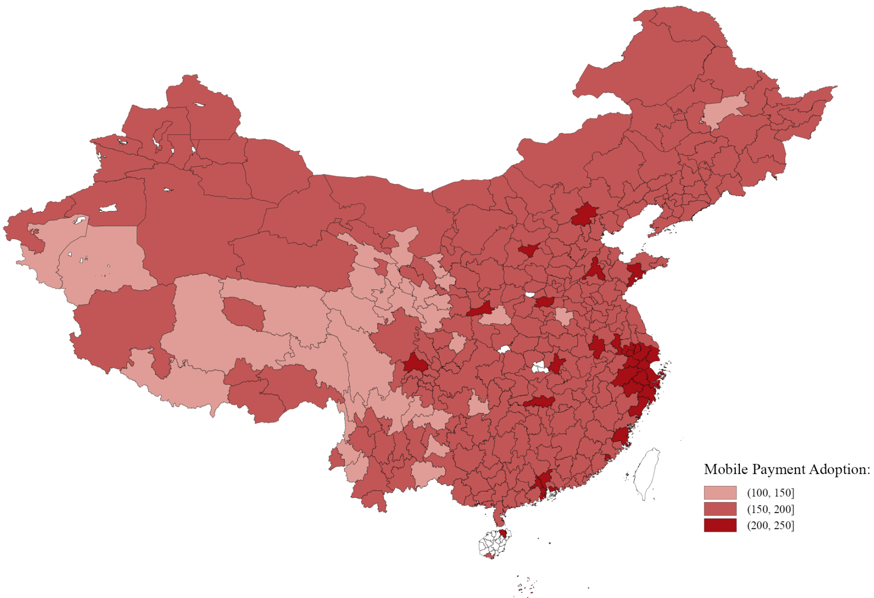


Figure A.6: Trend of Share of Arrests with Mobile Payment Records



Panel A: Main Measurement - Digital Financial Index (Breadth)



Panel B: Alternative Measurement - Digital Financial Index

Figure A.7: Spatial Distribution of Mobile Payment Adoption Across Prefectures

Table A.1: Arrest-level Summary Statistics

	All Data	
	Number	Mean
Panel A. Police Enforcement in Sex Industry		
Arrests for Sex Business	238012	1.000
Arrested Sex Workers	85431	0.359
Arrested Organizers	71375	0.300
Arrested Clients	81206	0.341
Arrests with Online/Offline Records	71557	1.000
Arrests with Mobile Payment Records	16444	0.230
Arrests Apprehended at the Crime Scene	55113	0.770
Arrests with Private/Public Records	142400	1.000
Arrests with Private Crime Scene	47816	0.336
Arrests with Public Crime Scene	94584	0.664
Types and Severity of Punishment	238012	1.000
Warning	542	0.002
Fine	77618	0.326
Confiscation of Illegal Gains	46274	0.194
Detention	202275	0.850
Amount of Fine (CNY)	214730	4799
Amount of Confiscation (CNY)	214730	1731
Days of Detention	214730	111
Prices of Sex Services (CNY)	72451	362
Panel B. Police Enforcement for Other Illegal Activities		
Arrests for Sexual Violence	58276	1.000
Arrests for Sexual Harassment	19275	0.331
Arrests for Rape	39001	0.669
Arrests for Theft	1115679	1.000
Arrests for Robbery	88445	1.000

Notes: This table reports arrest-level summary statistics. Panel A provides the summary statistics for police enforcement in sex industry. Panel B presents the summary statistics of police enforcement for other illegal activities.

Table A.2: Digital Inclusive Finance Indicator System

Primary Dimension	Secondary Dimension	Specific Indicator
Coverage Breadth	Account Coverage Rate	Number of Alipay accounts per 10,000 people
		Proportion of Alipay accounts with linked bank cards
		Average number of bank cards linked to each Alipay account
Usage Depth	Payment Services	Average number of payments per user
		Average payment amount per user
		Proportion of highly active users (50 or more transactions per year) among users active at least once a year
	Money Market Fund Services	Average number of Yu'e Bao purchases per user
		Average amount of Yu'e Bao purchases per user
		Number of Yu'e Bao purchasers per 10,000 Alipay users
	Credit Services	Number of Alipay users with internet consumer loans per 10,000 users
		Average number of loans per user
		Average loan amount per user
		Number of Alipay users with internet microenterprise loans per 10,000 users
		Average number of loans for microentrepreneurs
		Average loan amount for microentrepreneurs
	Insurance Services	Number of insured Alipay users per 10,000 users
		Average number of insurance policies per user
		Average insurance amount per user

	Investment Services	Number of Alipay users participating in internet investment and wealth management per 10,000 users Average number of investments per user Average investment amount per user
	Credit Services	Average credit inquiries per natural person Number of Alipay users utilizing credit-based services (including finance, accommodation, travel, social, etc.) per 10,000 users
Digitalization Level	Mobile Payment	Proportion of mobile payments in total transactions Proportion of mobile payment amount in total transaction volume
	Affordability	Average loan interest rate for microentrepreneurs Average loan interest rate for individuals
	Credit-based Payment	Proportion of Huabei payments in total transactions Proportion of Huabei payment amount in total transaction volume Proportion of transactions exempt from deposit via Sesame Credit (compared to cases requiring a deposit) Proportion of exempted payment amount via Sesame Credit (compared to cases requiring a deposit)
	Convenience	Proportion of QR code payments in total transactions Proportion of QR code payment amount in total transaction volume

Notes: This table lists the components of DFIIC index.

Table A.3: Summary Statistics for Provincial Level Variables

	Mean	S.D.	Obs
Incidence of STIs Per 100,000			
AIDS	3.87	3.84	186
HIV	6.86	6.03	155
Gnorrhea	8.15	7.28	186
Syphilis	37.36	18.37	186

Notes: This table reports summary statistics for provincial-level public health variables.

B Additional Results

In this Appendix, we provide additional results, including complementary results and robustness checks for the results in the context. These checks are classified into three types: alternative measurements of mobile payment adoption, alternative samples, and alternative datasets. The first set of robustness checks includes (i) using binary treatment as a proxy for mobile payment adoption and (ii) using total DFIIC intensity as a measure of mobile payment adoption. The second type includes (i) excluding Dongguan City to account for the effect of the "Sin-City" of China and (ii) excluding Hangzhou City and Shenzhen City, the headquarters of Alipay and Wechat Pay, respectively. The third set includes (i) using only the CAP dataset and (ii) using only the CJO dataset.

We briefly summarize these additional results in this Appendix as follows. Table B.1 lists legislative clauses related to sex industry in China. Table B.2 reports the results of the real-name reform on police enforcement for different participants in sex industry. Table B.3 provides the robustness checks for the effect on the share of private crime scene. Table B.4-Table B.5 present the robustness checks for the effect on the amount of fine and days of detention, respectively. Table B.6 reports the results of the real-name reform on different types of punishments for sex business. Table B.7 shows the robustness checks for the effect on the prices of sex services. Table B.8-Table B.10 show the robustness checks for the effect on the number of arrests for sexual violence, sexual harassment, and rape, respectively. Table B.11 reports the results of the real-name reform on sexual violence involving sex workers and other women. Table B.12 provides the robustness checks for the effect on the number of cases for divorce due to marital infidelity. Table B.13 presents the robustness checks for the effect on the number of cases for domestic violence. Table B.14 reports the additional heterogeneous results on male sex ratio and police recruitment.

Table B.1: Clauses Related to Sex Industry

No.	Article
	Panel A. Criminal Law
358	Whoever organizes or forces anyone else into prostitution shall be sentenced to imprisonment of not less than five years but not more than ten years in addition to a fine; or be sentenced to imprisonment of not less than ten years or life imprisonment in addition to a fine or forfeiture of property if the circumstances are serious. Whoever organizes or forces any juvenile into prostitution shall be given a heavier penalty in accordance with the provisions of the preceding paragraph. Whoever commits the crime in the preceding two paragraphs and also commits murder, injuring, rape, kidnapping or any other crime shall be punished according to the provisions on the joinder of penalties for plural crimes. Whoever recruits or transports persons for an organizer of prostitution or otherwise assists in organizing prostitution shall be sentenced to imprisonment of not more than five years in addition to a fine; or if the circumstances are serious, be sentenced to imprisonment of not less than five years but not more than ten years in addition to a fine.
359	Those harboring prostitution or seducing or introducing others into prostitution are to be sentenced to five years or fewer in prison or put under limited incarceration or probation, in addition to paying a fine. If the case is serious, they are to be sentenced to five years or more in prison in addition to a fine. Those seducing young girls under 14 years of age into prostitution are to be sentenced to five years or more in prison in addition to a fine.
360	Those engaging in prostitution or visiting a whorehouse knowing that they are suffering from syphilis, clap, or other serious venereal diseases are to be sentenced to five years or fewer in prison or put under limited incarceration or probation, in addition to having to pay a fine.
361	Personnel of hotels, restaurants, entertainment industry, taxi companies, and other entities who take advantage of their entities' position to organize, force, seduce, harbor, or introduce others to prostitution are to be convicted and punished according to articles 358 and 359 of this law. Main persons in charge of the aforementioned entities who commit crimes stipulated in the above paragraph are to be severely punished.

362	Personnel of hotels, restaurants, entertainment industry, taxi companies, or other entities who inform law offenders and criminals while public security personnel are checking prostitution and whorehouse visiting activities, if the case is serious, are to be convicted and punished according to Article 310 of this law.
	Panel B. Public Security Administration Punishments Law
66	Anyone who whores or goes whoring shall be detained for not less than 10 days but not more than 15 days, and may be concurrently fined not more than 5,000 yuan. If the circumstances are relatively lenient, he (she) shall be detained for not more than 5 days or shall be fined not more than 500 yuan. Anyone who finds customers for any prostitute at a public place shall be detained for not more than 5 days or shall be fined not less than 500 yuan.
67	Anyone who induces, shelters, introduces any other person to prostitute shall be detained for not less than 10 days but not more than 15 days, and may be concurrently fined 5,000 yuan. If the circumstances are relatively lenient, he (she) shall be detained for not more than 5 days or shall be fined not 500 yuan.

Notes: This table lists the clauses related to sex industry in the Criminal Law and Public Security Administration Punishments Law.

Table B.2: Real-Name Reform and Police Enforcement for Different Participants in Sex Industry

	Number of Arrests for Sex Business Per 100,000					
	Sex Organizer		Sex Worker		Sex Buyer	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption	0.057***	0.057***	0.068***	0.064***	0.076***	0.071***
× Post	(0.018)	(0.019)	(0.025)	(0.024)	(0.023)	(0.022)
Observations	1,710	1,710	1,710	1,710	1,710	1,710
R-squared	0.726	0.726	0.734	0.735	0.767	0.769
Pre-Shock Mean Y	0.520	0.520	0.243	0.243	0.279	0.279
Control Vars	No	Yes	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of real-name reform on the number of arrests for different types of sex business. Columns (1)-(2) focus on the effect on the number of arrests for pimp per 100,000. Columns (3)-(4) examine the effect on the number of arrests for prostitute per 100,000. Columns (5)-(6) reports the effect on the number of arrests for client per 100,000. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.3: Robustness Checks for the Effect on the Share of Arrests with Private Crime Scenes

	Alternative Adoptions		Alternative Samples		Alternative Datasets	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen	Only CAP Dataset	Only CJO Dataset
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption (Binary)	4.937**					
× Post	(2.329)					
Mobile Payment Adoption (Total)		0.255***				
× Post		(0.067)				
Mobile Payment Adoption			0.172***	0.196***	-0.122	0.130***
× Post			(0.049)	(0.045)	(0.159)	(0.042)
Observations	1,200	1,200	1,194	1,188	275	1,176
R-squared	0.399	0.404	0.401	0.406	0.717	0.357
Pre-Shock Mean Y	21.519	21.519	21.502	21.490	36.203	19.497
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the effect on the share of arrests with private crime scenes. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Columns (5)-(6) use alternative datasets, using only CAP dataset or only CJO dataset. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.4: Robustness Checks for the Effect on the Amount of Fine

	Alternative Adoptions		Alternative Samples		Alternative Datasets	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen	Only CAP Dataset	Only CJO Dataset
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption (Binary) × Post	2,837.092					
	(2,061.592)					
Mobile Payment Adoption (Total) × Post		123.732*				
		(68.136)				
Mobile Payment Adoption × Post			93.519**	81.617	-43.223	72.254
			(47.143)	(49.846)	(35.150)	(48.943)
Observations	1,206	1,206	1,200	1,194	277	1,182
R-squared	0.578	0.578	0.576	0.573	0.639	0.369
Pre-Shock Mean Y	549.529	549.529	549.969	551.967	9.689	702.361
Observations	1,092	1,092	1,086	1,080	262	1,080
R-squared	0.489	0.491	0.492	0.490	0.651	0.494
Pre-Shock Mean Y	10843.948	10843.948	10789.288	10915.356	3918.873	11860.875

Notes: This table reports the robustness checks for the effect on the amount of fine. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Columns (5)-(6) use alternative datasets, using only CAP dataset or only CJO dataset. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.5: Robustness Checks for the Effect on the Days of Detention

	Alternative Adoptions		Alternative Samples		Alternative Datasets	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen	Only CAP Dataset	Only CJO Dataset
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption (Binary)	84.687**					
× Post	(38.692)					
Mobile Payment Adoption (Total)		2.322**				
× Post		(0.923)				
Mobile Payment Adoption			1.648***	1.611***	0.008	1.610*
× Post			(0.584)	(0.610)	(0.013)	(0.946)
Observations	1,206	1,206	1,200	1,194	277	1,182
R-squared	0.578	0.578	0.576	0.573	0.639	0.369
Pre-Shock Mean Y	549.529	549.529	549.969	551.967	9.689	702.361
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the effect on the days of detention. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Columns (5)-(6) use alternative datasets, using only CAP dataset or only CJO dataset. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.6: Real-Name Reform and Different Types of Punishments for Sex Business

	Share of Fines (%)		Share of Expropriation (%)		Share of Detention (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption	-0.052*	-0.050*	0.035	0.034	0.023	0.020
× Post	(0.030)	(0.029)	(0.053)	(0.054)	(0.022)	(0.022)
Observations	1,206	1,206	1,206	1,206	1,206	1,206
R-squared	0.869	0.870	0.586	0.586	0.651	0.653
Pre-Shock Mean Y	92.688	92.688	24.854	24.854	97.144	97.144
Control Vars	No	Yes	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of real-name reform on the share of different types of punishments for sex business. Columns (1)-(2) focus on the effect on the share of fines. Columns (3)-(4) examine the effect on the share of expropriation. Columns (5)-(6) reports the effect on the share of detention. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.7: Robustness Checks for the Effect on the Prices of Sex Services

	Alternative Adoptions		Alternative Samples		Alternative Datasets	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen	Only CAP Dataset	Only CJO Dataset
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption (Binary)	12.161					
× Post	(33.280)					
Mobile Payment Adoption (Total)		1.834**				
× Post		(0.926)				
Mobile Payment Adoption			1.313**	1.292*	-0.941	1.596**
× Post			(0.638)	(0.670)	(1.217)	(0.640)
Observations	1,149	1,149	1,143	1,137	131	1,127
R-squared	0.457	0.459	0.457	0.457	0.648	0.452
Pre-Shock Mean Y	310.830	310.830	309.219	308.912	225.302	318.991
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the effect on the prices of sex services. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Columns (5)-(6) use alternative datasets, using only CAP dataset or only CJO dataset. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.8: Robustness Checks for the Effect on the Number of Arrests for Sexual Violence

	Alternative Adoptions		Alternative Samples		Alternative Datasets	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen	Only CAP Dataset	Only CJO Dataset
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption (Binary)	0.176**					
× Post	(0.084)					
Mobile Payment Adoption (Total)		0.014***				
× Post		(0.004)				
Mobile Payment Adoption			0.010***	0.010***	0.006***	0.005***
× Post			(0.002)	(0.003)	(0.002)	(0.001)
Observations	1,710	1,710	1,704	1,698	1,710	1,710
R-squared	0.778	0.787	0.796	0.799	0.686	0.823
Pre-Shock Mean Y	0.344	0.344	0.344	0.341	0.018	0.326
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the effect on the number of arrests for sexual violence. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Columns (5)-(6) use alternative datasets, using only CAP dataset or only CJO dataset. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.9: Robustness Checks for the Effect on the Number of Arrests for Sexual Harassment

	Alternative Adoptions		Alternative Samples		Alternative Datasets	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen	Only CAP Dataset	Only CJO Dataset
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption (Binary)	0.164***					
× Post	(0.051)					
Mobile Payment Adoption (Total)		0.011***				
× Post		(0.003)				
Mobile Payment Adoption			0.008***	0.007***	0.006***	0.003***
× Post			(0.002)	(0.002)	(0.002)	(0.000)
Observations	1,710	1,710	1,704	1,698	1,710	1,710
R-squared	0.703	0.720	0.726	0.732	0.684	0.734
Pre-Shock Mean Y	0.076	0.076	0.075	0.073	0.015	0.060
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the effect on the number of arrests for sexual harassment. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Columns (5)-(6) use alternative datasets, using only CAP dataset or only CJO dataset. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.10: Robustness Checks for the Effect on the Number of Arrests for Rape

	Alternative Adoptions		Alternative Samples		Alternative Datasets	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen	Only CAP Dataset	Only CJO Dataset
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption (Binary)	0.034					
× Post	(0.044)					
Mobile Payment Adoption (Total)		0.003**				
× Post		(0.001)				
Mobile Payment Adoption			0.002**	0.003**	0.000**	0.003**
× Post			(0.001)	(0.001)	(0.000)	(0.001)
Observations	1,710	1,710	1,704	1,698	1,710	1,710
R-squared	0.795	0.797	0.799	0.798	0.535	0.797
Pre-Shock Mean Y	0.252	0.252	0.252	0.251	0.003	0.249
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the effect on the number of arrests for rape. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Columns (5)-(6) use alternative datasets, using only CAP dataset or only CJO dataset. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.11: Real-Name Reform and Sexual Violence Involving Sex Workers and Other Women

	Number of Arrests for Sexual Violence Per 100,000			
	Sex Workers		Other Women	
	(1)	(2)	(3)	(4)
Mobile Payment Adoption	0.0001	0.0001	0.0114***	0.0109***
× Post	(0.0000)	(0.0000)	(0.0029)	(0.0026)
Observations	1,710	1,710	1,710	1,710
R-squared	0.3696	0.3710	0.7903	0.7913
Pre-Shock Mean Y	0.003	0.003	0.332	0.332
Control Vars	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of real-name reform on the number of arrests for sexual violence involving sex workers and other women. Columns (1)-(2) focus on the effect on the total number of arrests for sexual violence involving sex workers per 100,000. Columns (3)-(4) examine the effect on the number of arrests for sexual violence involving other women per 100,000. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.12: Robustness Checks for the Effect on the Number of Cases for Divorce due to Marital Infidelity

	Alternative Adoptions		Alternative Samples	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen
	(1)	(2)	(3)	(4)
Mobile Payment Adoption (Binary)	1.135			
× Post	(0.755)			
Mobile Payment Adoption (Total)		0.057**		
× Post		(0.024)		
Mobile Payment Adoption			0.035**	0.035**
× Post			(0.016)	(0.017)
Observations	1,710	1,710	1,704	1,698
R-squared	0.840	0.841	0.841	0.840
Pre-Shock Mean Y	11.486	11.486	11.525	11.499
Control Vars	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the effect on the number of cases for divorce due to marital infidelity. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.13: Robustness Checks for the Effect on the Number of Cases for Domestic Violence

	Alternative Adoptions		Alternative Samples	
	Binary Treatment	Total DFIIC Intensity	Drop Dongguan	Drop Hangzhou and Shenzhen
	(1)	(2)	(3)	(4)
Mobile Payment Adoption (Binary)	0.307			
× Post	(0.204)			
Mobile Payment Adoption (Total)		0.022***		
× Post		(0.006)		
Mobile Payment Adoption			0.014***	0.014***
× Post			(0.004)	(0.004)
Observations	1,710	1,710	1,704	1,698
R-squared	0.856	0.859	0.859	0.858
Pre-Shock Mean Y	2.768	2.768	2.777	2.770
Control Vars	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the robustness checks for the effect on the number of cases for domestic violence. Columns (1)-(2) use binary treatment and total DFIIC intensity as alternative measurements for mobile payment adoption. Columns (3)-(4) use alternative samples, dropping Dongguan City or Hangzhou and Shenzhen City. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.

Table B.14: Heterogeneity on Male Sex Ratio and Police Recruitment

	Number of Cases/Arrests Per 100,000					
	Divorce due to Marital Infidelity	Domestic Violence	Human Trafficking	Divorce due to Marital Infidelity	Domestic Violence	Human Trafficking
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Payment Adoption	0.035	0.002	-0.000			
× Post × Male Sex Ratio	(0.029)	(0.007)	(0.000)			
Mobile Payment Adoption				-0.004	-0.002	-0.001*
× Post × Police Recruitment				(0.027)	(0.007)	(0.000)
Observations	1,710	1,710	1,710	1,710	1,710	1,710
R-squared	0.842	0.859	0.465	0.842	0.859	0.466
Pre-Shock Mean Y	11.486	2.768	0.047	11.486	2.768	0.047
Control Vars	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of heterogeneity on male sex ratio and police recruitment. Columns (1)-(3) provides results for heterogeneity on male sex ratio. Columns (4)-(6) presents results for heterogeneity on police recruitment. Control variables include the logarithm of GDP per capita, fiscal revenue per capita, and fiscal expenditure per capita. Standard errors are clustered at the prefectural level. * significant at the 10% level. ** significant at the 5% level. *** significant at the 1% level.