Four Essays in Empirical Economics

by

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Declaration

I submit this thesis to the University of Warwick in accordance with the requirements of the degree of Doctor of Philosophy in Economics. I declare that it has not been submitted for a degree at another university. Chapters 1 and 2 are individual work. Chapter 3 is co-authored with Yatish Arya (University of Warwick). I conducted all analysis, composed the first version of the text, and helped in later revisions. Chapter 4 is co-authored with Song Yuan (University of Warwick). I contributed equally in data collection, analysis and revising the draft.

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Abstract

This thesis studies four topics in empirical economics as summarized below.

Chapter 1 documents the roles of heterogeneity, sorting, and complementarity in a framework where workers, managers, and firms interact to shape productivity. I show that the source of heterogeneity in the form of manager ability is an important driver of differences in firm productivity. I empirically identify complementarities between workers, managers, and firms using my estimation methodology. Counterfactual results show that reallocating workers by applying a positive assortative sorting rule can increase police department productivity by 10%.

Chapter 2 documents that growth of Airbnb is likely to affect the local housing rental market by reducing the supply of properties. I combine data from Airbnb and Zoopla and examine how the price of individual houses evolves over time, as Airbnb penetrates the market in the area of Greater London. Leveraging the fact that properties with more than three bedrooms are less exposed to Airbnb, I use a difference-in-differences strategy by year and house type. I find that a 10-percent increase in the number of Airbnb properties in a ward increases real rents by 0.1 percent.

Chapter 3: Religious groups sometimes resist modern welfare-enhancing interventions, adversely affecting the group's human capital levels. In this context, we study whether the two largest religious groups in India (Hindus and Muslims) resisted western education because they shared religious identity with the rulers deposed by the British colonisers. We find that Muslim literacy in an Indian district under the British is lower where the deposed ruler was a Muslim, while Hindu literacy is lower where the deposed ruler was a Hindu.

Chapter 4: We digitize the financial disclosure of elite bureaucrats from India and combine this novel data with web-scraped career histories to study the private wealth accumulation of public servants. Employing a difference in difference event study approach, we find that the annual growth rate is 10% higher for the value of assets and 4.4% higher for the number after bureaucrats being transferred to an important post with the power to make influential policies. We document that the results are consistent with a rent-seeking explanation.

1 Do workers, managers, and stations matter for effective policing? A decomposition of productivity into three dimensions of unobserved heterogeneity.

1.1 Introduction

A central question in economics is what makes some firms more productive than others. Past literature has shown that misallocation of factors of production can account for productivity differences across firms. Therefore, the aggregate productivity of the economy can be increased by reallocating the resources across firms (Banerjee and Duflo, 2005; Hsieh and Klenow, 2009). Misallocation studies have identified underlying sources of misallocation such as regulation, market imperfections, and even government corruption (Restuccia and Rogerson, 2017). However the studies often assumes homogeneous production function across firms, and so the importance of effects of heterogeneity in firms and workers for aggregate productivity remains unanswered. Worker and firm heterogeneity can shape the wage and productivity distribution (Bonhomme et al., 2019; Abowd et al., 1999), and uncovering heterogeneity can reveal the importance of sorting and complementarities for workers and firms. Another significant branch of literature (Lazear et al., 2015; Bloom and Van Reenen, 2007; Bloom et al., 2013) shows that managerial quality may partly explain the productivity gap across firms. In an economy, workers, managers, and firms interact simultaneously, so attempts to explain the productivity gap through two-sided heterogeneity between workers and firms or between managers and firms is inconclusive.

In this paper, I estimate the role of heterogeneity of workers, managers, and firms in police productivity. Most importantly, I document the complementarities and patterns of sorting among workers, managers, and firms. The empirical analysis relies on the quality and extent of the data I use. I webscrape novel crime reports data [1] from the Indian police department to create a matched database of employment histories of both workers (officers) and managers (station head officers). This data allows me to track the job movements of workers and managers across police stations. In a separate web scraping exercise, I match the outcomes of the half-million crime cases to construct a measure of productivity. I use the time taken to submit the final report or charge sheet in criminal cases as a productivity measure.

[1] Half a million crime reports were web scraped for the Indian police department

Then, I use an employee-manager-firm data set linked to this productivity measure to identify how workers and managers working across police stations contribute to productivity.

To empirically estimate workers', managers', and police stations' contributions to police department productivity, I model the production function without any parametric assumptions. I extend the standard model of Abowd et al. (1999, 2002) (henceforth AKM) and Bonhomme et al. (2019) where only workers and firms contribute to productivity by adding a third source of heterogeneity in the form of manager ability. Thus, my approach adds managers and the interaction among workers, managers, and establishments to the extant model. Therefore, in this paper's three-sided model of productivity, heterogeneity comes from workers (investigation officer), managers (station head officer), and firms (police station).

I also model the complementarities between workers, managers, and firms as unrestricted rather than additive, as described in the fixed-effects literature (AKM models). I assume that heterogeneity in the economy can be represented by discrete types of workers, managers, and firms. The identification of the individual contribution of workers and managers is a challenging problem even with microdata. However, since I have employee-manager-firm matched data, I use workers' job mobility and manager types across police stations to infer individual contributions. I represent the job transition of workers and managers using a first-order Markov chain process. The model is estimated using a two-step approach where, in the first step, I map managers and police stations to discrete classes representing quality. The first step is a dimension reduction technique, and I use the classification algorithm of k-means clustering to map the individual managers and firms to discrete types. The second step uses the estimated manager and firm classes from the first step as input to estimate the individual effect of workers, managers, and firms. The second step estimates the model parameters using a finite mixture model, where a specific distribution of productivity is realised based on workers moving between manager and firm classes in a short panel. Using a grid computation technique, I estimate the model using the conditional Expectation-Maximixation (EM) algorithm to converge to the solution (Meng and Rubin, 1993).

The estimation methodology adopted in the paper has numerous advantages. Firstly, the literature on managerial quality frequently uses the fixed-effects model popularised by Abowd et al. (1999) and finds that the best managers are allocated to the least productive workplaces or i.e. there is negative assortative matching of managers with firms. Due to this, evidence on the presence of complementarity are inconclusive as Becker (1973) shows that sign of sorting should be positive if complementarities are present and more recently Shimer and Smith (2000) and Eeckhout and Kircher (2011) emphasise the importance of sorting of workers in the efficient production of output . Thus, the AKM model is restrictive and often gives results that are not reconcilable with theoretical models. In addition to the above issue, results obtained from the additive model of worker, manager, and firm productivity can produce erroneous results in the counterfactual analysis when the researcher aims to determine which sorting pattern of workers can maximise the aggregate productivity. In this study, I keep the interaction unrestricted in a three-sided model of workers, managers, and firms. So, I can estimate the match-specific contribution or the complementarities arising from the worker, manager, and firm heterogeneity on the productivity gap.

Secondly, the model's assumption of finite classes of managers and police stations reduces the problem of limited mobility bias. In the AKM class of models, the correlations between the worker and firm effects are negatively biased due to a small number of workers moving across individual managers and police stations (Andrews et al., 2008). Rather than considering the job moves of individual workers across managers and firms, I map the managers and firms to a small number of classes. Hence, the number of job movers across manager and police station classes is large enough, and this dimension reduction technique solves the problem of limited mobility bias. The manager and police station classes are the inputs in the second step of the estimation, where I recover the model parameters leveraging job mobility as the source of identification.

Thirdly, using the structural estimates of the model, I empirically identify the heterogeneity and the degree of complementarities between the workers, managers, and firms. After structurally modelling the interaction among workers, managers, and firms in the production function, whether total productivity in the economy can be increased by reallocating the workers can be answered. This is possible if worker-manager-firm match specific complementarities enable gains from matching different types of workers with different types of managers and firms. For example, reallocating a low-productivity worker to a better manager would produce a larger increase in productivity than moving a high-productivity worker to a lower quality manager. I then use these estimates in the second part of the paper, where I perform counterfactual simulations by varying the sorting patterns between workers and manager-police station types. I use these simulations to find the sorting pattern that generates the police department's maximum aggregate productivity.

I do these simulated experiments by using the estimated productivity distributions of workers and the worker-manager-firm complementarities obtained by estimating the three-sided model.In other words, I answer the question; do we increase the police department's aggregate productivity by reallocating workers across police stations?

Measurement of productivity in government-controlled public services is a well-known issue in the literature (Ostrom, 1973; Cook, 1979; Mastrobuoni, 2020) because the government does not maximise profits. Due to the difficulty in productivity measurement, the productivity of public services is not documented extensively like it is for the private sector. This gap in research becomes prominent in the case of performance measurement of public services like police departments due to the lack of data in developing countries. Apart from measuring productivity, there is limited research that shows that managers matter in the public sector, and specifically in the law enforcement department of the government. Understating the sources of the productivity gap in the police department will help identify the drivers of efficiency in civil services like the police.

The results of this study are three fold. Firstly, the results delineate the individual contributions of workers and managers to the productivity of the police departments. Using the variance decomposition exercise (Abowd et al., 1999; Card et al., 2013; Andrews et al., 2008), I find that managers individually account for 6% of the explained variation in productivity. This result on manager "fixed effects" is comparable with the literature (Fenizia, 2019) that estimates how much of the contribution of productivity in firms is explained by managerial talent. I also find that the police station effect (the firm level fixed effect) is 6% which is significantly smaller than the individual effect due to workers (57%). This significant difference in police station effect (6%) and worker effect (57%) is reminiscent of the wage dispersion literature (Abowd et al., 1999; Bonhomme et al., 2020), in which a large variation in earnings across firms is found to come mostly from workers.

Secondly, using the three-sided estimator, I find that worker, firm, and manager heterogeneity is present and is an essential factor in determining productivity. There are substantial complementarities between workers, managers, and establishments/police stations. My estimates are based on the number of manager classes M=2 and police station classes K=2. Low-type workers are 57% more productive when matched with high-type managers and more productive police stations rather than low-type managers and low-performing police stations. High-type workers are 87% more productive when matched with high-type managers and more productive police stations rather than low-type managers and less-productive police stations. Thus the productivity of workers depends on which types of managers and firms they are matched with. The fact that the gains from matching high-type workers

(87%) are higher than those of low-type workers is utilised to find the sorting rule that increases the aggregate productivity in the police department. In the variance decomposition, the part of the variation in productivity explained by the covariance of worker type with the manager and the police station type is 10.3% and 10.6% respectively. This shows the prevalence of positive worker sorting in the police department productivity – workers in police departments sort moderately towards high-productivity managers. Similar positive worker sorting is reported in the literature (Bonhomme et al., 2020) on wage determination, where high-wage workers tend to sort to firms that offer high wages (Bonhomme et al., 2019). This result reaffirms the presence of complementarity in organisations.

Thirdly, the results show evidence of the magnitude of misallocation of resources in the police department. The previous result shows the presence of heterogeneity as well as complementarities between workers, managers, and firms. The allocation of workers to managers and police stations can increase police productivity depending upon the nature of complementarities. I simulate various matching rules such as matching high type workers with high type managers (positive assortative matching) or low type managers (negative assortative matching). The counterfactual exercise allows me to conclude that if the current sorting level is raised using the optimal matching rule (positive assortative matching), then there is an 10 % increase in the aggregate productivity of the police department. Hence, social planner can maximize aggregate productivity of the police department by following the optimal worker reallocation strategy.

This paper contributes to three strands of literature.

First, it contributes to the literature that studies the worker and firm-specific effects on wage or productivity using employee-employer matched data (Abowd et al., 1999; Bonhomme et al., 2019; Card et al., 2013; Goldschmidt and Schmieder, 2017). I add managers as an additional source of heterogeneity and provide a computationally tractable model to estimate the productivity distributions. I also add to the literature that studies the matching process of workers and firms (Jackson, 2013; Finkelstein et al., 2016). In a three-sided model, I study the match-specific complementarities that arise due to the interaction of workers with different managers and firms (police station types).

Second, this paper contributes to the literature on how managers and management practice impact firm-related outcomes (Bloom et al., 2013; Bloom and Van Reenen, 2007; Lazear et al., 2015). Past research has shown that high-wage workers sort themselves to the firms that offer higher wages (Abowd et al., 1999). However, there is limited research on match-specific complementarities and the sorting patterns of worker-manager and managers-firms. Recently, Fenizia (2019) and Adhvaryu et al. (2020) have shown that manager ability explains some of the productivity gaps across heterogeneous establishments, but their results are inconclusive on manager-firm complementarity. I add the non-linear match-specific effects of the manager on police performance and show that the manager indeed contributes significantly to productivity. Managers contribution is significant in providing match-specific complementarities with the workers.

Third, my work is also related to research that evaluates the performance of public services (Best et al., 2017; Janke et al., 2019). The output measures for the government-controlled public sector have been scarce, which has limited research into the productivity of the government sector. This gap in research is large in developing countries, and I fill this gap by providing a worker-level productivity measure in the Indian police department. I use the time to clearance as a productivity measure to calculate police effectiveness (Council, 2004). My work also contributes to research that has studied the impact of civil servants on the performance of public institutions (Bertrand and Schoar, 2003; Best et al., 2017; Rasul and Rogger, 2017; Finan et al., 2017). I extend this literature by showing that the police officers' and their managers' effects on the police's performance is substantial, and present results on match-specific interactions between worker, manager, and police station.

The measure of productivity I use in the paper is documented to be better than other productivity measures in the literature like the clearance rate, crime incidence, and survey-based police perception or performance indicators (Ostrom, 1973; Cook, 1979; Eeckhout et al., 2010). My measure of time to charge sheet in Indian law enforcement agencies is used to provide the empirical measure of productivity and also identify the sources of variation of productivity across police stations.

The remainder of the paper is organised as follows. Section 1.2 provides relevant information regarding the institutional context. Section 1.3 details the theoretical model which establishes a framework for the empirical analysis. Section 1.4 describes the identification of the model. Section 1.6 documents the estimation of the parameters of my three-sided model. Section 1.7 describes the data and Section 1.8 presents the estimates of the model. Section 1.9 shows the results of counterfactual simulations done using worker reallocation. Section 1.10 presents the conclusion.

1.2 Background

1.2.1 Police structure in India

Police in India come under the state government's purview, and each of the 28 states has its own police force. The central government also has a small specialised unit primarily used to assist the state police in investigating major events and to help state governments with tasks such as intelligence gathering and research. The police force is responsible for maintaining law and order by preventing and investigating crimes. Every state is divided into various field units: zones, ranges, districts, sub-divisions or circles, police stations, and outposts for effective policing (Mitra and Gupta, 2008). For instance, a state will comprise two or more zones; each zone will comprise two or more ranges, and ranges will be sub-divided into the other field units similarly. The critical field unit in this setup is the police station within a district (Verma, 2010).

A police station is generally engaged with (i) registration of crimes, (ii) local patrolling,(iii) investigations, (iv) handling of various law and order situations (e.g., demonstrations, strikes), (v) intelligence collection, and (vi) ensuring safety and security in its jurisdiction (reference) (Mitra and Gupta, 2008; Das and Verma, 1998). A police station is headed by a Station Head Officer (SHO), generally of the rank of Inspector and occasionally of Sub-Inspector. In the hierarchy of police, the manager of the police station is the SHO, and other police workers assist him in the functioning of the police station. Junior police officers are of the rank of sub-inspector, assistant sub-inspector, and constable. When a police officer investigates a crime, he or she is called the Investigation Officer (IO) in the official documents. I treat IOs as workers.

1.2.2 Crime reporting and investigation

The main responsibiliy of the police is to investigate crimes. Crime reporting and investigation in India are well-established by the statutory, administrative, and judicial frameworks. Victims of an offence or anyone on the victims' behalf, including police officers, can file a complaint. Generally, a First Information Report (FIR) is registered with the police station under whose jurisdiction the geographic location of crime falls. The crimes covered under the Criminal Procedure Code (CrPc) are documented [2] in a First Information Report (FIR) (Bayley, 2015; Kumar and Kumar, 2015). An FIR is a crucial document as it sets the process of criminal justice in motion. It is only after the FIR is registered in the police station that the police can investigate the case. The FIR gets assigned to an Investigation Officer (IO) who takes up the investigation and is supervised by the Station head Officer (SHO).

The investigation of crime has many possible steps including collecting evidence,

[2] Non-serious crimes such as forgery, cheating, and defamation, which are categorised as non-cognisable in the Indian criminal codes, require prior authorisation by a magistrate before police can start investigating them

identifying suspects, recording statements of the accused, statements of witnesses, arrests, forensic analysis, and gathering expert opinion if required (Mitra and Gupta, 2008; Bayley, 2015). Criminal investigation requires skills, training, and other resources such as adequate forensic capabilities and infrastructure. The ability of the police workers plays a crucial role in criminal investigation. The quality of police officers may vary with their training, expertise, and legal knowledge in the department. The manager of the police station, or SHO, plays a vital role in supervising the police officers, as their input and direction can help speed up the investigation (Lambert et al., 2015). High-quality managers can efficiently allocate resources within a police station across multiple simultaneous investigations (Raghavan, 2003). On completion of the investigation, the police submit the final report or charge sheet to a magistrate. The submission of the charge sheet is another important step in a criminal investigation that leads to the start of a legal trial. Unsolved cases where police cannot identify suspects are closed after the magistrate's approval, and details are submitted as the final report.

1.2.3 Time to submit final report/charge sheet as productivity measure

There is a long-standing debate in the literature about how to measure the productivity and performance of individual police officers and police institutions (Ostrom, 1973; Verma and Gavirneni, 2006; Cook, 1979). To measure police productivity, I use the time to clear the crime as a productivity measure which is calculated as the difference between the final report/charge-sheet submission date and crime registration (FIR) date. This time to clear the crime measure is associated with police productivity as the probability of clearance of the case falls over time. The "cold case" phenomenon in criminal investigations is widely seen as an indication of poor police performance; therefore, time taken to complete the investigation directly relates to the police performance (Regoeczi and Hubbard, 2018; Addington, 2008). The time to file a charge sheet to the judicial magistrate also reflects the quality of the investigation carried out by the Indian police (Iyer et al., 2012; Amaral et al., 2019). The longer the police take to complete the investigation, the more time the accused has to manipulate the evidence and even abscond from the law. The larger times to submit a charge sheet are generally due to a longer time taken by police to record witness statements (Law, 2015). The delay in recording statements can affect witnesses' recollections of events related to crime and the identities of the accused (Read and Connolly, 2017).

Another reason I use the time to submit the charge sheet as a productivity measure is that a delay in charge sheet filing has consequences for criminal justice outcomes. The Law Commission of India (2015) survey states that 55% of pending cases in courts are delayed at the investigation stage due to the inordinate delays in filing of the charge sheets by the police. The survey [3] reports that the time gap in charge sheet filing is the most prominent reason for the delay in a criminal convictions. Low conviction rates in criminal cases are indicative of poor performance of law enforcement agencies. India follows the adversarial system of legal justice, where the onus of proof is generally on the state (prosecution) to prove a case against the accused. Unless the allegation against the accused is proven beyond a reasonable doubt, the accused is presumed to be innocent. Therefore, a delay in the investigations also leads to more acquittals because the accused are more likely to get bail in such cases (Krishnan and Kumar, 2010). Judges in India were asked the following question in the survey: *"Does delay in filing charge sheets adversely affect the prosecution of cases?"*. 100% of the randomly sampled judges answered yes (N=50) [4].

This measure of police productivity is related to the clearance rate, which has been widely used in the literature to measure police effectiveness (Cook, 1979; Mastrobuoni, 2020). The clearance rate is generally measured at the year-end cut-offs when crime statistics are published. These clearance rates are frequently adjusted in the upcoming reports as crimes occurring towards the year-end pose survival bias. This data adjustment causes the clearance rate statistics to be unstable because the past clearance rate improves as time passes. I use the time to charge sheet or time to solve the case as a stable measure of individual productivity at the intensive margin, whereas the clearance rate is a time censored variable. My measure of police effectiveness is also validated by Blanes Vidal and Kirchmaier (2018), who show that police response time directly affects the crime clearance rate and time to clearance.

Individual criminal cases can have characteristics, observed or not, that may determine the difficulty of solving the case itself. In my analysis, I do not control for the individual characteristics of crime. However, this may not bias the result because I control the location or police station fixed effects. For example, some police stations would encounter certain types of crime more with different difficulty levels in solving these crimes. By controlling the location fixed effects, I control the composition of crime at the police station level. However, this relies on the assumption that crime

[3] Law Commission of India (2015) survey; random sample size of 1630 responses

[4] Report of Bureau of Police Research and Development (BPRD) on increasing acquittals in India, 2013

composition does not change at the police station level, which is likely to be satisfied because I rely on a short panel to estimate my results.

1.3 Model

I model the production in an economy where heterogeneity is three-sided and comes from workers, managers, and firms. I assume that discrete classes can represent heterogeneity (Bonhomme et al., 2019; Bonhomme and Manresa, 2015). The discrete nature of heterogeneity means that there are finite types or classes of workers, managers, and firms in the economy.

Let us assume that there are N workers, H managers, and J firms in the economy. N workers are indexed by i or $i \in \{1, ..., N\}$. H managers are indexed by h or $h \in \{1, ..., H\}$. J firms or establishments are indexed by j or $j \in \{1, ..., J\}$. I assume workers are of L different types and this type index of the i'th worker is represented by α_i where $\alpha_i \in \{1, ..., L\}$. I represent h_{it} as the identifier of the manager with whome worker i is employed at time t. I partition managers into M classes, which represents the heterogeneity across managers. I denote $m()$ as the mapping function which maps individual managers h_{it} to their classes m_{it} or $m_{it} = m(h_{it}) \in \{1, ..., M\}$. The heterogeneity across firms or establishments is described by the finite number of K partitions or classes. j_{it} is the identifier of the establishment where worker i is employed at time t. Individual firms are mapped to their classes k_{it} using the function $k()$ which takes firm identity j_{it} as the input or $k_{it} = k(j_{it}) \in \{1, ..., K\}$.

The *latent* classes m_{it} of managers and the latent classes k_{it} of firms are to be estimated, and in section 1.6.1 I describe this dimension reduction method. Nonetheless, the model allows the number of individual managers and firms to be equal to the number of classes or $M = H$ and $K = J$. The implication of allowing this is similar to equating the manager and firm identifiers to the class membership indicators as $m_{it} = j_{it}$ and $k_{it} = j_{it}$.

There are two time periods in the model. In time period t, the worker draws log productivity from a distribution, that depends on the worker type α_i, the worker's manager class m_{it} and the firm class k_{it} where the worker is employed. The conditional cumulative distribution function of log productivity can be represented as below.

$$Pr[Y_{it} \leq y | m_{it} = m, k_{it} = k, \alpha_i = \alpha] = F_{mk\alpha}(y)$$

Workers at the end of the time period t who remain with the same manager and firm class is indicated by $s_{it} = 0$, these are "stayers". Workers can change either manager classes, firm classes, or both. These are "movers", end of period moves are represented by $s_{it} = 1$ and log-productivity in the next time period $t+1$ is drawn from a distribution which depends on the worker type α_i, manager type $m_{i,t+1}$ and firm type $k_{i,t+1}$. Here, $Y_{i,t+1}$ is drawn from a distribution that depends on the parameters denoting worker state $(\alpha_i, m_{i,t+1}, k_{i,t+1})$ and t time period productivity Y_{it}. The probability that type α worker moves is not restricted in the model, and I use assumptions 1 and 2 below to simplify its dependence on specific worker states.

The following two assumptions are used in the model.

Assumption 1

A worker's probability of moving (s_{it}) and subsequent match with manager and firm (m_{it+1}, k_{it+1}) are both independent of workers current period productivity Y_{it} conditional on the worker type (α_i), current manager class (m_{it}), firm class (k_{it}) and previous moves (s_{it-1})

$$s_{it}, m_{it+1}, k_{it+1} \perp\!\!\!\perp Y_{it} | m_{it}, k_{it}, \alpha_{it}, s_{it-1}$$

Assumption 2

This assumption relates to the serial independence of productivity conditional on current state. In time period $t+1$ worker draws productivity Y_{it+1} that depends only on α_i, m_{it+1} and k_{it+1} but not on its past productivity Y_{it}, past worker states $(m_{it}$, $k_{it})$ and previous worker moves s_{it-1}

$$Y_{it+1} \perp\!\!\!\perp Y_{it}, m_{it}, k_{it}, s_{it-1} | m_{it+1}, k_{it+1}, \alpha_{it}$$

I now discuss these assumptions, their prevalence in the literature, and their implications for the model. The assumptions are related to models where the next period wage is determined only by the current state (static model of Bonhomme et al. (2019); Shimer (2005)). This means that there is no historical dependence on worker productivity beyond their current and t-1 period matches with managers and firms. Thus the model is also compatible with the class of the models where the state variables are (α, m_t, k_t) (Delacroix and Shi, 2006). The productivity drawing process is similar to the first-order Markov chain process where the current worker, manager, and firm matches break with some finite probability, and the next state is reached through a stochastic process. The model assumes that there is no human capital accumulation or on-the-job learning/training in a short period of time. This no human capital accumulation is evident in the model as workers do not change types in a short panel. My model adds managers as a *third source* of variation in the outcome (productivity), and can be seen as an extension of the two-sided labour market models where wages are the outcomes of the match between worker types and firm classes (Card et al., 2013; Alvarez et al., 2018; Bonhomme et al., 2019; Lentz et al., 2020; Abowd et al., 1999).

In my institutional context, the assumption states that Investigation Officers (worker) mobility is random, conditional on Station Head Officer (manager), police station, and time fixed effects. The assumptions allow workers to sort themselves based on manager and police station match specific productivity realizations. Thus sorting of workers does not violate the identification assumption. There are particular scenarios where these exogenous mobility assumptions will be violated. For example, workers whose productivity declines over time are reallocated to managers or police stations who have not been performing well in the past. There is less likelihood of this assumption being violated in my scenario because I work with a short period that leaves less scope of Human-capital depletion or reduction in ability in few years.

Using the above model, I will recover the distributions of the joint production function for different worker types and their match with a different manager and firm classes. I would also focus on recovering the proportions of different worker types employed within all manager and firm classes. These productivity distributions will be essential to identify the complementarities in the production functions where heterogeneity is three-sided. Apart from complementarities, the sorting patterns of workers will be recovered from data using the worker proportions. The measure of complementarities and sorting will be used to run counterfactual simulations to observe the role of heterogeneity in maximizing the total productivity in the economy.

1.4 Identification

In this section, I use the model described in the previous section and apply assumptions 1 and 2 to show formal identification using the observable data. There are two time periods in the model. In time period 2, worker of type α draws log productivity y_1 from cumulative distribution function $F_{mk\alpha}(y_1)$ working with manager m and firm k. Similarly the cumulative distribution function of log-productivity in period 2 is defined as $F'_{m'k'\alpha}(y_2)$. In the case of job mobility ($s_{it} = 1$), either the manager, firm class is different ($m \neq m'$ or $k \neq k'$), or the worker changes both manager and firm class ($m \neq m'$ and $k \neq k'$). I define $p_{mm',kk'}(\alpha)$ as the probability distribution of the job movers of α types between different manager and firm classes. So for moves between classes (m, k) to (m', k'), the sum of probability across worker types $\sum_{\alpha=1}^{L} p_{mm',kk'}(\alpha)$ is equal to 1. $\pi_{mk}(\alpha)$ is the distribution of α type workers in manager class m and firm class k. I can write the distribution of job movers as

$$Pr[Y_{i1} \leq y_1, Y_{i2} \leq y_2 | m_{i1} = m, m_{i2} = m', k_{i1} = k, k_{i2} = k'] = \sum_{\alpha=1}^{L} p_{mm',kk'}(\alpha) F_{mk\alpha}(y_1) F'_{m'k'\alpha}(y_2) \quad (1.1)$$

Equation 1.1 for job movers is derived after applying the assumptions 1 and 2. Assumption 1 states that the first period log productivity Y_{1t} does not depend on the next period manager (m_{i2}) and firm (k_{i2}) classes for *movers* ($s_{it} = 1$). The independence of Y_{i1} is conditional on the current match specific state of type α_i worker, manager (m_{i1}) and firm k_{i1} class. Assumption 2, which relates to serial independence, makes productivity Y_{i2} at time period 2 independent of the previous period productivity (Y_{i1}) and worker's state (m_{i1}, k_{i1}) in the previous time period. This independence assumption is conditional on the worker's match state (m_{i2}, k_{i2}) after a job move $s_{i1} = 1$. In contrast to additive model of productivity with fixed effects (Card et al., 2013; Fenizia, 2019), equation 1.1 allows that job mobility of workers to be endogenous in nature. Workers change job not only according to their own type, manager classes and firm types but also due to complementarity associated with the match specific realizations with managers and firms in current and future period.

I can also define the log-productivity in period 1 as below:

$$Pr[Y_{i1} \leq y_1, Y_{i2} | m_{i1} = m, k_{i1} = k] = \sum_{\alpha=1}^{L} \pi_{mk}(\alpha) F_{mk\alpha}(y_1) \quad (1.2)$$

I want to identify the following parameters in the model: Productivity distributions in both time periods: $F_{mk\alpha}(y_1)$, $F'_{m'k'\alpha}(y_2)$. Transition probabilities: $p_{mm',kk'}(\alpha)$. Worker proportions (sorting patters): $\pi_{mk}(\alpha)$. I rely on Theorem 1 of (Bonhomme et al., 2019) that shows the identification for a two-sided model of workers and firms. The identification of the three-sided model follows the argument that managers and firms are defined as discrete classes so the manager-firm class can be taken as a cartesian product. The replacement of firm classes with manager×firm classes only increase the dimensionality in the BLM's identification setup, and I perform the simulations in section 1.6 to test if I can recover the three-sided model parameter estimates using my model.

1.5 Manager and firm classes identification

Identification in the previous section assumes that there are M classes of managers and K classes of firms. This dimension reduction removes the limited mobility bias (Andrews et al., 2008; Bonhomme et al., 2020), since by using finite numbers of classes, mobility of workers is from one manager or firm class to another. Thus making the number of job movers within the classes sufficiently large to avoid the small sample bias caused when job mobility within the individual managers and firms are considered. In the model illustrated in section 1.4, distribution of log-productivity of manager id h and firm id j does not depend on its identity beyond its manager class m and firm class k. First period log productivity shown in equation 1.2 can be rewritten as equation 1.3 for manager h and firm j. In equation 1.3, the left hand side depends only on the manager and firm classes which are obtained from the mapping functions $m = m(h)$ and $k = k(j)$.

$$Pr[Y_{i1} \leq y_1 | h_{i1} = h, j_{i1} = j] = \sum_{\alpha=1}^{L} \pi_{mk}(\alpha) F_{mk\alpha}(y_1) \tag{1.3}$$

The aim is to identify the class membership of managers and firms from theirs individual identifiers and productivity data. I first start with the intuition of identification to recover the manager classes then using a similar identification strategy firm classes can be recovered. For illustration , I assume that number of manager classes (M) = 2, the firm classes (K) = 2 and number of worker types (L) is also 2. This simplifies the graphical representation of the distribution of productivity. Figure A.1 below shows the tree diagram of the distribution represented in equation 1.3. There are different combinations of manager and worker classes that a worker can work with. In the example where M=2 and K=2, these combinations are (m_1, k_1), (m_1, k_2), (m_2, k_1) and (m_2, k_2). Within each of these combinations, there are 2 types of workers $\alpha = 1$ and $\alpha = 2$ which draw productivity from match specific distribution $f_{mk\alpha}$. Next, I combine worker and firm classes together. In my example, within manager class 1 (m_1), now there are four types of worker-firm classes namely $k_1\alpha_1$, $k_1\alpha_2$, $k_2\alpha_1$ and $k_2\alpha_2$. In figure A.1, $\pi_m(k_\alpha)$ is the combined worker proportion in the manager class where $k_\alpha \in \{k_1\alpha_1, k_1\alpha_2, k_2\alpha_1\, k_2\alpha_2\}$. Thus equation 1.3 can be re-written as in equation 1.4 after combining the firm and worker classes to $K \times L$ discrete classes.

$$Pr[Y_{i1} \leq y_1 | h_{i1} = h] = \sum_{\alpha_k=1}^{K \times L} \pi_m(\alpha_k) F_{mk\alpha}(y_1) \tag{1.4}$$

It follows from equation 1.4 that the first period distribution of workers matched with manager id h is identical to the distribution of its manager class m. Thus the recovery of manager classes is essentially a classification problem where we classify the managers having similar productivity distribution to the same class. My identification strategy is similar to the Bonhomme et al. (2019) and Bonhomme and Manresa (2015), where firms classes are recovered in a two sided model. The approach to recover the firm classes follows a similar methodology, where I combine manager and worker types together. In our example above, within firm class 1 (k_1), there are four types of combined worker-manager types: $m_1\alpha_1$, $m_1\alpha_2$, $m_2\alpha_1$ and $m_2\alpha_2$. I can rewrite equation 1.3 conditional only on the firm id j in equation 1.5 below, combining the manager and worker classes to $M \times L$ classes. Equation 1.5 shows that firms who are of same type have identical productivity distribution, Thus recovering the firm classes is also a classification problem.

$$Pr[Y_{i1} \leq y_1 | j_{i1} = j] = \sum_{\alpha_k=1}^{M \times L} \pi_k(\alpha_m) F_{mk\alpha}(y_1) \tag{1.5}$$

1.6 Estimation

The estimation methodology of the model is divided into two steps in this section. Since the productivity distribution in Section 1.4 is identified using the finite manager and firm classes, I first estimate the class membership of managers and firms. The first step in Section 1.6.1 describes this dimension reduction methodology. Once I have classified the manager and firms into distinct classes, then I estimate the model parameters in step 2, shown in Section 1.6.2.

1.6.1 Estimating manager and firm classes

I recover the manager and firm class using a clustering algorithm. I partition H managers into M classes and J firm into K classes. This estimation strategy follows directly from equation 1.4 and 1.5. I start with recovering the managers class by solving the following equation: the three-sided counterpart of the Bonhomme et al. (2019) two-sided classification model for firms.

$$\min_{m(1),\ldots,m(H),H_1,\ldots,H_M} \sum_{h=1}^{H} n_h \sum_{d=1}^{D} \left(\widehat{F}_h(y_d) - H_{m(h)}(y_d)\right)^2 \tag{1.6}$$

In the above equation, $\hat{F}_h$ is the empirical CDF of log-productivity of manager h having finite support and discretized into D grids. $H_{m(h)}$ are CDFs of the manager classes. n_h is the number of workers employed under manager h. I partition the managers into M classes having cdfs $H_1, \ldots.H_k$ so that sum of the squared error within the cluster is minimized. I weight this least square minimization problem with the number of workers in each cluster. I minimize the equation using large number of partitions in an iterative algorithm following Steinley (2006) and Bonhomme et al. (2019). The weighted k-means clustering algorithm is widely used in literature (Bonhomme et al., 2020; Zhang et al., 2019). The manager classes computed using the above k-means clustering have workers working with different firms, which is consistent with the equation 1.4 where I combine the worker and firm classes to $(K \times L)$.

I now recover the firm classes identified in equation 1.5 by combining the worker and manager type employed within a firm to $M \times L$ classes. I use a similar clustering algorithm to partition the firms by solving the equation below.

$$\min_{k(1),\ldots,k(J),H_1,\ldots,H_K} \sum_{j=1}^{J} n_j \sum_{d=1}^{D} \left(\widehat{F}_j(y_d) - H_{k(j)}(y_d)\right)^2 \tag{1.7}$$

where $\hat{F}_j$ is the empirical CDF of log productivity of firm h. n_j is the number of workers employed in a firm j. I minimize the within-cluster sum of squared error to partition the firms to K classes having $H_1, ...H_K$ cdfs. This methodology results in firm class clusters having $M \times L$ types of latent worker classes according to equation 1.5.

Using equations 1.6 and 1.7, I estimate the firm and manager classes in the framework of Bonhomme et al. (2019) but applied to the three-sided model having a manager and firm classes. The methodology can be treated like a nested approach where I combine worker-firm types to recover manager classes and worker-manager types to estimate the firm classes. One of the advantages of this methodology is that the estimated firm and manager classes behave like Bonhomme and Manresa (2015). When the number of firms and firm size both increase to a sufficiently large number, then the estimated firm classes converge to population classes. This result directly applies to equation 1.6 and 1.7, when number of managers and firms grows or $H \to \infty$ and $J \to \infty$. Additionally, when worker per manager class is large $n_h \to \infty$ and firm size is large $n_j \to \infty$, then model estimation done in the next section is not affected by the error due to the classification step (recovery of manager and firm classes).

1.6.2 Estimation of model parameters

In the previous section, I estimated the manager and firm class membership. In other words, I estimated $\widehat{m}(h)$ and $\widehat{k}(j)$, and can obtain the class $\widehat{m}_{it}$ and $\widehat{k}_{it}$ for each worker. I now use these manager and firm classes in the second step to estimate the model parameters. I assume that there ar L types of workers in the model. These are L latent types of worker, capturing unobserved heterogeneity from the worker side. In the model specification, I now define the parametric vectors. Let $f_{mk\alpha}(y_1;\theta_f)$ be the first period earnings distribution for worker type α employed with manager class m and firm class k. θ_f is the parameter vector of the distribution. For example, if the distribution $f_{mk\alpha}$ is Gaussian, then the parameter θ_f contains the mean and standard deviation (μ_f, σ_f). In the estimation, I will assume that the distribution of log productivity is Gaussian. When matched with the manager and firm class, every worker type has a different distribution, which implies that the Gaussian distribution of productivity differs along the lines of parameter θ_f. $f'_{m'k'\alpha}(y_2;\theta_{f'})$ is the productivity distribution in the second period. For the job movers of type α who change their manager and firm classes from (m,k) to (m',k'), the worker-type proportion is $p_{mm',kk'}(\alpha;\theta_p)$. θ_p is the parameter vector in the probability distribution having the length equal to the number of worker types L. Worker type proportions in the manager class m and firm class k are $\pi_{mk}(\alpha;\theta_\pi)$. θ_π is again the parameter vector whose length is equal to L types of workers. The inclusion of the two different distributions f and f' at consecutive time periods gives the model flexibility of time interaction even in the short panel. Thus the productivity distribution can vary across time and incorporates the "time fixed effects" from a Card et al. (2013) type model. I use equation 1.1 to write the log-likelihood function of productivity for job movers shown in equation 1.8 below. As previously explained in section 1.4, the distribution of log productivity in both time periods are independent of each other conditional on the match state of worker types with the manager and firm classes in both time periods. The log-likelihood equation is

$$\sum_{i=1}^{N}\sum_{m=1}^{M}\sum_{m'=1}^{M}\sum_{k=1}^{K}\sum_{k'=1}^{K}\mathbf{1}\{\widehat{m}_{i1}=m\}\mathbf{1}\{\widehat{m}_{i2}=m^{'}\}\mathbf{1}\{\widehat{k}_{i1}=k\}\mathbf{1}\{\widehat{k}_{i2}=k^{'}\}\times$$
$$\ln\left(\sum_{\alpha=1}^{L}p_{mm',kk'}(\alpha;\theta_p)f_{mk\alpha}(y_1;\theta_f)f'_{m'k'\alpha}(y_2;\theta_{f'})\right) \quad (1.8)$$

In equation 1.8 above, N is the number of job movers. I estimate $\widehat{\theta}_p, \widehat{\theta}_f, \widehat{\theta}_{f'}$ by maximising equation 1.8, and is equivalent to a mixture model representation where I do not observe the latent class of the worker. Job moves from one state (m,k) to another state (m',k') happens for al types (L) of workers. I use a modified Expectation Maximisation algorithm (Dempster et al., 1977) to estimate the parameters.

One of the drawbacks of the Expectation Algorithm is that it has a slow convergence rate towards an optimal solution. I increase the convergence rate by using the Conditional Expectation-Maximization (CEM) algorithm, which maximizes conditional likelihood (Meng and Rubin, 1993; Lentz et al., 2020).

I estimate the proportion of workers in each manager class m and firm class k represented by $\pi_{mk}(\alpha;\theta_\pi)$. θ_π is the parameter vector whose length equals the number of worker types (L). I use equation 1.2 to write the maximum likelihood function of the worker's productivity as

$$\sum_{i=1}^{N}\sum_{m=1}^{M}\sum_{k=1}^{K}\mathbf{1}\{\widehat{m}_{i1}=m\}\mathbf{1}\{\widehat{k}_{i1}=k\}\times\ln\left(\sum_{\alpha=1}^{L}\pi_{mk}(\alpha;\theta_\pi)f_{mk\alpha}(y_1;\theta_f)\right) \tag{1.9}$$

I maximize the likelihood in equation 1.9 to estimate the parameter vector θ_π for every manager and firm class. Since I have already estimated the log productivity distribution $f_{mk\alpha}(y)$ in equation 1.8, the maximisation problem in equation 1.9 is solved by linear programming.

I now summarise the two-step estimation of the three-sided model of productivity. In Step **1**, I estimate the manager and firm classes using the classification algorithm. In Step 2, I use the manager and firm classes to estimate the parameter values for the productivity distributions and worker proportions, and the transition matrix for the different types of workers who change states. The two-step estimation approach described above is computationally tractable and combines the approach of the recent two-sided heterogeneity literature (Bonhomme et al., 2019; Lentz et al., 2020), while adding a third layer of managers.

1.6.3 Estimation using simulated data

I now democtrate the performance of the two-step three-sided estimator described above using simulated data. I assume the number of manager classes $M = 2$, the number of firm classes $K = 2$, and also the number of workers' types $L = 2$. I then simulate data using arbitrary parameter values from Gaussian distribution: $\theta_p, \theta_\pi, \theta_f, \text{and}\, \theta_{f'}$. I also simulate the manager and firm IDs from the discrete classes using random draws from a uniform distribution where the mean is set to an 100 workers per manager and firm. I use this simulated data as the input to my two step, three-sided estimator described in section 1.6. To compare the means of estimated parameters to original values, I use the Monte Carlo simulation technique. I find that my classification method can recover the true manager and firm classes accurately as shown in appendix A.1 (A.4 and A.5). I also find that the second step of the estimation strategy in section 1.6.2 produces the productivity distribution and worker proportions are close to "true" parameter values as shown in appendix A.1 (Figure A.6 - Figure A.7).

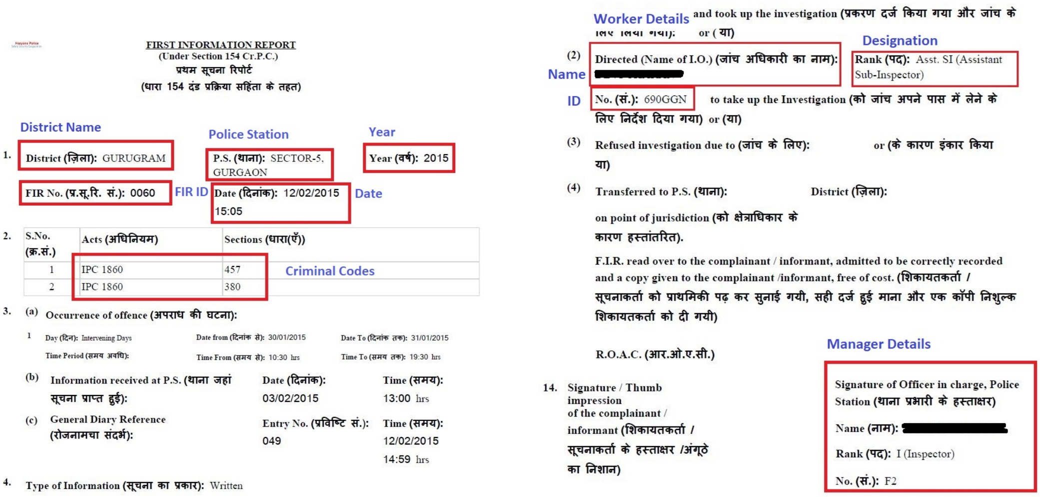
The asymptotic properties of the estimator are presented using the Monte Carlo simulation approach. In appendix A.1, I show the distribution of the parameters estimated using randomly drawn data simulated using fixed model parameters. I show the asymptotic normality of the estimator by increasing the sample size, making the number of movers in the data substantially large ($N_m \to \infty$).

Though the mathematical proof of the asymptotic normality of the estimator is not provided formally, the intuition comes directly from past research (Bonhomme and Manresa, 2015; Bonhomme et al., 2019). I satisfy the assumptions used in the Bonhomme and Manresa (2015) to show that asymptotic normality holds for my model. The first assumption in Bonhomme and Manresa (2015) states that misclassification error in the estimated manager and firm class should approach zero as the sample size grows. This assumption is likely to be satisfied in my model because my estimation methodology for recovering manager and firm classes is similar to a two-sided model where firm classes are recovered. The difference in my setting is primarily nested in nature, because I combine the worker types with firm and manager classes to determine the individual classes. The second assumption states that the properties of estimator in step 2 is like maximum likelihood estimator. This is also true as increasing the degree of freedom by adding the manager classes does not alter the properties of the maximum likelihood estimator (equation 1.8). Thus using the validity of the two assumptions of Bonhomme and Manresa (2015) and Bonhomme et al. (2019), my three-sided model satisfies the properties that characterize the estimator as asymptotically normal, and the same is shown using Monte Carlo simulation in appendix A.1 (Figure A.8).

1.7 Data

Crime reports data: I use data on First Information Reports (FIRs) for the state of Haryana in India. Haryana is a state located in the northern part of India (Figure 1.2), and the Haryana police department has 283 police stations sprawled across 44 thousand square kilometres (Figure 1.3). I web scraped the individual FIRs for crimes reported between 2015 and 2018. The crime reports have detailed information such as the crime registration date, the administrative district where the crime is registered, the name of the police station, the crime occurrence date, and details of criminal codes applicable as per the Indian law. Each FIR also contains the identity of the Investigation Officer or IO working in the police station, who is responsible for solving the crime. FIR also records the name of the Station Head Officer (SHO), who is the Investigation Officer's (IO's) manager. A sample FIR of the police department is shown in figure 1.1. The figure highlights the data described above. I web scraped 472,082 of these crime reports for analysis. I then converted the unstructured data in these FIRs to machine-readable data using programmable text extraction techniques.

Figure 1.1: Sample First Information Report (FIR) with highlighted data



FIRST INFORMATION REPORT
(Under Section 154 Cr.P.C.)
प्रथम सूचना रिपोर्ट
(धारा 154 दंड प्रक्रिया सहिंता के तहत)

1. District (ज़िला): GURUGRAM P.S. (थाना): SECTOR-5, GURGAON Year (वर्ष): 2015
FIR No. (प्र.सू.रि. सं.): 0060 Date (दिनांक): 12/02/2015 15:05

2.

S.No. (क्र.सं.)	Acts (अधिनियम)	Sections (धारा(एँ))
1	IPC 1860	457
2	IPC 1860	380

3. (a) Occurrence of offence (अपराध की घटना):
1 Day (दिन): Intervening Days Date from (दिनांक से): 30/01/2015 Date To (दिनांक तक): 31/01/2015
Time Period (समय अवधि): Time From (समय से): 10:30 hrs Time To (समय तक): 19:30 hrs
(b) Information received at P.S. (थाना जहां सूचना प्राप्त हुई): Date (दिनांक): 03/02/2015 Time (समय): 13:00 hrs
(c) General Diary Reference (रोजनामचा संदर्भ): Entry No. (प्रविष्टि सं.): 049 Time (समय): 12/02/2015 14:59 hrs

4. Type of Information (सूचना का प्रकार): Written

and took up the investigation (प्रकरण दर्ज किया गया और जांच के लिए लिया गया): or (या)

(2) Directed (Name of I.O.) (जांच अधिकारी का नाम): [redacted] Rank (पद): Asst. SI (Assistant Sub-Inspector)
No. (सं.): 690GGN to take up the Investigation (को जांच अपने पास में लेने के लिए निर्देश दिया गया) or (या)

(3) Refused investigation due to (जांच के लिए): or (के कारण इंकार किया या)

(4) Transferred to P.S. (थाना): District (ज़िला):
on point of jurisdiction (को क्षेत्राधिकार के कारण हस्तांतरित).

F.I.R. read over to the complainant / informant, admitted to be correctly recorded and a copy given to the complainant /informant, free of cost. (शिकायतकर्ता / सूचनाकर्ता को प्राथमिकी पढ़ कर सुनाई गयी, सही दर्ज हुई माना और एक कॉपी निशुल्क शिकायतकर्ता को दी गयी)

R.O.A.C. (आर.ओ.ए.सी.)

14. Signature / Thumb impression of the complainant / informant (शिकायतकर्ता / सूचनाकर्ता के हस्ताक्षर /अंगूठे का निशान)

Signature of Officer in charge, Police Station (थाना प्रभारी के हस्ताक्षर)
Name (नाम): [redacted]
Rank (पद): I (Inspector)
No. (सं.): F2

Figure 1.2: Map showing India and the state of Haryana is shaded (red)

Productivity measure (time to submit a final report or charge sheet): The Haryana Police Department also publishes the individual case-level final report or charge sheet filing date. I construct the charge sheet data using another web

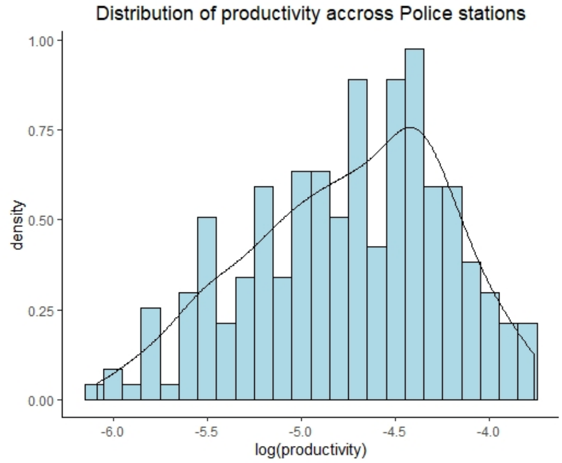
Figure 1.3: Location of police stations in Haryana shown as dots (black)

scraping exercise. I then match all the crime reports using the unique FIR id to their outcome, i.e., the time to submit the final report or charge sheet (Appendix A.1, Figure A.2) .

Worker-manager-establishment matched data set and job mobility: My methodology of matched data set construction of the three-sided model (worker-manager-firm) follows the approach extensively used in literature (Abowd et al., 2002; Bonhomme et al., 2020) that uncovers worker and firm fixed effects using matched employee-employer data. The case's name and the unique employee id of both the Investigation officers (IO) and their supervisors, i.e., the Station Head Officers (SHO) are observed in the FIR data. To create the matched data set, I use the anonymised unique ids of the employees of the police department. In a few reports where the employee id is missing or erroneous, I created synthetic employee ids using the officer name. To draw the analogy from the three-sided model described in Section 1.3 to the crime reports data of the police department, I consider the investigation officer (IO) as the worker, the station head officer (SHO) as the manager, and the police station as the establishment or firm. I infer the job mobility of an investigation officer (IO) when he/she moves to different managers and police stations. Hence, from the data, I can observe the job mobility patterns of workers across managers and police stations.

Figure 1.4 shows the distribution of log productivity of employees across police stations in Haryana for the year 2017. There is a large dispersion visible in productivity across police stations. The top decile police station is 2.75 times more productive than the bottom decile police station. Productivity comparison of police is scarce in the past literature. Hence I use the benchmark from firm-level log-productivity distribution from Syverson (2011). It reports the within plant productivity gap of 2.9 in India, comparable to the police productivity gap across police stations.

Figure 1.4: Distribution of log productivity across police stations in Haryana



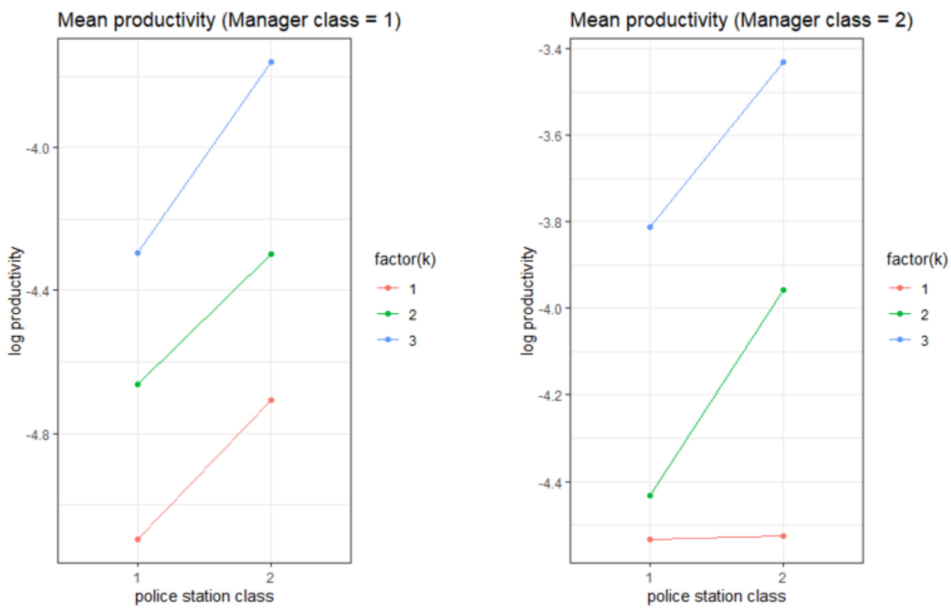
Note: Log productivity in the x-axis is the negative transformation of log(Time to chargesheet)

1.8 Results

I use the worker-manager-police station matched data set of all crime cases registered from 2015 to 2018. I follow the sample selection methodology described in Bonhomme et al. (2019), Friedrich et al. (2019), and Fenizia (2019), which uses weekly wage data in employee-firm matched data sets. Following Friedrich et al. (2019), in my analysis, I consider workers who have worked for at least three months in a police station. I use at least three months for a worker because I want to exclude the temporarily seconded employees. They are sometimes posted in a police station as a trainee or short-term replacement of a police officer. Occasionally, the employee id column is entered manually, which might cause an error in inferring the job mobility of workers and managers across police stations. In such situations, I use the names of employees to avoid ambiguity in id matching. I track job changes by capturing all state changes of a worker due to his or her matches with managers and police stations. In addition to the model having different distributions of productivity of workers for different periods, the inclusion of such higher frequency job mobility will also be useful in incorporating time fixed effects (Lentz et al., 2020). I use the aggregated case-level outcomes for each employee to derive the employee-level productivity measure. Employees with higher charge sheet time are considered less productive.

I now estimate the model assuming the number of classes of managers as $M = 2$ and classes of police stations as $K = 2$. Two factors guide this assumption of a finite number of classes. The first one relates to past literature, which assumes that a small number of groups can represent the substantial heterogeneity in the classes. For example, Bonhomme et al. (2019) assume ten firm classes in the Swedish data and recently they have also assumed 10 classes in the research on the labour market in the USA and Italy (Bonhomme et al., 2020). The substantial earnings difference across all classes (either manager or firm) is critical for assuming the number of classes. The second criteria relates to the restriction posed by the finite sample available for analysis. The research based on economy-wide employee-employer matched data (Bonhomme et al., 2019) has a large sample size of 0.5 million workers in 42K firms. Therefore, at an average of 140 workers per firm, Bonhomme et al. (2019) can choose to have several firm classes equal to 10 and still have many workers present within each class. The sample size of the police data I use is smaller when compared with economy-wide administrative data used in previous research. The police department sample has 9581 police officers (Investigation officers), 1007 managers (Station head officers) employed within 282 police stations. This amounts to around 9 workers per manager and 30 workers per police station in my data.

Figure 1.5: Estimates of the static model on police department data of Haryana. Estimates of means of log-productivity, by worker type (IO), manager (SHO), and police station class. I order the manager class (M = 2) and firm class (K=2) (on the x-axis) by mean log-productivity. On the y-axis we report estimates of mean log-productivity for the L = 3 police officer/Investigation Officer types.



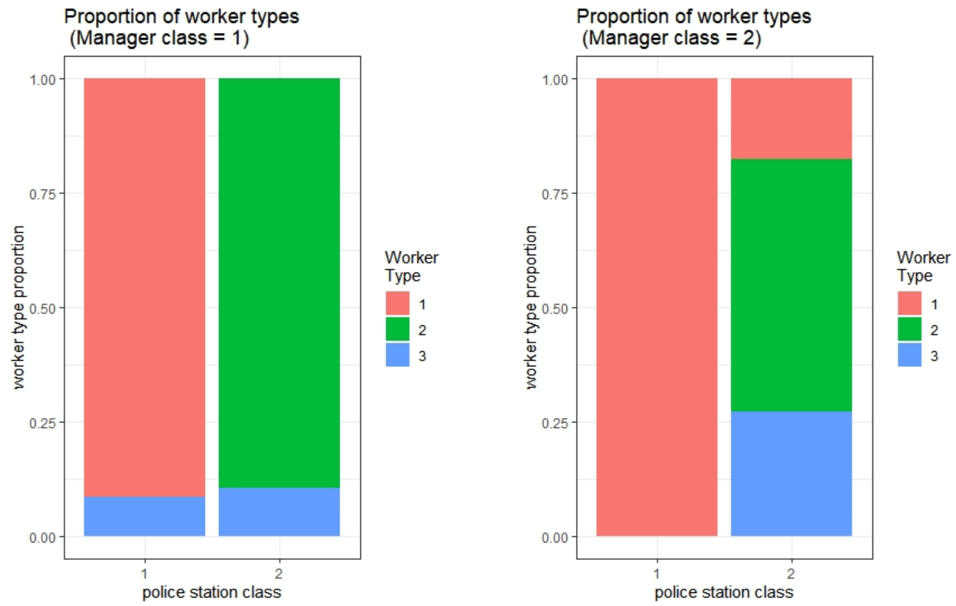
Note: Log productivity in the x-axis is the negative transformation of log(Time to chargesheet)

I estimate the manager and firm classes by weighted k-means clustering described in Section 1.6.1. I estimate the model parameters using step 2, shown in Section 1.6.2. My estimates are based on the number of manager classes M=2 and police station classes K=2. I use the Gaussian finite mixture in equation 1.1 assuming the number of worker types L = 3. I estimate the productivity distribution and proportion of job movers across managers and firms using equation 1.8, and then I estimate the worker proportions using equation 1.9. As described in Section 1.6.2, I estimate the finite mixture model using the ECM (Expectation Conditional Maximisation) algorithm. A well-known problem associated with the ECM algorithm is that it can converge at local maxima and consequently fail to reach global maxima (Wu, 1983). To alleviate this concern, I estimate the parameters using multiple starting points using a grid-based parameter search methodology (Biernacki et al., 2003). I then choose the result (global maxima) that has the maximum likelihood among the converged solutions.

The results of mean worker productivity are presented in Figure 1.5. The estimation results show the mean log-productivity of workers when matched with low type managers (m=1) and high type managers (m=2) separately. Within the manager classes, police station classes are shown ordered by productivity. So police station class (k=1) shown on the x-axis has lower productivity than the class k=2. In both panels in the Figure 1.5, I show the mean log productivity of the 3 types of workers in each type of police station class. The difference in log productivity (Figure 1.5) among different worker types across the manager and police station classes shows the worker-manager-police station heterogeneity. The estimates indicate the complementarities between worker, manager, and police station types, as the mean productivity of the same worker type plotted across police station types is not parallel. There is growth in the productivity of high-type workers when matched with the high-type police station and manager. For example, suppose I match the high type worker ($\alpha = 3$) to a highly productive manager and police station. In that case, there is a 40% benefit in doing so when compared with matching the lower type worker ($\alpha = 1$) to the highly productive manager and police station. Thus, the match-related complementarities are large in magnitude, suggesting that workers can gain immensely by matching with the right type of manager and police station.

I also present the estimates of $\pi_{\alpha mk}$ or the proportions of workers in the manager and police-station classes. Figure 1.6 represents the worker proportions. I show worker proportions within low productivity managers (m = 1) in the left figure, whereas in the right figure, they are for high productive managers (m=2). I observe that, within the less productive manager class (m=1) and least productive police station (k=1), most of the workers are of the lowest type $\alpha = 1$. These figures also then, show the sorting pattern that exist in the police force. The highest type worker proportion monotonically increases with the higher productive classes, i.e.,

Figure 1.6: Estimates of the proportions of worker types. Worker proportion in manager class m =1 (left) and m=2 (right) across police station classes



the positive sorting of workers to manager-firm classes. The proportion of high type workers is 10% with the lowest manager type and firm class, whereas 70% of the workers have the highest manager and firm classes. This positive sorting of workers resembles what has been found in the wage heterogeneity literature. The variation in log earnings is due to sorting patterns, i.e., high-productivity firms employ high type workers disproportionately. My model of three-sided heterogeneity reveals a large difference in worker productivity due to the strong presence of complementarities that are not observed in the wage dispersion literature.

1.8.1 Variance-Covariance decomposition of productivity

In this subsection, I propose a variance decomposition of the productivity. I extend the methodology of Abowd et al. (1999), Card et al. (2013), and Fenizia (2019) to my model where the heterogeneity comes from three sides. In my model, the variation in productivity is explained by worker quality α_i, manager m_i, and firm heterogeneity k_i. I follow the Bonhomme et al. (2019) methodology, in which I perform the three-sided decomposition of productivity by linearly projecting the log productivity on the worker, manager, and police station classes indicators, without interaction. The variance-covariance decomposition of the linear model is given below.

$$
\begin{aligned}
Var(Y_{it}) = \; & Var(\alpha_i) + Var(m_{it}) + Var(k_{it}) + Var(\epsilon_{it}) + \\
& 2\,Cov(\alpha_i, m_{it}) + 2\,Cov(\alpha_i, k_{it}) + 2\,Cov(m_{it}, k_{it})
\end{aligned} \tag{1.10}
$$

where α_i is employee type, m_{it} is manager class and k_{it} is police station class. Equation 1.10 decomposes the variance of log productivity into the variances of worker type effect α , manager class m, police station k, the combination of the covariances, and residual variation. The results of the variance-covariance decomposition from equation 1.10 are shown in Table 1.1. The worker productivity component explains 57% of the total variation. The worker share is high and comparable to recent estimates of worker effects in wage dispersion (Bonhomme et al., 2019; Lentz et al., 2020; Bagger et al., 2013; Abowd et al., 1999; Card et al., 2013). Managers explain 6.2% of the productivity described in the three-sided model, and the effects of the police station are similar (6.4%). Thus the effects of the manager on productivity are comparable to firm-specific effects on productivity. In my estimation, the manager (Station Head Officer) effect is in line with the literature discussing the role of management on firm productivity (Fenizia, 2019; Lazear et al., 2015; Bloom and Van Reenen, 2007; Bloom et al., 2013).

Table 1.1: Variance decomposition exercise

	Variance share
Var(Worker)	57.3
Var(Manager)	6.2
Var(Police station)	6.4
2Cov(Worker, Manager)	10.3
2Cov(Worker, Police station)	10.6
2Cov(Manager, Police station)	9.1
Corr(Worker, Manager)	27.4
Corr(Worker, Police station)	27.9
Corr(Manager, Police station)	72.1
R squared	31.9

Notes: Linear regression $Y_{it} = \alpha_i + m_{it} + k_{it} + \epsilon_{it}$ on the estimated values of model

Table 1.1 also shows the share of productivity variation explained by the covariance between workers, managers, and police stations. The covariances explain 30% of productivity variation. The correlation between the manager and police station is 72%, which shows a high degree of sorting between the managers and police stations. The degree of correlation between workers and managers is 27%, similar to the correlation between workers and police stations. This moderate correlation between worker-manager and worker-police station types shows the presence of positive sorting. Similar positive sorting of workers is reported in the literature on wage determination, where high-wage workers tend to sort to firms that offer high wages (Bagger et al., 2013; Card et al., 2013; Abowd et al., 1999; Lentz et al., 2020). The presence of moderate sorting of workers will be important in the counterfactual exercise shown in the next step. In the next section, I increase the degree of positive assortative match of workers with managers and police stations.

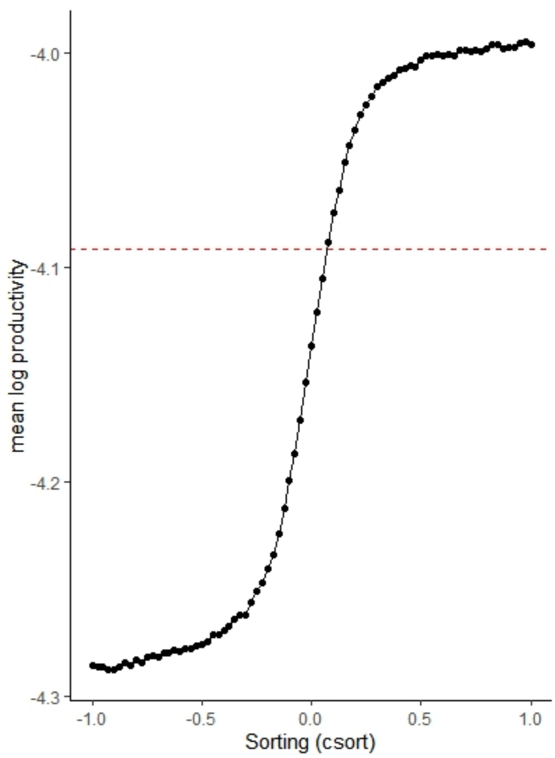
1.9 Reallocating workers: Counterfactual simulations

I have estimated the underlying parameters of the productivity distribution in the previous section. The estimation of equations 1.8 and 1.9 gives estimates of the underlying structural parameters of the model described in Section 1.3. In this section, I execute a counterfactual exercise to show that the changes in the matching pattern of workers with managers and firms can increase aggregate productivity. I change the matching rule by reallocating workers to different managers and police stations while keeping the number of workers and their quality fixed. While performing the counterfactual exercise, I rely on the complementarity of production shown in the estimates of mean log productivity in Figure 1.5. The constraint on the number of workers of specific types within manager and police station classes is taken from the estimates shown in Figure 1.6. I assume that the log productivity distribution remains identical when workers are matched with different classes of managers and police stations/firms.

There are certain matching rules defined in the literature that provide optimal aggregate productivity when the production function has complementarities between input factors. Becker (1973), and Eeckhout and Kircher (2011) both states that positive assortative matching is optimal when the production function or the match surplus exhibits supermodularity (a strong form of positive complementarity). In the Indian police, productivity gains from matching the high-quality worker with a highly productive manager are higher (87%) when compared with matching a low-quality worker with a highly productive manager (57%). So the optimal matching rule will be to pair high-type workers with high-type managers and low-type workers with the less-productive manager (Topkis, 2011; Eeckhout and Kircher, 2011). On the contrary, if the complementarities are negative or the submodularity exists in the production function, then the optimal matching rule should be negative assortative matching.

I follow the following algorithm to vary the degree of assortative matching. I compute the counterfactual worker proportion in each manager and firm type for two matching rules, namely positive and negative assortative matching. In Figure A.3, worker proportions are calculated using the pure positive assortative matching rule. I compute the counterfactual proportions in Figure A.3 by rank ordering the worker, manager, and police station by their types/classes and then allocating the workers to manager and police station classes as per their rank. Similarly, counterfactual allocation of worker types $\pi_{mk}^{nam}(\alpha)$ for negative assortative matching is calculated. I then simulate the intermediate sorting patterns by randomly allocating some workers within the manager and police station classes. To get a sequence of multiple sorting patterns, I increase these randomly chosen worker proportions iteratively (by 0.5% of the total worker population). The degree of positive assortative is matching increasing in these sequences.

Figure 1.7: Haryana police department's aggregate productivity (Y-axis) calculated using multiple degrees (X-axis) of workers matching with managers and police stations.



Note: csort in x-axis is the simulated sorting pattern. Corner values represent the positive (+1) and negative (-1) assortative matching rule

I use the simulated sequence of sorting patterns $\pi_{mk}^{cf}(\alpha)$ described above to generate the counterfactual productivity by using the parameter estimates from Section 1.6. Figure 1.7 shows the counterfactual simulation results. The x-axis shows the simulated sorting pattern, which I generated using the algorithm described above. In the x-axis, corner values represent the positive (+1) and negative (-1) assortative matching rule. I estimate the benefit of reallocating police officers by using the productivity distribution of all the simulated match rules (x-axis) and find the optimal sorting pattern of workers that maximises total productivity in the police department.

The results in Figure 1.7 show that the police department's aggregate productivity increases monotonically as the degree of workers matching with managers and police stations changes from negative assortative to positive assortative. The supermodular nature of the production function in the three-sided case shows pure positive assortative matching as the optimal solution. Table 1.2 shows the estimates of change in productivity between the original and counterfactual states. Results show that the police department can increase productivity by 9.2% by reallocating the workers using a positive assortative match rule, i.e. matching high-quality workers with highly productive managers and police stations. I also compare the counterfactual distribution of productivity with the current productivity distribution in the police department. The optimal match leads to higher benefits in the top 90% percentile of the productivity distribution. Table 1.2 shows that the 90% percentile receives a 30% improvement in productivity. This is because the current allocation of high-quality workers in the police department is sub-optimal in terms of matching. High gains can be achieved by leveraging the strong complementarities between workers, managers, and police stations.

Table 1.2: Estimates of productivity at optimal matching rule

Reallocation exercise ($\times 100$)			
Mean	Median	10% quantile	90% quantile
Positive Assortative matching			
9.2	6.7	-3.9	30.7

Differences in the means, quantiles of log productivity between two samples: counterfactual sample where workers are reallocated optimally, and the original sample

1.10 Conclusion

In this paper, I decouple the effects of workers, managers, and firms on productivity and show that heterogeneity matters. The worker, manager, and firm types heterogeneity are essential determinants of productivity. The empirical analysis uses data from an Indian police department. It shows that a manager's contribution to productivity is significant, and a central planner can increase productivity by leveraging the complementarities between worker and manager-firm matching. Counterfactual simulation shows that if high-type workers are matched to high-type managers and highly productive police stations, then aggregate productivity of the police department can be increased by ten percent. This suggests misallocation of resources within the police department.

Identifying the roles of workers, managers, firms, and their interaction relies on the job moves observed in my micro-level data. The estimation methodology adopted in the paper has the advantage of beingmore robust than linear fixed effects models, since it does not have a functional assumption like additive and linear assumptions of the AKM's fixed-effects model. The model does not restrict the match-related complementarity arising from workers placed with different types of managers and police stations. This methodology helps me recover the structural estimates of the parameters that define heterogeneity in the production function. Moreover, this methodology adopts an approach that classifies managers and firms into discrete types, thereby circumventing the limited mobility bias issues debated in the literature of two-sided heterogeneity.

This paper brings new insights into the productivity of public institutions like police departments, which is difficult to measure, especially in developing countries like India. The enormous productivity gap across the police stations arises from the underlying heterogeneity of workers, managers, and firms. This paper shows that similar to the private sector, managers are relevant in police departments too. The significant manager effect helps to understand the functioning of public institutions from the perspective of managerial talent and leadership. The results also reconcile the theoretical framework where complementarities in production function can lead to different optimal matching rules. This study shows that the optimal matching rule in the Indian police department is positive assortative matching. The positive assortative matching rule is due to positive complementarity between worker and the manager-firm match types.

The methodology adopted in this paper is general for scenarios when the outcome is generated from a process where heterogeneity is three-sided. However, I use police department productivity to show the presence of heterogeneity. Therefore, the empirical estimates of the magnitude of misallocation can be extrapolated to police departments only. Future research can adapt this methodology to specific sectors of the economy and the public sector departments.

As previously discussed, this paper uses job mobility to identify misallocation of resources in the public sector in India and also persistent productivity gap across locations. How this persistent gap remains incentive-compatible in the public sector, remains an open question.

2 Effects of Airbnb on the housing market: Evidence from London.

2.1 Introduction

The rise of Airbnb, a short-term rental platform has been exponential. The influence of Airbnb on local housing markets, particularly its impact on housing prices, is widely debated in research [1]. A digital platform like Airbnb has faced criticism that it negatively impacts the tenants in the local housing market by increasing the rental prices. However, Airbnb is also associated with the negative externality[2] caused by tourists to the local housing market, like noise and pollution that can reduce the rental prices in the neighborhood. Thus, the effect of Airbnb on rental market prices is ambiguous. The resolution of this ambiguity of the Airbnb effect is essential for local authorities and policymakers who need to balance the renter and landlord's welfare in the local economy. Worldwide, Airbnb has faced strict regulations in major cities like New York, London, Amsterdam, Berlin, Paris, and many more[3]. One reason regulators cite is the increasing cost for living of residents due to platforms like Airbnb. Thus, the estimates of the Airbnb effect on local housing prices can guide the policymakers to take informed decision.

In this paper, I study the effect of Airbnb on housing rentals in the Greater London area by combining two novel datasets. The first dataset is from Zoopla, UK's largest website for rental housing listings. I collected the individual property level data listed on the rental market from 2008 to 2017 on the Zoopla website. From this data, I create a panel of individual-level house rental prices and property characteristics. I combine this data set with Airbnb's property supply data, collected from the Airbnb website. I use the difference-in-differences strategy to identify the effect of Airbnb on housing rental prices. I treat properties with more than three bedrooms as the control group because Airbnb has less than one percent of total properties with more than three bedrooms, while the rental market has a higher proportion (10%) of properties with more than three-bedrooms. Thus, Airbnb should not constraint the supply of more than three-bedroom properties in the long-let market. The primary identifying assumption that both treated and

[1] Horn and Merante (2017); Àngel Garcia-López et al. (2020); Barron et al. (2021); Koster et al. (2021)

[2] Sheppard and Udell (2016); Horton (2015)

[3] San Francisco, Los Angles, Vienna, Tokyo, Hobart (Wegmann and Jiao, 2017; von Briel and Dolnicar, 2020)

control properties located in a small neighborhood should show similar trends in rental prices without Airbnb is validated by examining the parallel trends of rental prices for property types in pre-Airbnb years. Thus, DID estimates the impact of Airbnb on rental properties.

The difference-in-differences also deal with the endogeneity problem where growth in the supply of Airbnb is due to unobserved changes in amenities that attracts tourists within the local housing market itself. Since the long-term housing rental market also responds to neighborhood quality shocks, the endogeneity concerns between Airbnb supply and traditional market rental prices of homes can bias the results severely. This paper uses the DID identification strategy that relies on the individual property panel. Therefore, any ward-level shock that affects the local housing market is controlled by including the ward-year fixed effect in regressions.

Using the DID estimation, I found that a 10% increase in the Airbnb properties in the neighborhood ward increased the real rents of less than equal to three-bedroom properties by 0.1% compared to the control group consisting of more than three-bedroom properties. The growth in the number of Airbnb listings in London was thirty percent in 2017, leading to a large impact on the rental prices of properties. This paper also estimates the heterogeneous impact of Airbnb according to property size. The results show that the rental price in the smaller one-bedroom properties increased to 1.4% from the average effect of 0.1%. This heterogeneous effect on smaller properties is greater in magnitude because one-bedroom properties substitute for hotel rooms, and homeowners supply a higher proportion of properties on Airbnb, thus further reducing the supply of one-bedroom property in the long-term market.

Few studies have estimated the effect of Airbnb on the housing market. Barron et al. (2021) looked at the impact of Airbnb on US cities using shift-share instrument strategy. They found that a 1% increase in Airbnb properties leads to a 0.018% increase in rent. Koster et al. (2021) studied Airbnb properties in Los Angeles area using local government regulation and found the rent to be down by 5% when Airbnb was banned across the border. Àngel Garcia-López et al. (2020) found a similar effect in Barcelona. My results are closest to Barron et al. (2021), though nearly half in magnitude, which shows the importance of including the ward level time-varying fixed effects. These results thus show that Airbnb can impact the rental prices in London, which has seen an exponential increase in Airbnb listings.

The mechanism through which the home-sharing phenomenon impacts the housing market can be through supply reallocation (Sheppard and Udell, 2016; Zervas et al., 2017). With the entry of Airbnb, now the owner of the property can choose to supply the house between short let market through a platform like Airbnb or supply the property in the traditional long let market. As the demand side market of Airbnb and the long-let rental market caters to different types of people, there are differences in willingness to pay rent for the same property. If renting out property through Airbnb is more profitable, the traditional rental market will face supply constraints as landlords move their property in the short-let market. This reduction in the property supply can cause the rental price to increase in the traditional rental market. Barron et al. (2021); Horn and Merante (2017) show the reallocation of the housing stock from the long term to the short term rental market, making the supply reallocation channel a prominent mechanism of rental price rise in the neighborhood due to Airbnb.

There are few reasons why Airbnb should not impact rent. Airbnb market size is not large enough to impact the traditional housing market. Owners might be very risk-averse and may want a constant income stream through rent rather than a high price through renting out on Airbnb, which comes with the occupancy risk of property like the market of hotel rooms (Coyle and Yeung, 2016; Kim et al., 2017). The negative externality caused by tourism by increasing noise and pollution in the neighborhood also can decrease the rent (Filippas and Horton, 2017). The estimates show that the supply constraint effect dominates the net effect on rental prices. The effect of Airbnb on smaller sized properties is highest, as the one bedroom property is the perfect substitute for hotel rooms. The growth of Airbnb is the primary reason for the supply constraint in this property segment, thus, leading to the maximum increase in price.

I further show the robustness of the difference-in-differences results by testing a placebo effect. Airbnb started its London operations in 2011; therefore, Airbnb's supply from 2011 to 2017 should not impact the rental prices in 2008-2010. I test two placebo strategies - in the first, placebo treatment is given to the pre-Airbnb years (2008-2010) by assigning ward-level supply of Airbnb properties in 2012, 2013, and 2014 to 2008, 2009, and 2010 respectively. In the second strategy, ward-level supply of Airbnb properties in 2014, 2015, and 2016 is assigned to 2008, 2009, and 2010 respectively. Results do not show any impact on the rents.

In the second robustness test, I test whether Airbnb causes more rental price increase in areas with better local amenities. Past research has shown that school quality has a significant impact on housing prices. Airbnb's effect on rental prices is higher in wards where changes in school quality drive positive local demand shocks. I measure positive school quality change as schools converted into academies or new academies opened in the neighborhoods.

I add to the growing literature on Airbnb, which attempts to estimates its effect on the housing market. Barron et al. (2021), Koster et al. (2021), and Àngel Garcia-López et al. (2020) for the USA, Los Angeles, and Barcelona, respectively. Past research has used spatially aggregated data on prices. Spatially aggregated average prices are prone to biases due to changes in the composition of population that is renting and owning the properties. They also produce biased results as neighborhood-level unobserved amenities can impact the entry of Airbnb and long-term rental demand simultaneously. I contribute to the literature by using the individual property panel data in a difference-in-differences methodology to estimate the impact of Airbnb, which is less prone to biases.

I also contribute to the literature by showing that rents of smaller properties increased more due to Airbnb's entry. I use reduced form estimates to document the heterogeneous effect of Airbnb on the housing market based on the size of the property. Smaller properties are in higher demand in the tourist accommodation market thus, homeowners of smaller properties shift more towards the short-term market due to high rental yields. The heterogeneity analysis adds to the recent literature (Calder-Wang, 2021; Almagro and Domınguez-Iino, 2019), which estimates the effect of Airbnb on the welfare of heterogeneous agents.

This study estimates the impact of Airbnb in London, which is a large tourism hub. The local government of London has already regulated Airbnb by creating the licensing mechanism for landlords who want to short-let the property for more than 90 days. The results of this study are important for policymakers because policymakers' welfare function can now take into account the relationship between the presence of Airbnb and rent. Urban local bodies who want to regulate Airbnb can also devise policies based on the property size. This study shows the increase in rent in smaller properties is higher than large properties, so the renters seeking small properties face higher welfare loss than the others.

2.2 Background

Airbnb is a marketplace that enables people to rent short-term properties. The company does not own any properties but matches property owners or prospective landlords and short-term tenancy seekers and generates revenue from the transaction fees per booking. Airbnb started in 2008 with its first booking in San Francisco as Airbed & Breakfast (Brown, 2016), and now it has over 3,000,000 lodging listings in 65,000 cities across 191 countries. Airbnb is the most prominent home-sharing platform in the UK (Guttentag, 2015). About 1.5 million people reported staying in Airbnb lets in London between 1 September 2015 and 31 August 2016 (Snelling et al., 2016). Levin (2011) shows that this exponential growth is the distinctiveness of internet platforms that can scale start-up-level operations to sizeable industrial-scale operations in a small time frame and lower costs.

2.2.1 Effects of Airbnb on housing supply

Traditionally the supply-side market has been segmented. Hotel businesses supplied properties to the short-let market, and the traditional housing market supplied to the long-let market. The emergence of peer-to-peer digital market like Airbnb has caused significant changes to this segmented market. Technology lowered the cost of entry for individual owners and provided a flexible supply framework. Properties on Airbnb now compete with traditional avenues like hotels, thus making them a substitute for a hotel room (Einav et al., 2016). According to the data provided by the government's Valuation Office Agency, there are 3.5 million residential homes in London. Total number of properties supplied on Airbnb in London (2017) is around 3.4% of the London's total housing supply. Few studies have empirically shown a negative effect on hotel revenue due to Airbnb's entry (Zervas et al., 2017; Dogru et al., 2019).

The consequences of Airbnb's entry is that property owners who were only supplying in the long-term rental market, now have an additional option of supplying the property in the short-let market. The entry of Airbnb reduces supply in the long-term housing rental market. In short run, if the supply is sufficiently inelastic, the long-term rental price will increase (Barron et al., 2021; Horn and Merante, 2017). UK Housing market is generally known to have an inelastic supply (Hilber and Vermeulen, 2016), and this can make the effect of Airbnb more prominent on the long-term rental market. The magnitude of increase in prices also depends on the land available in the city and the regulations determining the supply (Gyourko and Molloy, 2015).

The quantity of the supply shift of properties from long-term rental to short-term markets and the magnitude of price increase depends on many factors. The homeowner might short-let the spare room and live in the property simultaneously in the genuine home-sharing sense (Quattrone et al., 2016). This would have a negligible effect on the rents as a homeowner does not affect the rental market supply. Without Airbnb, the empty room would not have gone to the long-term rental market. However, this might not be true if the renter can sub-let the property in the short-let market. Subletting provides the existing tenant with the additional income source from unused space and drives up the rents.

The magnitude of Airbnb's effect also depends on the risk averseness of the property owner. Risk-averse landlords might prefer the constant income stream of rent through the long-term rentals rather than the revenue stream subjected to occupancy risk in the short term market. The short term bookings by tourists are inherently risky in terms of assured occupancy. Thus, these risk-averse owners will cause no reallocation of supply, and hence, no effect on prices (Coyle and Yeung, 2016).

Short-let marketplaces like Airbnb can also affect the traditional long-term rental market in ways that can reduce the prices. There can be negative externalities on a neighborhood having a large number of Airbnb rentals. The noise and high tourist inflow can make the neighborhood less desirable to residents (Horton, 2015) and cause downward pressure on rents. However, Airbnb's net inflow of tourists can also increase rents as local businesses may flourish due to tourists. This can lead to higher real estate demand as businesses would want to enter areas with high Airbnb growth. Farronato and Fradkin (2018), and Basuroy et al. (2020) find the positive relationship between Airbnb and restaurant employment, and Jaffe et al. (2017) shows the effect of the positive externality on the neighborhood.

In this paper, I focus on the rental prices, but the price of a property should rise as the expected discounted future rental income rises (Poterba, 1984). The effect of Airbnb should directly reflect on property prices. However, the behavior of the homeowner looking to purchase a property might be different from the renters. The homeowner may value the negative externality due to a high number of Airbnbs in the neighborhood. For example, they might be more sensitive towards noises. If such a case is there, there might be no direct relation between Airbnb growth and increased prices through supply constraints only. Thus I restrict the analysis to short-term rental prices and Airbnb growth in the neighborhood.

The effects of Airbnb on the rental prices in the traditional long-let market can be ambiguous. The property owner can supply in Airbnb market, and by making this choice, the property owner can reduce supply in long let market. This would lead to increase in long-term rents, whereas, the negative externality can make the neighborhood with high Airbnb listings less desirable to residents thus, putting downward pressure on the rents. The net effect of Airbnb is analyzed in this paper, and I found this net effect on the property rentals to be positive.

2.3 Data

2.3.1 Airbnb

I am using data from the Airbnb website to infer historical Airbnb supply in the neighborhood. I combine two different sources to achieve the complete data set for the yearr 2008-2017. The first source is the Inside Airbnb[4] initiative, which collects data from the Airbnb website for all the major cities of the world. Researchers have used this data source to show the impact of Airbnb on housing market for eg. Àngel Garcia-López et al. (2020) for Barcelona and Duso et al. (2020) for Berlin. Data for the year 2017 is missing from Inside Airbnb. I use web scraping techniques to get the missing data from the Airbnb website[5]. The data is at the listing or property level and contains information about the property characteristics like the number of bedrooms, various amenities, per day price, address[6], geographic coordinates[7], calendar level availability, host-related information, and property reviews. Airbnb also provides information about the date when the property entered the Airbnb marketplace. I have used this information to construct the history of property activity in the short-let market. This approach has been followed by Zervas et al. (2017), and Barron et al. (2021) to calculate the Airbnb intensity in the neighborhood. Average length of stay of guest is around three days (Haywood et al., 2017), therefore, I classify property listed on Airbnb as a short-term rentals.

I aggregate Airbnb supply using ward boundaries from the Office of National Statistics (ONS). Wards represent the small administrative unit that coincides with the electoral boundaries. Greater London has 633 wards. Ward is chosen as the unit of analysis because they represent the housing market boundaries that have less heterogeneity. The demography of residents and neighborhood amenities have small within ward variations. The spillover across wards is unlikely to cause any significant bias to the results because a recent study by González-Pampillón (2019) finds that spillover effects due to supply shock tend to vanish after nearly 200 meters. The average area of the London ward is two sq. km; therefore, the spillover effect due to properties on the boundary of wards will be small.

2.3.2 Property rental prices

Data on the traditional long-term rental market is from the online property portal Zoopla. Zoopla attracts 40 million visitors monthly for property search and has the most exhaustive property advertisements. Zoopla has made available historical advertisements of all properties on it's website. I use the data obtained from

[4]Details about the data can be accessed through `http://insideairbnb.com/about.html`.

[5]In December 2017, using automated programs, I web scraped the Airbnb website to get the listing for London city

[6]Depending on the privacy settings, precise address sometime can only be shown to guests with a confirmed reservation

[7]Hosts can choose the privacy setting to show the approximate geocoded location of the listing. This feature was introduced in 2016 where a algorithm generates the random coordinates within 200-300 mts around original address

web scraping techniques using automated programs. The data includes the unique property identification, date of advertisement on the Zoopla portal, rental asking prices, property type (house, flat, bungalow, and maisonette), property size-related information (number of bedrooms, reception, and bathrooms), and address of the property. I use this novel data set to construct the rental supply history of all the properties in London.

Zoopla advertisement data might not represent housing market data because Zoopla has an online presence only. The validity of the data is checked by comparing the data with the representative sample of property market data from the Office of National Statistics (ONS) and Census data[8]. The report compares the rental price index generated from Zoopla property data and the ONS data. The trend lines shown in Figure B.1 of Appendix 1 are comparable. The report also shows a high correlation between the number of private residential households calculated using the 2011 Census and the number of private rental advertisements in Zoopla, showing that Zoopla property listings are a representative sample of the UK housing market (Appendix 1, Figure B.2). Livingston et al. (2021) compared the estimates of median monthly private rent price from the Valuation Office Agency (footnote) and the Zoopla median prices for all local authorities in England from 2014-2016. The analysis demonstrates the high correlation with R^2 values of 0.97-0.98 showing that Zoopla data is a good proxy of private rental prices.

The posted price of rent might differ from the final transaction price in the housing market. To alleviate this concern, I utilize the transaction-level data from the Zoopla website, which contains the dynamic bargained price history for all the properties. For the unique property listing, I consider the latest asking price to get the accurate rental price under the assumption that the latest asking price is the transaction price itself. Still, for some properties, the latest asking prices can differ from the final agreed-upon prices. However, this might not be a substantial problem as past research (Chapelle and Eyméoud, 2020) show that bargaining is less of an issue for rents, and online posted prices are a good measure of actual rents.

There does exist land registry data that has the property transactions related to purchase and changes in ownership. This data might be slow to adjust to the rental market changes in the short run. The average tenure of a property with the same owner is 12 years and this means that repeated house sales panel data will have fewer transactions in the periods when Airbnb enters the shot-let market.

[8] https://www.ubdc.ac.uk/media/2050/data-note-260418-analysis-of-zoopla-rental-listings-da
pdf

2.3.3 Data on schools and academies

Bertoni et al. (2020) show that families in England have a significant preference for schools that convert to academies. Schools that are 'rebranded' as academies are up to 14% more likely to be ranked as the most preferred choice relative to a baseline probability of picking a first-choice school at random. I use data on school conversion to academies and the opening of new academies to capture the perceived quality of education in the neighborhood. The UK Department of Education provides data on the education institutions. In this data, historical institution type of schools can be identified upto year 2019. I construct a variable identifying the yearly status of the school type indicating whether the school is an academy or not. I use two variables to construct this indicator. The first one has the conversion data of the school, and the second variable is a flag that indicates if the school has been operating as an academy from the day of opening itself. Since the data also provides location of the schools and academies, I finally constructed the ward and year-wise measure of a number of academies in the neighborhood from 2008 to 2017.

2.3.4 Descriptive statistics

Figure 2.1 shows the trend of the number of properties supplied through Airbnb marketplace. In the year 2008, Airbnb has no presence in London, but by 2017, the number of total properties listed on Airbnb has grown to 128,000. This significant increase in Airbnb can reallocate the housing supply from the long-term to short-run rentals. The exponential growth of Airbnb is not limited to London, but other cities around the world have encountered a similar trend, e.g. Barcelona (Àngel Garcia-López et al., 2020), USA (Barron et al., 2021), Los Angeles (Koster et al., 2021) , Boston (Horn and Merante, 2017). The London housing market faces supply constraints (Hilber and Vermeulen, 2016) due to planning regulations, and the additional supply constraints due to the growth of Airbnb can impact rental prices.

In figure 2.2, I show the Airbnb listings across the neighborhood level (ward) for 2017. The central part of the city that is popular with the tourists has higher Airbnb listings. Figure 2.3 shows the average weekly rents (£) in the wards for 2017. There is a high correlation between the number of Airbnb properties and weekly rents, but this may be because local amenities in the wards drive higher rents in long-term rental and Airbnb demand from tourism. So the causal claim that Airbnb is driving up the rents is a challenging research question.

In Table 2.1, I compare the average weekly rents landlords can receive in the long-

Figure 2.1: Number of Airbnb listings in Greater London area [2008-2017]

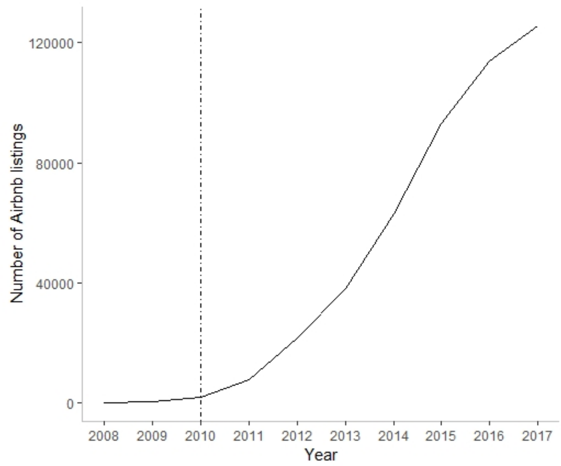
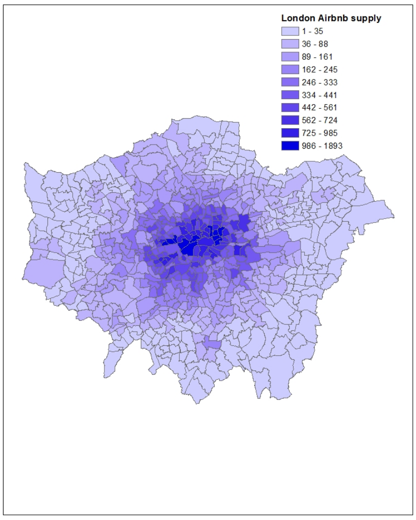


Figure 2.2: Airbnb supply in wards of Greater London in year 2017



let rental market (Zoopla) with the revenue they can expect from their property in the short-let market through Airbnb. I calculate average weekly rental prices and Airbnb prices in the same ward across different property sizes. Table 2.1 shows that landlords earn over 2.2-2.9 times more on Airbnb when compared to long-term rental market. This calculation assumes that the landlords' choices do not affect prices in both short-term and long-term markets. This differential in short-term and long-term rental prices also represents the inherent risk in renting out through Airbnb due to occupancy risks and can be driven by the selection effect. Still, the large magnitude reflects the high profitability few property owners can achieve by shifting supply from long-term market to short-term market places like Airbnb.

Figure 2.3: Average weekly rents (£) in wards of Greater London in year 2017

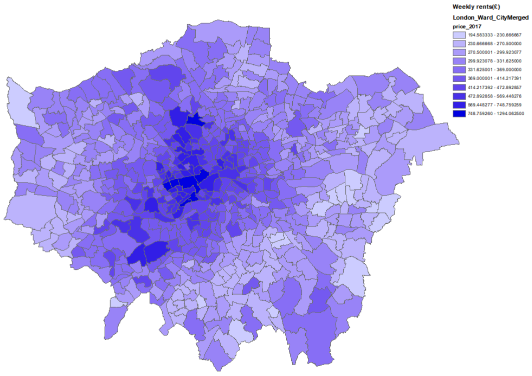


Table 2.1: Comparison of short-term rental market (Airbnb) and long-term rental market (Zoopla) rents for 2017 (London City)

Number of bedrooms	Rents weekly(£)	Airbnb revenue weekly(£)	Ratio of Airbnb to weekly rents
1	319	714	2.2
2	416	714	2.2
3	571	1596	2.8
3+	736	2130	2.9

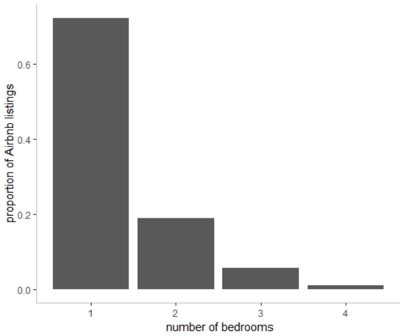
2.4 Empirical strategy

Identifying Airbnb's effect on the housing market is challenging because Airbnb listings are not randomly distributed across the city. Instead, they are concentrated in the areas that are simultaneously attractive to both the residents in the long-let market and the visitors/tourists in the short-let market (Koster et al., 2021; Snelling et al., 2016). So the growth in rents across the neighborhoods are susceptible to endogeneity concerns because the entry of Airbnb in these neighborhoods is itself driven by amenities (Àngel Garcia-López et al., 2020; Barron et al., 2021). Thus, the increase in long-term rents might be driven by the local amenities rather than by the growth of Airbnb properties.

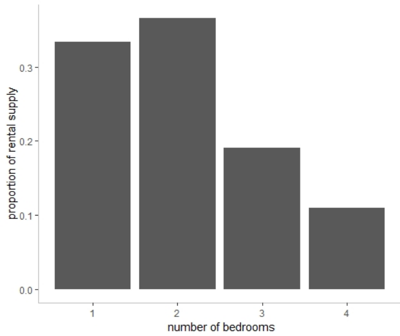
I address this identification challenge in two ways. Firstly, I use the size of the properties to define the control group or the property type whose supply is not impacted by Airbnb's entry. Airbnb generally provides the alternative to hotel rooms (Zervas et al., 2017) and mainly supplies the short-term rental properties that are substitutes to hotel rooms.

Figure (2.4) compares the composition of properties by the number of bedrooms between the short-let market in Airbnb and the long let market in Zoopla. The comparison in the figure is done using the data for London for the year 2017. The first figure (2.4a) shows that more than 75 percent of properties listed in Airbnb

Figure 2.4: Proportion of property types in Airbnb and rental housing market



(a) Airbnb



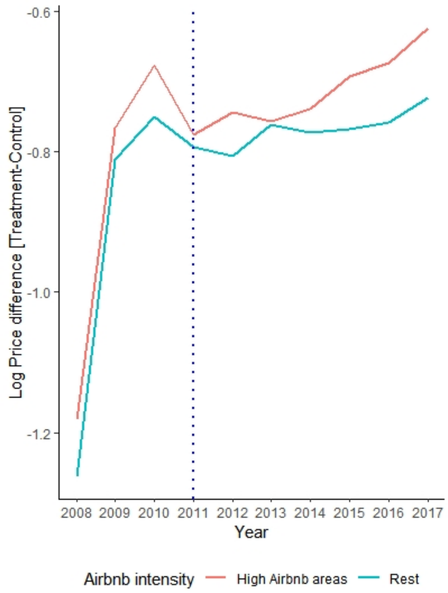
(b) Zoopla

have only one bedroom supporting the hotel substitutability argument. There are substantial differences between the composition of large-sized properties in Airbnb and the long-term rental market. If Airbnb mainly caters to tourists, it should have a negligible number of properties in the more than three-bedroom segment. The proportion of properties with more than three bedrooms is 10 percent in the long-let rental market, compared to less than 1 percent in Airbnb. Thus, the properties with more than three bedrooms should not encounter any supply constraints due to Airbnb. I use this rationale to use the bigger properties as the control group as Airbnb's growth in the neighborhood should not impact rental prices of more than three-bedroom properties.

The DID methodology also rests on the Stable Unit Treatment Value Assumption (SUTVA). SUTVA requires that the outcome of the unit depends only on the treatment that was assigned, not the treatment of others around him. The possible violation might occur when people start substituting into more than three-bedroom properties due to Airbnb's entry as they do not face supply constraints. This assumption is less probable because renters face budget constraints while substituting for large-sized properties. For example, properties with more than three-bedroom have 44% higher rent than the median treated property containing two bedrooms. This sharp increase in rental prices across properties of different sizes makes the SUTVA assumption more plausible.

Secondly, I use the panel data of individual property rental listings. I can control the unobserved neighborhood-level time-varying effect and the property level fixed effect using this novel data. Finally, I employ the differences-in-difference empirical strategy in the individual level panel data of properties. In the differences-in-difference strategy, I take properties with more than three bedrooms as control groups. The remaining properties in the neighborhood are considered as treated

Figure 2.5: Evolution of difference in log rent [Treatment-Control] in high Airbnb intensity wards vs the rest. Treated houses are with bedrooms ≤ 3 and control houses are having bedrooms > 3. High Airbnb areas: top 2 deciles of the Airbnb listings in 2017



units to test if their rental prices are affected by Airbnb, caused by a supply shift in the local housing market.

Figure (2.5) shows the graphical evidence of this empirical strategy. Each line in the figure tracks the difference in rental growth between Treated (<= 3 bedrooms) and Control (> 3 bedrooms) properties but for different neighborhoods. I compare the difference in rental price growth between neighborhoods with high Airbnb growth and the remaining areas of London. I define high Airbnb intensity neighborhoods as the wards whose growth in Airbnb listings lie in the top two deciles between 2011 and 2017. Figure (2.5) show that the gap between both lines has increased. This widening gap shows that areas with a higher Airbnb presence (red line) experienced more considerable growth in the price difference between the treated and control groups than the other areas (blue line). Moreover, the rent gap between the high Airbnb neighborhood and remaining areas of London increased by a larger magnitude post-2013, coinciding with the substantial increase in the Airbnb supply in London as depicted in figure (2.1).

2.4.1 Empirical specification

My main empirical specification consists of a difference-in-differences strategy where property rental prices are exposed to supply constraints brought about by the growth of Airbnb properties in the neighborhood. I estimate the regression equation (2.1) using the property panel data.

$$\ln P^s_{iwt} = \alpha_i + \gamma_{wt} + \eta(lnAirbnb_{wt}) + \beta(\ln Airbnb_{wt} \times D_i) + \epsilon_{iwt} \qquad (2.1)$$

In the the equation (2.1) P^s_{iwt} measures the rental price of property i in the ward w at year t. $Airbnb_{wt}$ is the number of Airbnb listings in the ward w at year t. I use the logarithm of Airbnb supply and a rental price to estimate the price elasticity of supply (reference?). D_i is the dummy variable indicating whether the property is a treated or a control unit. D_i is equal to one for treated units if the number of bedrooms is less than equal to three whereas, D_i equal to zero for control units having the number of bedrooms greater than three. The variable of interest here is the β as in the empirical strategy, large size properties with the number of bedrooms greater than three are not exposed to Airbnb supply growth and are treated as control units. β in equation 2.1 shows the differential impact of Airbnb growth on the smaller size properties ($D_i = 1$) when compared to control units in the same neighborhood across time.

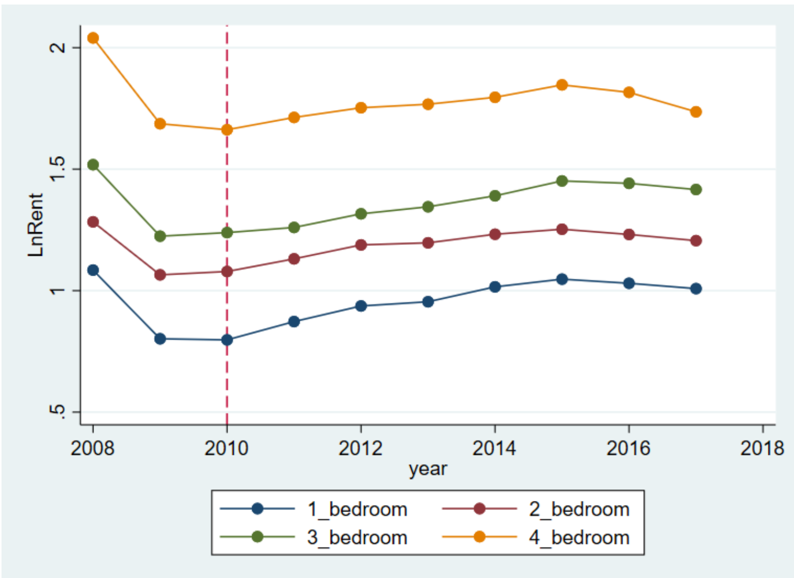
I also control for a rich set of fixed effects in DID equation to recover the unbiased estimate of the effect of Airbnb on the rental prices. The γ_{wt} represents the ward-time fixed effect. α_i represents the property level fixed effect. The endogeneity concerns due to unobserved ward level characteristics are alleviated by including the ward-time fixed effects. Shocks specific to the neighborhood (ward), such as urban revival and demographic changes that affect the housing market prices, can be controlled as Àngel Garcia-López et al. (2020) estimated the effect of Airbnb on the housing market of Barcelona. Including the property level fixed effects also controls the property-specific characteristics that might impact rental price. Thus, the inclusion of the fixed-effect helps correct the bias due to unobserved house quality and changes in the composition of house quality in the neighborhood. Housing market price show seasonal patterns within the year

The panel data collated at the property level is an unbalanced panel. Each unit of property is not observed every year because of the data generating process itself. Property is observed in the panel data when it is advertised for rent on the Zoopla website. The fixed-effects model will inconsistently estimate the model parameters if some property units are more likely to be listed in the market in the sample period. Selection of properties in the panel periods must be strictly exogenous, conditional on the individual property characteristics and neighborhood time-variant shocks. This exogeneity condition is most likely to be satisfied in my unbalanced panel, so my results produce consistent estimates (Wooldridge, 2009).

Housing market prices show seasonal patterns within the year. Property prices experience increase in prices and transactions during the spring and summer. In contrast, prices decrease during autumn and winter (Ngai and Tenreyro, 2014). Annual aggregation of data makes this seasonality fluctuation less of a concern. Ward is chosen as the unit of analysis because they represent the housing market boundaries that have less heterogeneity. Wards represent the small administrative unit that coincides with the electoral boundaries. Greater London has 633 wards. The demography of residents and neighborhood amenities have small within ward variations [9]. Wards are ideal as a unit of analysis because of low spillover effect in the housing markets due to boundary effects (González-Pampillón, 2019). The most important identification assumption in the DID equation (2.1) is that without Airbnb's entry, the growth in rental prices of treated units ($<= 3$ bedrooms) and control units (> 3 bedrooms) should have similar trends in the neighborhood. Thus, the key underlying assumption of difference-in-differences is the parallel trends assumption.

In the pre-treatment period, when Airbnb is not present, i.e. before 2010, we can test the parallel trends assumption from the data. Figure (2.6) shows the number of bedroom-wise rental price growth from 2008 to 2017. Though the number of pre-treatment years is only three, all the property types still follow the parallel trend. After Airbnb entered the market in 2010, there is a visible growth in the rental prices of one-bedroom properties in the aggregate data. This paper shows that this visible growth in the rental prices of properties can be linked partly to Airbnb's exponential growth in London.

Figure 2.6: Number of bedroom wise log rental price from 2008-2017 in London



[9]Profiles of each ward in Greater London. (Authority, 2016)

2.4.2 Heterogeneous effects of Airbnb on the property type

Earlier, in figure (2.4), we compared the composition of the properties by size. Airbnb serves as a substitute for certain types of hotels. Zervas et al. (2017) studies that hotels in the budget and economy segment have the highest negative impact due to Airbnb. These hotels generally have single rooms without any luxury or upscale amenities and are similar to Airbnb properties. Thus, one-bedroom properties are most exposed to Airbnb as demand for small property is highest from tourists. I measure the heterogeneous impact of Airbnb by the number of bedrooms in the property using the regression specification equation (2.2) below.

$$lnP^s_{iwt} = \alpha_i + \gamma_{wt} + \sum_{r=1}^{3}(lnAirbnb_{wt} \times d_{ir})\beta_r + \epsilon_{iwt} \tag{2.2}$$

Where d_{ir} is a dummy that indicates if house i has r bedrooms in it and β_r shows the heterogeneous effect of Airbnb on the rental price. I consider the properties having more than three bedrooms as the reference category.

2.5 Results

In Table (2.2), I report the results of Airbnb's impact on long-term rents using the empirical specification described in section (2.4.1). The dependent variable is a logarithm of rental prices of individual properties across the observation years (2008-2017). In column (1), I control for the property fixed effects. The result points that Airbnb supply is associated with the increase in the long-term rents. A 10% increase in Airbnb properties in the wards is associated with a 0.06% increase in real rents of smaller properties as compared to the larger or control properties.

In column (2), I control both for the ward $\times$ year fixed effect and property fixed effects. The ward-year fixed effects are incorporated to test if any ward-level time-varying characteristics are driving the results. The coefficient in column (2) is positive and significant, which implies that an increase in Airbnb listing causes the rental price of the treated properties (less than equal to 3 bedrooms) to be more than the control unit (properties larger than the 3 bedrooms). The magnitude of coefficient increased from column 1, showing that Airbnb might be affected by other confounding factors that could affect the results in column 1. This estimate implies that a 10% increase in the Airbnb properties in the wards pushes the real rents of smaller properties by 0.1% as compared to the larger properties.

Figure (2.7) reports the results of the heterogeneous effect on the rental prices described in the equation (2.2) of section (2.4.2). The figure (2.7) represents the coefficient explaining the effect of the property type by the number of bedrooms.

Table 2.2: Difference-in-differences estimates by year and treated house (property ≤ 3 bedrooms)

	ln Rental Price * 100	
	OLS	OLS
	(1)	(2)
LnAirbnb×Treated	0.6340***	0.9310***
	(0.0868)	(0.0928)
House FE	Yes	Yes
Ward*Year FE	No	Yes
Wards cluster	631	631
N	211,498	211,498

Notes. The dependent variable *ln Rental Price* is the logarithm of the rental price of the property listed on the Zoopla website for rental. ln *Airbnb* is lograthim of the number of Airbnb listing in the ward in the year of observation. *Treated* is the dummy equal to 1 when the property has less than equal to three bedroom. Standard errors clustered at the individual property level are reported in the parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

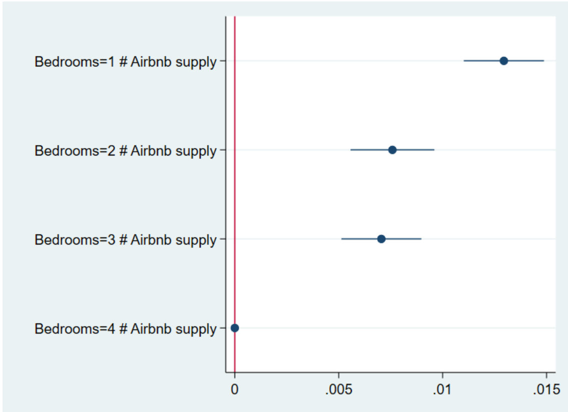
The specification already controls for the individual fixed effects and the ward-time fixed effects. The control group or the properties that have a number of bedrooms greater than three is the reference category. The difference-in-differences coefficient for smaller properties having one bedroom is the largest. Rental prices of one-bedroom increased by 1.4% due to a 10% increase in the Airbnb listings in the neighborhood.

The coefficients of the larger properties are smaller than those of one-bedroom properties and are statistically significant too. The results show that the rental price of properties having only one bedroom increased more than the larger sized properties. In the earlier section (2.4) using the figure (2.4), I made this argument through differences in supply constraints. The empirical analysis validated that Airbnb, a substitute for a hotel-like one-bedroom property, increases the rents of similar sized properties in the traditional rental market.

2.6 Robustness

The results in the previous section are estimated using the difference-in-differences strategy. In this section, I discuss two potential threats to my identification strategy and provide empirical evidence that the results in the section (2.5) are robust.

Figure 2.7: Heterogeneous treatment effect of Airbnb on the property type relative to control group (> 3) bedrooms



2.6.1 Time-varying trends between treatment and control units

The validity of the difference-in-differences approach relies on the parallel trends assumption or under the hypothesis that no time-varying differences exist between the treatment and control groups apart from the differential effects causing changes to the treatment groups. The difference-in-differences strategy relies on the parallel trend assumption between treatment and control group. Though the parallel trend assumption is difficult to prove, researchers have shown (Galiani et al., 2005; Bertrand et al., 2004) that visual evidence is one way to access its validity. In the section (2.4.1) I provide graphical evidence of the common trend assumption, but I can also assess its validity by performing the placebo test. One way is to give fake treatment to some treated units and then access if this produces zero impact. I follow a strategy similar to Schnabl (2012) and add the post-treatment effects in pre-treatment years to test the placebo effect to support the robustness of the results.

Airbnb started its operations in London in 2011. Therefore Airbnb's supply from 2011 to 2017 should not impact the rental prices in 2008-2010. I use two placebo strategies to show that the time-variant Airbnb exposure is causing the increase in the long-term rents. In the first robustness test, placebo treatment is given to the pre-Airbnb years (2008-2010) by assigning ward-level supply of Airbnb properties in 2012, 2013, and 2014 to 2008, 2009, and 2010 respectively. Similarly, in the second test, I give placebo treatment to the pre-Airbnb years (2008-2010) by assigning ward-level supply of Airbnb properties in 2014, 2015, and 2016 to 2008, 2009, and 2010 respectively. I then use this placebo test to estimate the DID equation (2.1) with placebo treatments.

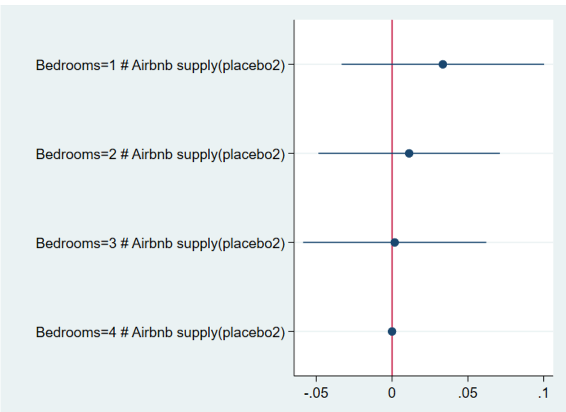
Table 2.3: Difference-in-differences (placebo) estimates by year and Treated (less than equal to 3 bedrooms)

	ln Rental Price * 100	
	Placebo 1	Placebo 2
	(1)	(2)
LnAirbnb(placebo)×Treated	0.0987	-1.040
	(0.4060)	(1.2100)
House FE	Yes	Yes
Ward*Year FE	Yes	Yes
N	26,214	26,214

Notes. The dependent variable *ln Rental Price* is the logarithm of the rental price of the property listed on the Zoopla website for rental. ln *Airbnb* is logarithm of the number of Airbnb listing in the ward in the year of observation. *Placebo 1:* The number of airbnb properties in 2012-2014 is re-coded to the same wards in 2008-2010. *Placebo 2:* The number of airbnb properties in 2014-2016 is re-coded to the same wards in 2008-2010. *Treated* is the dummy equal to 1 when the property has less than equal to three bedroom. Standard errors clustered at the individual property level are reported in the parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table (2.3) presents the results of the placebo treatment. In column (1), the DID coefficients have a positive and small coefficient but large standard errors. Similarly, column (2) has a negative coefficient but has large standard errors. It is plausible that we can't reject any impact of placebo effects for some property type, so I test my placebo strategy using the equation (2.2) of heterogeneous treatment effect. Figure (2.8) shows the estimated coefficient of the heterogeneous treatment effects, estimated for placebo treatment strategy where greater than three-bedroom properties are taken as control or reference category. The coefficients indicate that no impact on the rental price due to Airbnb placebo cannot be rejected for all the types of properties.

Figure 2.8: Heterogeneous treatment effect of Airbnb placebo treatment on the house type [2008-2010]



2.6.2 Demand of houses in neighborhood and entry of Airbnb

One of the assumptions in the identification strategy is that the neighborhood times year fixed effects can control neighborhood-level trends. The neighborhood-level amenities should not create bias in the results as we can control for these time-varying neighborhood-level fixed effects. This paper adopts the identifying assumption that all property types encounter the same growth in rental prices due to unobserved neighborhood amenities and uses the difference-in-differences approach. Still, we can test whether segmenting the housing market according to local amenities causes an effect of a different magnitude on the housing market. I do this by segmenting the wards of London into two categories using education quality in the neighborhood as the measure.

Past research has shown that school quality is one of the most influential factors determining property prices (Nguyen-Hoang and Yinger, 2011). The neighborhoods which have high-quality schools face high demand for properties from the population. Another important fact is that school quality does not drive Airbnb's short-let properties' market as tourists' preferences are independent of school quality. Suppose there are two subsets of wards, the first one has higher-quality schools, and the second subset has lower-quality school and there is a similar growth of Airbnb listings in both types of wards. In that case, the neighborhoods providing higher quality education should see higher rental price growth than neighborhoods with fewer quality schools (Collins and Kaplan, 2017; Machin, 2011; Gibbons et al., 2013). This is because the effect of supply constraint is more significant at a location facing demand booms. Hilber and Vermeulen (2016) show this phenomenon in the local housing prices of England where supply constraints due to scarcity of developable land are mainly through regulations.

I use the opening of new academies and the conversion of schools to academies as a variable to measure the increase in the neighborhood's attractiveness due to the perceived increase in education quality. Academies in England are autonomous educational institutions associated with higher academic outcomes (Gibbons et al., 2013). The public school admission process is based on the distance to school from the primary address of the pupil. In the school admission process, parents are generally asked to rank their school preferences in the neighborhood. Bertoni et al. (2020) documented that parents rank academies higher than traditional schools in the admission process and prefer to reside in areas closer to them.

So the presence of academies in the neighborhood (wards) is a sound proxy of the education quality. I divide the wards into two samples to proxy the education quality in the analysis's time frame from 2008 to 2017. The first subset consists of wards with fewer academies, and the second sample includes wards with a higher number of academies (greater than three).

Table 2.4: Heterogeneous effect of Airbnb: School quality represented by number of Academies in the neighbourhood

	Ln Rental Price * 100		
	Full sample	Academies > 3	Academies <= 3
	OLS	OLS	OLS
	(1)	(2)	(3)
LnAirbnb×Treated	0.931***	1.212***	0.767***
	(0.0928)	(0.1571)	(0.0587)
House FE	Yes	Yes	Yes
Ward*Year FE	Yes	Yes	Yes
Wards cluster	631	83	547
N	211,498	19,562	211,498

Notes. The dependent variable *ln Rental Price* is the logarithm of the rental price of the property listed on the Zoopla website for rental. ln *Airbnb* is lograthim of the number of Airbnb listing in the ward in the year of observation. *Treated* is the dummy equal to 1 when the property has less than equal to three bedroom. Standard errors clustered at the individual property level are reported in the parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

I then run the DID specification (2.1) on both the samples. Table (2.4) presents the impact of Airbnb growth on the rents for subsamples based on education quality in the neighborhood. Column (2) shows the magnitude of coefficient for wards with a number of academies larger than three, whereas column (3) shows the remaining wards. The impact of Airbnb on the rents of wards having higher school quality is 80% larger than the remaining wards. The differential effect of Airbnb based on education quality shows that amenities like school quality make an impact that Airbnb amplify in the housing market. The market segmentation based on education quality validates the main result and shows that local amenities do matter in Airbnb's impact on the housing market.

2.7 Conclusion

This paper studies the effect of Airbnb on the housing market. The exponential growth of short let platforms like Airbnb has disrupted the hotel industry and its impact on the housing markets is increasingly debated. Concerns about the adverse effects on the local housing market have caused the need to investigate the consequences of the Airbnb phenomenon on the traditional housing market.

I identify the effect of Airbnb on long-term rental prices using the difference-in-differences strategy where smaller properties are exposed more to the Airbnb marketplace. Large-sized properties are less affected by the Airbnb phenomenon because Airbnb does not supply more than three-bedroom properties. The identification relies on the rich source of novel property level panel data of long-term rental advertisements. I use one of the largest property listing website's administrative data and merge that data with the Airbnb listings data to estimate the difference-in-differences coefficients.

I focus on the Greater London area and take the control group as the larger properties because Airbnb supplies less than one percent of the total listings in that segment. I control for time-varying ward fixed effects and the individual property fixed effects and find that Airbnb raises property rents. Airbnb constraints supply in the housing market and causes the rental price to increase.

The results show that a 10% increase in Airbnb properties causes a 0.1% increase in rents. The Airbnb impact on the rents of smaller or one-bedroom properties is the largest. This high impact on the one-bedroom properties is in line with the hypothesis that Airbnb is the substitute for hotel rooms, and most of the properties supplied by Airbnb have features of one-bedroom hotel room-like property. I also test the robustness of the results using the placebo test, where I give the placebo treatment of future Airbnb growth to treated units in the pre-Airbnb time. I also test whether Airbnb is more prominent in the areas in demand by the residents. I do this by measuring the changes in education quality as the factor that make the housing market more sensitive to any further constraint in supply due to Airbnb.

A digital market like Airbnb is a new phenomenon, and there is growing research that studies the effect of these non-tradition peer-to-peer markets. The paper adds to the past research in three ways. Firstly, this paper adds London to the growing list of cities that are used as a case study to analyze the effect of Airbnb on the towns and cities worldwide. It adds to the finding that London too faces the rental impact due to Airbnb.

Secondly, I use the novel microdata of individual properties from 2008 to 2017 to build panel data of repeated rents. The magnitude of the Airbnb's impact on the rental market has been debated due to the biases caused by the time-varying neighborhood-level unobserved factors. Using my novel data and applying it to a difference-in-differences strategy, my estimates have less tendency to be biased and produce results that are more accurate and robust.

Thirdly, I show that Airbnb's effect is heterogeneous and depends upon which type of properties face the most supply constraint. Thus, within the ward, not all properties are affected similarly. This paper indicates the importance of property composition as a critical variable that past research has not been able to control.

The results of the paper imply that Airbnb does affect the long-term housing market. This effect has distributional consequences as individuals who seek to rent smaller properties face the most significant rental price increase. The Airbnb effect on rental prices is amplified in the areas which have better amenities like schools. The results of paper are important for policymakers. The local government in major cities is particularly interested in balancing the welfare between the homeowners who typically gain with Airbnb and the renter who loses due to increased rents. This paper shows that renters face an increase in rent in London due to Airbnb, and policymakers should include this in the welfare calculation. If an urban local body or regulator limits the permanent reallocation of supply from the traditional housing market to the Airbnb market, this can increase the renters' welfare.

The paper also shows that the heterogeneous impact on the property type is also an essential factor. Instead of a blanket ban on all property types, regulators can devise property size-specific Airbnb market regulations. For example, London has banned both large and small properties rented out in Airbnb for more than 90 days without permission from the local authorities. The size of the property can be used to reevaluate the welfare calculation in deciding the regulation.

Finally, the limitation of the study is the data of Airbnb is imperfect as it comes from a publicly available Airbnb website that does not have the precise information on the date of exit of the property. This could bias the magnitude of the impact on rental prices. Nevertheless, the fundamental phenomenon that the supply constraint in residential housing due to Airbnb can cause price increases in areas remains valid.

3 Resisting Modernisation due to Foreign Occupation: The Role of Religious Identity

with Yatish Arya

3.1 Introduction

Religious groups sometimes resist modern inventions/institutions that lead these groups to lower human capital outcomes.[1] In this context, we study whether religious groups living under colonial regimes are affected by institutions introduced by the coloniser. There is some anecdotal evidence that suggests that this might happen. For example, Iranians have expressed apprehensions about the COVID-19 vaccines after their 'supreme leader', Ali Khamenei banned such vaccines from the US and Britain.[2] In this paper, we particularly focus on how deposing a ruler affects the literacy outcomes of his religious group under foreign occupation.

Deposing the ruler can affect the literacy outcomes of his religious group due to many reasons. For instance, foreign occupiers might discriminate against the religious group of the deposed ruler due to fear of rebellion. It can also be the case that, when the ruler is deposed, his religious community may feel aggrieved. Thus, they might refuse to take up modern education introduced by the occupiers, even against their economic interests. On the other hand, the impact of foreign occupation can also be positive. For example, the religious group of the ruler might have acquired certain economic advantages under his regime and continue to prosper under the foreign rulers. Similarly, suppose the local ruler and foreign occupier reach an amicable settlement on the terms of rule. In that case, the ruler may facilitate the participation of his religious community in the education system introduced by the occupier.

We study this question in the context of the colonisation of India. Two large religious communities, Hindus and Muslims, lived together in the country before British colonisation. The British, during the process of colonisation, deposed many existing rulers. These rulers belonged to different religions, predominantly Hinduism and Islam.[3] We construct a novel data set combining the religion of the deposed ruler

[1] See Martinez-Bravo and Stegmann (2020)

[2] https://indianexpress.com/article/world/iran-covid-vaccine-ban-us-uk-7138369/
After this, the Iranian Government disallowed foreign companies to test COVID-19 vaccines on the Iranian people (See: https://www.thehindu.com/news/international/iran-bans-foreign-companies-from-testing-covid-19-vaccines-on-iranians-says-president/article33536728.ece)

[3] Others include rulers of religions like Sikhism. We discuss this in greater detail in the main body of the paper

using the Imperial Gazetteer of India (Hunter, 1908), with the literacy outcomes of Hindus and Muslims at the district level using census data for 1881, 1911 and 1921.

We find that Muslim literacy is two percentage points (p.p.) lower in districts where the ruler deposed by the British was Muslim. Similarly, Hindu literacy is 1.5 p.p. lower in regions where the deposed ruler was Hindu. These results are robust to controlling for demographic variables such as population shares of different religions, population shares of different castes, and average household size. They are also robust to including local geographic factors like a coastal dummy, major census city, altitude, latitude, and longitude. We also include local development measures as controls, including urbanisation, occupation classes (industry and agriculture) and port city.

Moreover, though we have many geographic, demographic and economic controls, bias caused by omitted variables is still a possibility. We deal with it in two ways. First, we take the difference in literacy rates of the two religious communities as the dependent variable. This difference cancels out any variable affecting literacy across districts. Our results remain robust to this specification.

Second, we use an instrumental variable approach. We use the spatial progression of the Maratha Hindu rebellion from the birthplace of Shivaji to identify the exogenous variation in the religion of the ruler. Shivaji was a rebel king who became a symbol of the Maratha Hindu Rebellion (Vartak, 1999).Results are robust to this specification as well.

Exploring mechanisms, we find a set of results consistent with the hypothesis that when the western colonisers replaced Islamic rulers, Muslims' 'sense of pride' was hurt. Thus, they refused to take up western education (Lewis, 2003; Aziz, 1967). Abdul Lateef, a Muslim reformer promoting modern education in colonial Bengal (province in India), describes the condition in 1885, in his own words[4]

> *"Mahomedan youth kept themselves aloof from the English schools and the new knowledge. This was attributed to the natural pride and the great bigotry of the Mahomedans .... It was an obvious effect of history"*

Belmekki (2007), reviewing the impact of British rule on Muslims in India, states that[5]

> *"When Muslim hegemony was gone and real power lay with the British, the Muslims would not, could not, forget that they had once ruled over the land. Their reaction was bitter and truculent"*

[4]For the full quote, see Section 3.3. These excerpts are taken from Firdous (2015).

[5]Belmekki (2007) refers to Aziz (1967)

The above argument depends on the subjects identifying with the ruler. We posit that this 'self-identification' with the ruler will be higher in the *core* of the kingdom than in the *periphery*.[6] Thus, it should be the case that the resistance to western education is stronger at the *core* of the kingdom than the *periphery*. We define the *periphery* as the districts that share a border with states ruled by kings of other religions (all others are considered *core*). We find that all the negative effect on literacy associated with the religion of the deposed comes from the *core* of the annexed kingdom.

Thus, we not only find evidence consistent with the hypothesis that Muslims resisted western education because they did not like losing political power, but ours is the first paper to document a similar effect for Hindus. Though the historical literature focuses on Muslims not taking up western education, we find Hindu literacy is also lower where a Hindu ruler was deposed. Thus, the results shed light on the fact that even followers of non-Islamic religions disliked their rulers being removed and refused to take up western education.

We consider other plausible mechanisms that could explain the above results. For example, Metcalf and Metcalf (2006) argue that the British excluded the old (Muslim) aristocracy from all higher posts in the government because they discriminated against the community that had previously held political power. This discrimination could lower the education outcomes of Muslims because this would lower their incentives to get educated. However, using employment records of the British bureaucracy, we find that Muslim employment rates in these services are not lower in regions where the final ruler was Muslim. The same is true for Hindus.[7]

Another plausible reason for these results could be that Muslim literacy is lower under Muslim kings and Hindu literacy lower under Hindu kings, even if the ruler is not deposed by the British. To check the importance of the deposition of the ruler, we document literacy outcomes of those regions in India that were under the indirect rule of the British.[8] In these regions, the local rulers were not deposed.

[6]Many historians have argued that the sovereignty of kings at the end of the medieval period in India (after the year 1707) existed only in core regions of their state and not in the periphery. See, Malik (1990),and Stein (1999). Also, political theorists who study kingdoms and empires argue that the relationship between rulers and subjects in the *periphery* is different from the relationship between rulers and subjects in the *core*. We discuss this more in Section 3.3

[7]The British might not discriminate at the employment level against the community of the deposed ruler but might provide fewer educational opportunities to them at the level of the provisioning of schools and educational scholarships. However, this does not seem to be true as they particularly made sure that communities that were not doing well in terms of school enrollment (usually Muslim) were eligible for scholarships and reduced fees in public schools, and the colonial government established a number of schools in Muslim majority districts (Progress of Education in India, Quinquennial Reviews, 1897–1927, (Cotton, 1898)).

[8]See, Iyer (2010)

They were responsible for the local administration and collected revenue on behalf of the British. Chaudhary and Rubin (2016) found higher Muslim literacy in districts ruled by Muslim kings and did not find a negative effect for Hindus under Hindu kings. These results are consistent with the claim that the ruler's deposition plays a vital role in lowering the literacy outcomes of his religious group.

We see our paper as the first to provide empirical evidence that foreign occupation can adversely affect the literacy outcomes of the religious group of the deposed ruler. Though providing evidence for the exact mechanism is beyond the scope of this paper, the set of results are consistent with the hypothesis that when foreign occupiers dislodge local rulers, the religious group of the local rulers show resistance to the inventions/institutions introduced by the occupiers. Thus, we give some quantitative evidence supporting the hypothesis espoused by many historians like Lewis (2003), and Aziz (1967). However, we also show that, though these historians have mainly discussed this resistance hypothesis for Islam and its followers, we find similar effects for Hindus in India.

3.1.1 Related Literature

Religion and Human Capital formation: Our paper contributes to the literature on how the religion of people affects their human capital formation (Becker and Woessmann (2009), Saleh (2018)). These papers discuss how certain **religious practices** affect human capital formation. Our work departs from these papers by highlighting the role of **religion as an identity** rather than as just a practice.[9] Our paper documents results that strongly suggest that religious identity can make individuals and groups take decisions that decrease their human capital outcomes, thus hurting their economic interests.

Religion and modernity: Another strand of literature that our paper contributes to is the literature that studies the relationship between religion and modernity (Carvalho (2013), Binzel and Carvalho (2017), Bazzi et al. (2019)). These papers focus on how modern life and reforms led to a revival of religious practices in various places. Our paper focuses on how religious groups resisted modernity because of their religious identity. We find evidence consistent with the hypothesis that Islamic civilisation resisted modern education because of losing political power (Lewis (2003), Aziz (1967)). We also provide evidence that this resistance was not limited to Muslims. Hindus in British India also resisted western education where the deposed ruler was Hindu.

[9] There is a strand of literature on identity and economic outcomes starting from Akerlof and Kranton (2000).

Resistance to western interventions: Finally, our paper contributes to the literature that studies resistance to specific western interventions by people most likely to gain from those interventions. Lowes and Montero (2018) argue that forced medical interventions reduced trust in medicine in Africa. Martinez-Bravo and Stegmann (2020) argue that misinformation against vaccines by the Taliban was effective in reducing the demand for them in Pakistan. We contribute to this literature by providing evidence consistent with the hypothesis that resistance to western education emerged in religious groups because of their opposition to the foreign occupation that deposed their local ruler.

The rest of the paper is structured as follows. The next section discusses the conceptual framework. Section 3.3 discusses the historical background and data sources used in the empirical analysis. Section 3.4 discusses the main results of the paper. Section 3.5 discusses the plausibility of various other mechanisms and robustness checks. Finally, Section 3.6 concludes.

3.2 Conceptual Framework

In this section, we discuss the different channels through which deposing a ruler can change the literacy outcomes of his subjects under foreign occupation. In particular, we discuss how two different yet plausible mechanisms give different testable predictions. The framework developed helps us disentangle how deposing the ruler changed the literacy outcomes of his religious group.

First, we will discuss the reason proposed by Lewis (2003) and Aziz (1967), and what kinds of predictions should be seen in the data if this reason was valid. These historians have argued that followers of Islam were reluctant to pursue education provided by the West because they resented losing political power to western regimes. If this argument is correct, then the first prediction that should hold is that Muslims should have lower literacy in those regions where Islamic rulers directly lost power to western occupiers as opposed to regions where they did not hold political power when western powers took over.

Moreover, though these historians have discussed this behaviour only among Muslims, the above argument is independent of Islam's religious practice or teachings. Any religious group whose ruler is deposed by a foreign power should then resist the education system introduced by the foreign occupier. Thus, even though historians have not discussed this effect for Hindus in India, we still should find similar effects for them. Hindus should also have lower literacy in those regions where Hindu rulers directly lost power to the British as opposed to regions where they did not hold political power when the British occupied the region.

However, the above argument does rely on a homogeneous religious identity of the subjects and their amicable association with the deposed ruler. Thus, if a religious group has more within-group fragmentation and some of these groups do not have an amicable association with the deposed ruler, they would not mind the British deposing the ruler. Thus, we would find that the negative relationship between literacy and religion of the deposed ruler will be lower for such a religious group. This sort of within-group fragmentation is usually considered to be higher among Hindus due to the historical presence of the caste system.[10] Moreover, some of these castes supported the British against the local Hindu rulers. For example, the caste of *Mahars* (considered untouchables in the caste hierarchy) supported the British against the local *Peshwa* (upper caste brahmin) Hindu rulers in the Battle of Koregaon[11]. Thus, the effect of deposing the local ruler should be lower among Hindus than a comparatively more monolithic identity of the followers of Islam.

The argument of Aziz (1967) crucially rests on subjects identifying with the deposed ruler. Historians argue that the sovereignty of kings did not extend beyond the *core* region of the kingdom at the end of the medieval period in India. Thus, subjects in *periphery* districts might not feel as associated with the ruler as subjects in the *core*[12]. If we assume that 'self-identification' with the ruler is higher at the kingdom's core than at the periphery, then the above hypothesis yields additional predictions. Particularly, given that subjects at the periphery do not consider the ruler to be sovereign, the resistance to western education should be weaker there than in the core. We test this prediction in Section 3.4.

Another prediction that emerges from analysing the above historical argument is that if the British colonisers and the local rulers reach an amicable settlement concerning the terms of rule, then the religious group of the local ruler should not resist western education. In the case of colonial India, this implies that districts that were under the indirect rule of the British[13] should behave differently than those under direct rule. Under indirect rule, the local rulers were not generally deposed but were responsible for the local administration and collected revenue on behalf of the British. Hence, if districts are ruled indirectly, then the literacy of the subjects should not be lower under the ruler of their religion. We also investigate this in our analysis.

Notice that the predictions discussed above not only follow from the hypothesis espoused by Lewis (2003) and Aziz (1967) but also from the arguments put

[10] see, Deshpande (2010)

[11] see, Geppert and Müller (2015)

[12] This is the time of the collapse of the Mughal Empire after 1707. For greater details, see section 3.3

[13] see, Iyer (2010) for greater details

forward by Metcalf and Metcalf (2006), that the British excluded the community that previously held political power from the higher posts in their government. If this were true, then the community of the deposed ruler will have lower incentives to get educated as they would have limited opportunities following the education acquired. This effect of discrimination in jobs would also reflect in the literary statistics. However, this argument requires that the employment records of British bureaucracy also show lower Muslim employment in regions where the deposed ruler was Muslim and lower Hindu employment in regions where the deposed ruler was Hindu. We thus test this prediction using the employment records of the British bureaucracy.

Note that even if some Muslims are not taking up education because of their dislike of the British colonisers who overthrew their king, those who do get educated will still find government jobs if the British do not discriminate against them. Thus, the hypothesis of Aziz (1967) is not disproved even if Muslims are well represented in government jobs in districts where the deposed ruler was Muslim.

In the next section, we discuss the historical background and the state of education in India before the 1881 census. This section provides the reader with a summary of political conditions in pre-colonial India, how the British annexed different kingdoms and how literate the population was before the British implemented their education policy.

3.3 Historical Background and Data

3.3.1 Background

The empire that dominated most of the modern-day region of India, Pakistan and Bangladesh for almost two centuries starting from 1526 is the Mughal Empire. It reached its peak in the 17th century when it extended over most of the Indian subcontinent and parts of Afghanistan. The empire territory extended over four million square kilometres (Turchin et al., 2006). The Mughal dynasty was Muslim, and the empire had an Islamic identity (Dale, 2009). We do our analysis on districts of colonial India which were part of the Mughal Empire in 1707 when it started to disintegrate after the death of Emperor *Aurangzeb*. Figure 3.2 gives the extent of the Empire.

The dissolution of the empire was followed by the emergence of small successive states ruled by Hindu and Muslim kings. Figure 3.4 shows the religions of different rulers across India. Meanwhile, the East India Company, which began as a trading company chartered in 1600, amassed significant profits and an army started annexing Indian territory, starting with Bengal in 1757 and the Battle of Plassey

Figure 3.1: Mughal Empire boundaries in 1707

Figure 3.2: Muslim Empire boundaries in 1707

(Metcalf and Metcalf, 2006). The East India Company conquered many kingdoms, deposed the kings, and established themselves as the supreme power in India. The British annexation continued up to 1857, which was the year of the Indian Mutiny or the First War of Independence. Then, the Company rule ended, and the British government took direct control over the territories.

These rapid changes in the Indian sub-continent brought major economic and social changes as well. In particular, the old political and social hierarchy went through a change. Nawab Abdul Lateef, a Muslim educator in the Bengal Province of colonial India[14], noticed how these political and social changes affected his religious community, i.e., the region's Muslims. In 1885, recalling his experiences as a District Magistrate in 24 Parganas (a district in Bengal), he wrote[15]:

> "*The Mahomedans saw themselves left behind in the race of life by their Hindu fellow-subjects, over whom they had not only exercised political power before the British regime, but also, not long before, and even under the British, had maintained a social ascendancy.*"

[14]He was noted as among the twelve most prominent Indian men in 19th century Bengal (Bradley-Birt, 1910)

[15]These excerpts are taken from Firdous (2015).

Figure 3.3: Religion of final ruler removed by British (1757-1857). Green (squares) - Muslim, Red (circles) - Hindu, Black (triangles) - Others

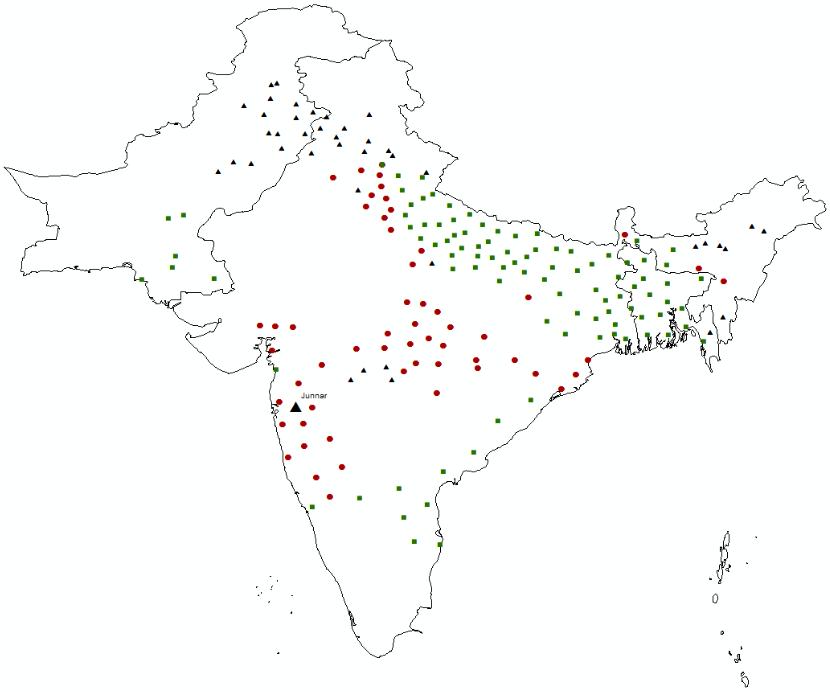


Figure 3.4: Religion of final ruler removed by British (1757-1857). Green(squares) - Muslim, Red (circles) - Hindu, Black (triangles) - Others

Trying to explain the reason for this condition, he adds:

> "*Mahomedan youth kept themselves aloof from the English schools and the new knowledge. This was attributed to the natural pride and the great bigotry of the Mahomedans. The imputation was not wholly unmerited, yet it was not the whole truth. The pride was somewhat a matter of course. It was the obvious effect of history, but no effort was made to soften it. The British government, in the consciousness of irresistible might, felt itself under no obligation to conciliate prejudice. The Mahomedan bigotry, such as it was, was not inherently worse than that of other communities.*"

This quote is insightful. First, it points to his belief that Muslims resisted English schools and western knowledge because of the 'natural pride' they felt, having once been the dominant political and social force in the region. Second, it also notes that this 'bigotry' was not 'inherently worse' among the Muslims than other communities. Thus, Lateef hints that other religious communities would behave the same if removed from political and social ascendancy.

Worried about the conditions of his fellow community members, Lateef made efforts to rid his people of this prejudice. In one such effort, he established the

Mohamedan Literary Society in 1863 and at its inauguration, he again notes:

> "*Being fully aware of the prejudice and exclusiveness of the Mohamedan community, and anxious to imbue its members with a desire to interest themselves in Western learning and progress, and to give them an opportunity for the cultivation of social and intellectual intercourse with the best representatives of English and Hindu Society, I founded the Mahomedan Literary Society* "

Many historians (Aziz (1967), Khan (1989), Masselos (1996)) in India have also attributed the Muslim community's resistance to modern education introduced by the British to resentment because the British supplanted Muslims as political masters. To quote one of them, Masselos (1996) claims that Muslims lived 'in a nostalgia of their past glories'.

> " *It was argued that psychologically they (Muslims) had not recovered from their loss of power when they were supplanted as rulers of the subcontinent by the British and that they lived in the past, in a nostalgic world of former glories* (page: 119)."

Though many historians have talked about Muslims resisting western knowledge because they lost political power, it seems that few historians followed up on Lateef's insight to look for similar 'bigotry' among the Hindus where they had lost political power. Though there is some discussion of how Hindus were not inclined to take up western education, which was linked to Christian missionaries (Majumdar, 1951), there is limited research that linked to them to losing political power. Our paper is, thus, (to the best of our knowledge) the first to test this hypothesis empirically for both communities and find the results consistent with Lateef's insight.

Further, in our conceptual framework, we note that, if we assume that the subjects associate themselves more with the king in the *core* of the kingdom than the *periphery*, then resistance to western education due to deposing the king would be higher in the *core*. We think this is a natural assumption to have given the historical context we are studying. When the Mughal Empire disintegrated, Malik (1990) argues that the concepts of *core* and *periphery* came to be defining features of 18th century pre-colonial India. Generally, the status of entities and individuals in the kingdom's core often significantly differs from that of the periphery. Often peripheral actors are kept at a distance and do not identify with the sovereignty of the kings who rule them. They are even subject to open discrimination and exploitation.[16]

[16] For a detailed discussion on this issue, look into Bevir (2010)

An excellent example of this phenomenon is the Maratha-Rajput rivalry in the late eighteenth/early nineteenth century in India.[17]. The Maratha (a Hindu sub-group geographically associated with the southwest region of India) Empire began with the rebel-king *Shivaji*. It became the dominant power in India at that time till the British defeated and tamed their power in the Anglo-Maratha Wars.[18] As they expanded north, they encountered resistance from Rajput kings (Hindu kings associated with the north-west region of India) who traditionally shared a good relationship with the Mughal Empire.[19] The Marathas were successful in their military expansion against the Rajput kings and forced them to pay tributes and taxes.[20] Thus, one would expect that Hindus who associated themselves with Rajput kings did not mind when Maratha rule was replaced by the British in their region.

In general, we think it is reasonable to assume that the association of Hindus with their kings would be higher in the *core* of the kingdom than far away. The same should be valid for Muslims as well. We find the results in line with this assumption in Section 3.4. In the following sub-section, we discuss the state of education in the Indian sub-continent before the 1881 census.

3.3.2 State of Education in the early nineteenth century

Unfortunately, there is no systematic record of literacy among the Indian masses before the British rule in India. The earliest anthropological surveys were carried out in the eastern region of India by Francis Buchanan between 1807-1814.[21] The surveys were again recompiled by Martin Montgomery.[22] Another set of report. called the Adam's Reports (Adam, 1835, 1836, 1838), prepared by a Scottish missionary on the state of vernacular education in Bengal and Bihar (1835-1838), is the first documented measure of literacy available that is disaggregated for different religious groups.

Before we summarise the findings of these surveys, we note that caution is necessary to make inferences. First, these are available only for a few districts in the eastern part of India. Second, these reports were created using second-hand information and hearsay.[23]. Thus, the scientific validity of these surveys is far from certain.

[17] To see extensive discussion on the Maratha-Rajput rivalry see Gupta (1970)

[18] For a review of the Anglo-Maratha wars, see Deshpande (2006)

[19] see Zaidi (1994)

[20] see Gupta (1970)

[21] Francis Buchanan also covered southern India in his surveys, comprising regions of Mysore, Canara and Malabar. These regions are not included in our sample because either they were not part of the Mughal Empire, and if they were, then they remained a Princely state.

[22] (Martin, 1838)

[23] Adam's report is a report collecting information from various sources and provides suggestions in great detail on how to improve the state of vernacular education in the region. Adam notes

However, they are important as they are still the best sources of information (even if partial) on the state of education in the early nineteenth century.

Table 3.1: District level education attainment survey done by Francis Buchanan during 1807-1814

District	Literate	Population	Literacy rate	Literacy rate (1881)
Purnea	16,550	2,904,360	0.6	2.7
Patna-Gaya	25,890	3,364,420	0.8	4.1
Shahabad	7,045	1,419,520	0.6	2.1

Note: Francis Buchanan surveyed the districts of East India Company from 1807-1814. The statistical tables and notes contain the state of education in the districts of Bengal and Behar. Literacy is taken as the number reported as men fit to act as the writers and born in the division. The survey also contains information on the demographics, including population. Districts in Buchanan's survey are mapped with the districts from the 1881 census. Behar and Patna city is mapped to Gaya and Patna (1881)

Both surveys agree that the state of education was in a bad situation. We present the summary statistics from Buchanan's survey in Table 3.1 and Adam's Report in Table 3.2. Table 3.1 provides literacy outcomes from three regions[24] in eastern India. The literacy rate for all districts was below 1% for all regions. Hence, this suggests that the overall literacy levels in India were low in the early eighteenth century.

Second, Table 3.2 indicates that even as early as the 1830s, Hindus seem to have taken more advantage of the educational institutions under the British rule than Muslims in the eastern part of India. It is important to note that Muslim kings ruled this region of India, and hence the early evidence is in line with our conceptual framework.

Overall, these results compared to the 1881 census data suggest that education among the masses only picked up once the British altered the mass education policy after Wood's despatch (1854).[25] Hence, we think that literacy and education were

down that his report is a collection of information from second-hand sources

> "*I have not introduced into this report any statement of facts resting on my observation and authority, but have merely attempted to bring into a methodised form the information previously existing in detached portions respecting the state of education. The details, therefore, which follow must be regarded as the results of the observations of others, and as depending upon their authority, and all that I have done is to connect them with each other and present them in consecutive order.* (page: 15)."

[24]There is also another region called Rangpur covered in Buchanan's survey. However, the data collection or reporting seems to be erroneous. It reports a literacy of 5.2% in this region in 1807, while other districts in the same region have less than 1% literacy. Moreover, the Rangpur region reports 6.2% literacy in 1881, implying only an increase of about 20%. Whereas the other districts which are reported in the Buchanan report 400-500% increase.

[25]To know more about the Wood's despatch see `https://babel.hathitrust.org/cgi/pt?id=`

Table 3.2: Literacy rates for Bengal and Bihar districts from Adam's report (1835)

District	Muslim literacy(%)	Hindu literacy(%)	Literacy(%)	Literacy (1881)
Moorshidabad	0.21	1.67	0.99	2.72
Beerbhoom	0.24	1.52	1.28	4.44
Burdwan	0.68	2.42	2.07	4.51
South Behar	0.98	0.93	0.93	2.07
Tirhoot	0.05	0.44	0.40	1.63

Note: Adam, in 1835, did the survey on the state of education in Bengal and Bihar. Adam's survey recorded the number of adults who can merely read and write. The data of surveyed district in 1835 with the district level literacy data from 1881 census. South Behar (1835) is mapped to Gaya (1881) and Tirhoot (1835) to Muzzafarpur (1881).

so rare before this period that they can be ignored without biasing our regression coefficients.

3.3.3 Data

We used the historical atlas of Schwartzberg (1978) to measure the extent of the Mughal Empire. We superimposed it onto the Indian census maps using Singh and Banthia (2004)[26] to get the districts in British India that we include in our sample. We collated district level GIS centroids from Donaldson (2018). The Indian Censuses of 1881, 1911 and 1921 cover most of the provinces of Assam, Bengal, Bihar & Orissa, Bombay, Central Province, Madras, Punjab and United Province.[27] The censuses provide data at a district level on literacy, population, area, religion, caste, occupation, urbanisation and geographical indicators like rainfall, latitude and longitude.

Enumerators consider a person literate when he or she can read or write in any language. To remain consistent with the definition of literacy, for the 1881 census, we removed those who were "under instruction" or still learning to read and write. The disaggregated literacy rate of Hindus and Muslims is available in the census.[28]

We followed the list of cities provided by the census of India and map the cities with districts containing those cities. We included the list of major medieval port cities from Jha (2013) in our empirical analysis. The year of annexation by the

`hvd.32044105337398&view=plaintext&seq=655&q1=bengal_20language`.

[26]We used the matching of Mughal Empire and Census boundaries using spatial overlay technique.

[27]We exclude Bombay, Calcutta and Madras cities as they are significantly different from the rural districts of India

[28]Age and gender-based specific literacy numbers are available to test for the robustness of results

British ranges from the year 1757 to 1871. We also include the years of Muslim rule as measured by Jha (2013).

Table 3.3: Descriptive statistics of the Colonial India districts (1911 & 1921)

	count	mean	sd	min	max
Muslim Literacy	367	0.06	0.05	0.01	0.24
Hindu Literacy	383	0.07	0.05	0.02	0.23
Literacy gap	367	0.01	0.07	-0.17	0.21
% Hindu	383	0.68	0.28	0.04	0.99
% Muslim	367	0.26	0.27	0.00	0.91
% Christian	389	0.01	0.02	0.00	0.28
% Sikhs	389	0.01	0.05	0.00	0.42
% Tribes	389	0.05	0.15	0.00	0.95
% Others	389	0.01	0.05	0.00	0.69
% Brahman Caste	389	0.05	0.04	0.00	0.24
% Low Castes	389	0.15	0.08	0.00	0.38
% Rural	389	0.90	0.09	0.32	1.00
Agriculture accp. %	389	0.71	0.13	0.28	1.18
Industry occup. %	389	0.11	0.06	0.00	0.34
Commerce occup. %	389	0.07	0.03	0.00	0.23
Profession occup. %	389	0.02	0.01	0.00	0.04
Normal rainfall	389	49.06	31.81	3.52	259.00
Latitude	387	24.81	4.42	13.06	33.57
Longitude	387	80.92	6.21	67.00	94.65
Total Area(sq km)	389	3624.51	2108.98	101.00	13888.00
Average Household size	389	4.79	0.47	3.56	6.22
Total population size	389	1032642.78	673051.61	39320.00	4837730.00
Real Income	324	22459573.95	16700272.81	248381.41	1.23e+08
Year annexed by British	387	1809.60	32.42	1757.00	1871.00
Years of Muslim rule	379	79.33	39.65	-98.00	161.00
Distance from Junnar	387	1157.79	473.51	76.64	2292.32

Note: This table lists the districts of British India defined by 1911 and 1921 Indian Census which were part of Mughal empire (1707) and ruled directly (excluding princely states).
[a] : Census document does not report the Literacy rate of Muslims in certain cities where there is negligible Muslim population. We do robustness checks excluding such sample completely.
[b] : Donaldson (2018) only reports the Income of districts where the agriculture data is available
[c] Years of Muslim rule is from the establishment of Muslim dynasty in India till the Annexation by British powers

The summary statistics of the variables in the data are shown in Table 3.3 for 1911 and 1921. The descriptive statistics in Table 3.3 reveal that the average literacy of Hindus and Muslims was similar with large heterogeneity across the districts. The Hindu-Muslim literacy gap across districts varied from -16% to 21% and shows a large difference in inter-religion education outcomes across districts of colonial India. The average population share of Muslims was 25% across districts against 70% of Hindus. It is clear that Muslims were not just a small minority but constituted a sizeable part of the Indian population.The summary statistics of the variables for 1881 is shown in Table C.1.

We also constructed a novel data set from the Imperial Gazette (Hunter, 1908) to get the religion and dynasty of the deposed ruler. It gives us the year of annexation. The Imperial Gazette is a twenty-six volume historical reference document. It lists the administrative provinces, districts, and town names in India and provides their socio-economic statistics. The Imperial Gazette otlines the history of every district. The history of the district contains information on past rulers and the date of annexation by the British. We use this gazette to determine the name of the last ruler and the year of annexation by British variables manually. To minimise the measurement error, we cross-check the details of the deposed ruler annexed by the British with historical sources (Majumdar, 1951).

Figure 3.4 shows the districts in 1911 marked by the religion of the deposed ruler. The data for the religion of the deposed ruler in the colonial Indian districts that existed as of the 1911 census is presented in Table 3.4. The British annexed 97 districts whose rulers were Muslim, and 57 districts that had Hindu rulers. Districts where the deposed ruler followed another religion or where the ruler's religion is uncertain because of the complex political climate of the time are dropped in robustness tests.

Table 3.4: Province-wise distribution of religion of last ruler in Districts (1911)

Province	Hindu	Muslim	Other	Total
Assam	2	3	7	12
Bengal	1	25	1	27
Bihar & Orissa	6	15	0	21
Cental Provinces	18	0	4	22
Madras	0	11	0	11
Punjab	4	0	24	28
United Provinces	9	35	4	48
bombay	16	8	0	24
Total	56	97	40	193

Note: This table lists the districts of British India defined by 1911 Indian Census which were part of Mughal empire (1707) and ruled directly (excluding princely states).Punjab province has majority of Sikh rulers who were deposed by British. Assam had neo-Tai and confluence of Tribal, Hindu and Buddhist religion which are tagged as others in table.

Finally, we constructed novel data on the employment of Indians in the British government using the civil list of 1871 (Quarterly Indian Civil List, October 1871). We digitised the provincial civil list of nine provinces of the British government. We used the "district distribution list" of the civil list to find the identity of civil servants employed in the district. We used the names to classify them into Indian-sounding names and European names. We then classified the Indian names using names and surnames into Hindu and Muslim (and others).

Given that historians like Metcalf and Metcalf (2006) and Ahmad (1991) have argued that the British kept Muslims from important posts of authority in the government, we focus on civil lists because it notes the important administrative jobs. These jobs are classified as necessary enough to call for loyalty and prestige from the crown as civil servants. Also, the remuneration was directly received from the crown of central colonial administration, which has a component of pension attached showing direct linkage to the colonisers (Mcilvenna, 2019).[29] The next section presents the main results of our paper.

3.4 Main Results

The main regression equations that we estimated are given below. We want to estimate the effect of the religion of the deposed ruler on the literacy of his subjects under British rule. First, we estimate equations (3.1) and (3.2) using ordinary least squares regressions with many district-level controls. These equations are given below:-

$$\textbf{Muslim Literacy}_{it} = \alpha_1 + \beta_1 \textbf{Muslim Deposed Ruler}_i + \gamma_1' X_{it} + \epsilon_{it} \tag{3.1}$$

$$\textbf{Hindu Literacy}_{it} = \alpha_2 + \beta_2 \textbf{Hindu Deposed Ruler}_i + \gamma_2' X_{it} + \mu_{it} \tag{3.2}$$

where Muslim and Hindu literacy is given for each district i in time 1881, 1911, and 1921. The Religion of Deposed Ruler in equation 3.1 is a time-invariant dummy that takes the value 1 if the deposed ruler is Muslim. The Religion of Deposed Ruler in equation 3.2 is again a time-invariant dummy that takes the value 1 if the deposed ruler is Hindu. X is the set of control variables for district i in time t. The demographic controls include population shares of different religions, population shares of different castes, and average household size. We also have a set of geographic controls: a coastal dummy, a dummy for a major census city including Calcutta and Bombay, and the altitude, latitude, and longitude of the district centroid. Finally, we added a set of economic controls which included occupation classes (industry, agriculture, services), port city and urbanisation. These controls are important as demography, geography and economic factors can be correlated with the religion of the deposed ruler and thus bias our estimates.

The first column of Table 3.5 shows that there is a negative relationship between

[29] The top rank we found was district collector / judge. The lowest position we can see is of Naib Tehsildar or assistant superintendent.

Table 3.5: Association between Religion of last Ruler and Muslim literacy in Colonial India

	Muslim Literacy			
	(1)	(2)	(3)	(4)
Muslim ruler	-0.0150***	-0.0205***	-0.0228***	-0.0194**
	(0.00520)	(0.00468)	(0.00719)	(0.00789)
Geographic controls	NO	YES	YES	YES
Demographic controls	NO	NO	YES	YES
Economic controls	NO	NO	NO	YES
Year FE	YES	YES	YES	YES
Observations	549	547	365	365

Notes: Significance levels at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Muslim literacy and the religion of the deposed ruler being Muslim. Muslim literacy is 1.5 p.p lower in a district where the deposed ruler was Muslim compared to a district where the deposed ruler was non-Muslim. It is statistically significant, even without any controls. In column 2 of Table 3.5, we add geographic controls. The magnitude of the coefficient of interest becomes larger after adding geographic controls. This suggests that Muslim rulers ruled geographical regions that had higher literacy.

In columns 3 and 4, we add demographic and economic controls. The number of observations in these columns decreases because we do not have these controls for 1881. A large Muslim population might be associated with the sorting of Muslims in poorer districts (Chaudhary and Rubin, 2011). We thus control for population shares of Muslims (and other religions). We also add occupation because occupations often were divided along religious lines.[30] Caste distribution within a district is also used as a control as it can affect literacy. Column 4 of Table 3.5 shows that the coefficient associated with the religion of the deposed ruler is still negative and statistically significant. Muslim literacy decreases by 1.94 percentage points. The mean Muslim literacy in 1911 was 6%. Thus, the Muslim literacy rate in the districts which Muslim rulers ruled is substantially lower than in those previously ruled by

[30]see (Jha, 2013). This paper also argues that port cities had affluent Muslim populations, and thus, port cities are also controlled for.

non-Muslims under colonial rule.

The first column of Table 3.6 reports the coefficient for the religion of the deposed ruler from equation 3.2, without controls. There is a negative relationship between Hindu literacy and the religion of the deposed ruler being Hindu. The coefficient is -2.5 p.p and statistically significant. In column 2, we add geographic controls and the coefficient decreases in absolute terms to -1.5 p.p. This is consistent with the results in Table 3.5 column 2, as it suggests that non-Hindu (Muslim) kings ruled geographical regions with higher literacy.

Table 3.6: Association between Religion of last Ruler and Hindu literacy in Colonial India

	Hindu Literacy			
	(1)	(2)	(3)	(4)
Hindu ruler	-0.0253***	-0.0152***	-0.00978*	-0.0106**
	(0.00501)	(0.00416)	(0.00508)	(0.00498)
Geographic controls	NO	YES	YES	YES
Demographic controls	NO	NO	YES	YES
Economic controls	NO	NO	NO	YES
Year FE	YES	YES	YES	YES
Observations	565	563	365	365

Notes: Significance levels at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

In columns 3 and 4 of Table 3.6, we add demographic and economic controls. We still have a negative association with the religion of the deposed ruler in the years 1911 and 1921, but with a smaller coefficient. As discussed in the conceptual framework, if the religious community of deposed rulers has within-group fragmentation, then that community will have a lower negative effect of deposing the ruler. The within-group fragmentation is considered higher for the Hindu religion than Muslims due to inter-caste fragmentation.[31] Our Y variable is not available at the caste level. Thus, even though we control caste shares in the population, in line with our conceptual framework, we find a lower effect of the religion of the deposed

[31] Many Hindu Communities fought against *Peshwa* rulers who were high caste Maratha rulers. Particularly, the low caste Mahars supported the British against them. See, pages 39-52 in Geppert and Müller (2015)

ruler on Hindu literacy.

Hence, Table 3.5 and Table 3.6 report results that are in line with the predictions discussed in Section 3.2 associated with the hypothesis of Aziz (1967) and Lewis (2003). Another prediction stems from extending this argument a little further. If subjects at the *core* of the kingdom are more closely associated with the ruler than those at the *periphery*, then the resistance to western education due to deposing the local ruler would be more in the *core* of the kingdom. We now test this prediction from our framework.

To test this we divide our sample into *core* districts and *periphery* districts, where *periphery* districts are the ones that share their boundary with kingdoms that are ruled by rulers of other religions. All the remaining districts are considered to be *core*. The above definition gives us 61 *periphery* districts and 132 *core* districts. The regression equations that we estimate are given below:

$$\begin{aligned}\textbf{Muslim Literacy}_{it} = \alpha_1 + \beta_1 \textbf{Muslim Deposed Ruler}_i + \beta_2 \textbf{Periphery}_i \\ + \beta_3 \textbf{Hindu Deposed Ruler} \times \textbf{Periphery}_i + \gamma_1' X_{it} + \epsilon_{it}\end{aligned} \tag{3.3}$$

$$\begin{aligned}\textbf{Hindu Literacy}_{it} = \alpha_1 + \beta_1 \textbf{Religion of Deposed Ruler}_i + \beta_2 \textbf{Periphery}_i \\ + \beta_3 \textbf{Religion of Deposed Ruler} \times \textbf{Periphery}_i + \gamma_2' X_{it} + \mu_{it}\end{aligned} \tag{3.4}$$

Tables 3.7 and 3.8 report the results. It is clear from both the tables that *periphery* districts in themselves hurt literacy in line with Foa (2016). Foa (2016) argues that pre-colonial states in India were in constant conflict with one another and thus this could lower the literacy rate in these periphery districts that were more exposed to inter-kingdom warfare. However, the interaction between the religion of the deposed ruler and the *periphery* district is positive, and even significant in case where the ruler was Muslim. It is also clear from the tables that all the negative effects of the religion of the deposed ruler on the literacy of the subjects can be found in *core* districts. These results strongly suggest that the negative effect on literacy is the outcome of the connection that subjects in the core of these kingdoms had with the kings with whom they shared a religious identity, which made them resist western education.

To alleviate concerns about omitted variables bias, we first reported results using a specification that estimates the literacy gap between Hindus and Muslims in a district. This specification rules out *across* district geographic, demographic and economic variables that might have been omitted effects. Although we control for many of these factors, there is still a possibility that some variable, for example,

Table 3.7: OLS : periphery districts and Muslim ruler

	Muslim literacy	
	(1)	(2)
Muslim ruler	-0.0333***	-0.0322**
	(0.0114)	(0.0125)
periphery	-0.0292***	-0.0279***
	(0.00947)	(0.00944)
Muslim ruler × periphery	0.0337**	0.0325**
	(0.0130)	(0.0128)
Geographic controls	YES	YES
Demographic controls	YES	YES
Economic controls	NO	YES
Year FE	YES	YES
N	357	357

Notes: Significance levels at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table 3.8: OLS : periphery districts and Hindu ruler

	Muslim literacy	
	(1)	(2)
Hindu ruler	-0.0214***	-0.0237***
	(0.00738)	(0.00708)
periphery	-0.0137**	-0.0133***
	(0.00569)	(0.00480)
Hindu ruler × periphery	0.00853	0.0112
	(0.00849)	(0.00762)
Geographic controls	YES	YES
Demographic controls	YES	YES
Economic controls	NO	YES
Year FE	YES	YES
N	357	357

Notes: Significance levels at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

quality of schools, is omitted to affect literacy rates. However, if we assume that these variables should affect different religious groups alike, then the literacy gap between the two groups should not be affected by these factors.

Thus we ran the literacy gap specification, i.e., Hindu literacy - Muslim literacy is regressed on a dummy for the religion of the deposed ruler (Muslim = 1, in columns 1 and 2) and found the literacy gap to be positive, consistent with our main results (Table C.2). The Hindu-Muslim literacy gap increases by three-fourth times the sample average (column 2) in regions with a Muslim king. In columns 3 and 4, we changed the dummy variable. Now it took the value 1 if the ruler was Hindu. Again the results were robust and statistically significant.

As a second robustness check, we ran an IV regression. Our instrument exploits the concentric diffusion of the Hindu (Maratha) empire from the birthplace of Shivaji, a Hindu king who rebelled against the Mughal Empire, thus becoming a symbol of Maratha Hindu identity.[32] Shivaji was born in 1630 in a place called *Junnar* in southwest India. Our instrument for the religion of the deposed ruler is the *distance* from Junnar, as districts closer to Junnar were more likely to be ruled by the Hindu Maratha kings. We construct a measure of *distance* using pre-industrial era measures of distance and transportation costs based on Ozak (2018). We use this measure of *distance* from Junnar as an instrument for the religion of the deposed ruler in colonial India.

The first column of Table 3.9 reports the first stage estimates of our instrument. We see that our instrument strongly correlates with the religion of the deposed ruler. The Kleibergen-Paap Wald F statistic of the instrument from the first stage is 33.4 (also reported in column 1 of Table 3.9). Together, these results provide evidence that our instrument has a strong first stage. Column 2 reports the IV estimates of the coefficient associated with the religion of the deposed ruler. The coefficient is negative as the OLS estimate, but the negative effect is larger for the IV estimate (-3.07 for IV versus -1.94 for OLS).

Table 3.10 presents IV results on Hindu literacy. The IV estimate is again negative as the OLS estimate, but (as for Muslims) the negative effect is larger for the IV estimate. This difference in estimates can be because of potential differences between the compliers and the full sample. Given that we argue in our conceptual framework that subjects living closer to the *core* of the kingdom feel more connected with the king, Hindus living in regions closer to Junnar may have a stronger 'self-

[32]Majumdar et al. (1958) describes Shivaji and his Maratha empire in these words "The Maratha nation he buillt up defied the Mughal Empire during and after Aurangzeb's reign and remained a dominant power in India during the 18th century. The Maratha power also competed with the English for supremacy in India till it was finally crushed in the time of Lord Hastings"

Table 3.9: IV results for Muslim literacy

	Muslim Literacy	
	(1)	(2)
Least Cost	0.0362***	
	(0.00627)	
Muslim ruler		-0.0307*
		(0.0176)
Geographic controls	YES	YES
Demographic controls	YES	YES
Economic controls	YES	YES
Year FE	YES	YES
N	365	365
Kleibergen-Paap Wald F statistics	33.4	

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

identification' with the Hindu kings. Similarly, Muslims living further away from Junnar may have stronger 'self-identification' with the Muslim kings. This could push the IV estimates upwards for both Hindus and Muslims.[33] It should be noted that the IV results are robust to using a Euclidean measure of distance from Junnar as well (Tables C.3 and C.4).

We can summarise the results in this section as follows. First, the literacy of a religious group is negatively associated with the religion of the deposed ruler if they shared religious identity. This negative effect is robust and valid for both Muslims and Hindus in colonial India. Second, the negative effect of the religion of the deposed ruler on literacy is much stronger at the *core* of a kingdom than at the *periphery.* We interpret these results as evidence for the hypothesis that when rulers are deposed, their subjects, who feel that they share an identity with them (usually the religious group of the ruler living in the core of the kingdom), resist participating in the institutions introduced by the occupier, even if it is against their

[33]The difference between OLS and IV estimates is larger for Hindus. This is probably because historians argue that Marathas, though Hindus, were still considered occupiers by Hindus in many regions away from their heartland, for example, among the Rajput kings of the north. Thus the potential differences between the compliers and the full sample are likely to be higher for Hindus than for Muslims. To see an extensive discussion on the Maratha-Rajput rivalry, see Gupta (1970)

Table 3.10: IV results for Hindu literacy

	Hindu Literacy	
	(1)	(2)
Least Cost	-0.0348*** (0.00654)	
Hindu ruler		-0.0607*** (0.0161)
Geographic controls	YES	YES
Demographic controls	YES	YES
Economic controls	YES	YES
Year FE	YES	YES
N	365	365
Kleibergen-Paap Wald F statistics	28.3	

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

economic interest. In the next section, we discuss some other mechanisms that can explain the results.

3.5 Other mechanisms and robustness checks

Another reason that could lead to an adverse effect of the religion of the deposed ruler on literacy rates under the British is that the British discriminated against the deposed ruler's religious community. Metcalf and Metcalf (2006) argue that the British discriminated against Muslims and kept them away from positions of authority because they were the previous ruling class. If this were true, then this would provide lower incentives for Muslims to become educated. By the same logic, the British will discriminate against Hindus in regions where Hindu kings ruled, thus lowering the literacy of Hindus.

However, this policy would imply that the employment patterns of the two communities should also follow a pattern similar to literacy, i.e. the Muslim community should have lower employment levels under the British where the deposed ruler was Muslim. Similarly, Hindus should have lower employment levels where the deposed ruler was Hindu. To test this, we collated a novel data set by digitising the civil lists of employees working for the British government in different districts in 1871

(Quarterly Indian Civil List, October 1871)[34]. We used the names of civil servants to classify them into Hindus and Muslims (and others)[35]. We then estimated the following regression equations.

$$\textbf{Muslim Employment}_{it} = \alpha_1 + \beta_1 \textbf{Muslim Deposed Ruler}_i + \gamma_1' X_{it} + \epsilon_{it} \tag{3.5}$$

$$\textbf{Hindu Employment}_{it} = \alpha_1 + \beta_1 \textbf{Hindu Deposed Ruler}_i + \gamma_1' X_{it} + \epsilon_{it} \tag{3.6}$$

Table 3.11: OLS Muslim employment (1881)

	Muslim Employment	
	(1)	(2)
Muslim ruler	0.0236	0.0534***
	(0.0201)	(0.0188)
Demographic (population)	NO	YES
Geographic controls	NO	YES
N	173	172

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

where Muslim Employment$_{it}$ is the number of Muslims in the civil list in district i divided by the population of Muslims in the district. Hindu Employment$_{it}$ is defined analogously. The results are reported in Tables 3.11 and 3.12. We did not find a negative effect on employment of a particular community in an Indian district because of the religion of the deposed ruler. On the contrary, Muslims were employed more in districts where the deposed ruler was Muslim. The positive association of the religion of the deposed ruler being Muslim with Muslim Employment might be because the British tried to promote Muslim participation in government institutions in regions where they were perceived to be left behind (Chaudhary and Rubin, 2011).

[34]Given that historians like (Metcalf and Metcalf, 2006) and (Ahmad, 1991) have argued that the British kept Muslims from important posts of authority in the Government, we focus on civil lists jobs defined by Mcilvenna (2019). See, the sub-section on data in section 3.3 for details

[35]Admittedly, there can be errors in classification based on names. However, this is the best possible available historical record for employment under the British. Also, the results are robust to be just driven by the wrong classification.

Table 3.12: OLS Hindu employment (1881)

	Hindu Employment	
	(1)	(2)
Hindu ruler	0.0298	0.0419
	(0.0276)	(0.0345)
Demographic (population)	NO	NO
Geographic controls	NO	YES
N	173	172

Notes: Significance levels at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Given that we know that Muslims were resisting western education in regions where their ruler had been deposed, the British might have employed more Muslims as civil servants to incentivise them to take up education. Moreover, controlling for this employment data does not alter the signs or affect the significance level of the coefficients of our main results in the 1881 data (see Tables C.5 and C.6 reporting the results estimating the following equations respectively)

$$
\begin{aligned}
MuslimLiteracy_{it} =& \alpha_1 + \beta_1 ReligionofDeposedRuler_i + \\
& \beta_2 Muslimemployment_i + \beta_3 Hinduemployment_i \\
& \gamma_1' X_{it} + \epsilon_{it}
\end{aligned} \tag{3.7}
$$

$$
\begin{aligned}
HinduLiteracy_{it} =& \alpha_1 + \beta_1 ReligionofDeposedRuler_i + \\
& \beta_2 Muslimemployment_i + \beta_3 Hinduemployment_i \\
& \gamma_1' X_{it} + \epsilon_{it}
\end{aligned} \tag{3.8}
$$

The British might not have discriminated against the community of the deposed ruler in government jobs but not provide that community with schooling opportunities. However, this argument is refuted by historical evidence (see Cotton (1898)). According to data reported from Progress of Education in India, Quinquennial Reviews (1897–1927), the British gave incentives to communities that were not doing well in school enrollment (usually Muslims) through scholarships, reduced fees and establishing many schools in districts that were lagging.

Another reason why the literacy of a religious community may have lagged in the region of the deposed ruler is that religious institutions of that religion were stronger there. These institutions can dissuade their followers from taking up secular education, thus lowering the group's literacy outcomes. Chaudhary and Rubin (2011) argue that the years of rule can be taken as a proxy for the strength of religious institutions and shows that years of Muslim rule is negatively associated with Muslim literacy.

We controlled for this effect in two ways. First, we controlled for the year of annexation in our main specification i.e., equations 3.1 and 3.2. Since a later date of the year of annexation implies more time under a ruler associated with religious institutions, the year of annexation becomes a proxy for the strength of religious institutions (in line with Chaudhary and Rubin (2011)). The results are reported in Tables C.7 and C.8. It is clear from Tables C.7 and C.8 that the coefficient associated with the religion of the deposed ruler remains negative and significant, even after including the year of annexation.

Second, we use years of Muslim rule since the medieval period in a district (as per Jha (2013)) as a proxy for the strength of religious institutions. We note that this proxy measure can also be considered to be the strength of the bond between the ruler and his subjects. One would expect that more years of Muslim rule created a stronger bond between the Muslim community and the ruling elite. Thus it is not clear whether its association with literacy rates represent the strength of Muslim institutions (Chaudhary and Rubin, 2011) or the religious identity based bond discussed by Aziz (1967). Moreover, this measure heavily correlates with the primary variable of interest, i.e. the religion of the deposed ruler. For instance, if the deposed ruler was Muslim in a district, it was more likely that Muslims had ruled that district for more years.

Nonetheless, we ran our primary OLS equations, controlling for years of Muslim rule. We present these results in Tables C.9 and C.10. As we see from Table C.9, the inclusion of years of Muslim rule causes the coefficient associated with the religion of the deposed ruler on literacy to fall in the case of Muslims. However, it remains negative and significant at the 10% level. Thus, even if religious institutions did play a role, the results indicate some independent effect of removing the ruler by the British. Table C.10 shows that years of Muslim rule does not predict Hindu literacy.

We now discuss the evidence that further highlights the importance of the British removal of the local ruler in making his religious community resist western education. The British had two distinct ways of governing the different parts of India (Iyer, 2010). First was by direct rule, under which the administration's command was under the Governor-General of the East India Company until 1857 and then under the command of the Viceroy of India, who was answerable to the British Parliament. The second was by indirect rule, under which local rulers administered the local population and collected taxes on behalf of the British.

Until now, our analysis only covers directly ruled British India because the rulers has been deposed in regions where direct rule had been established. Indirectly ruled regions, that also came to be known as princely states, continued to be ruled by local kings. These kings belonged to different religions. Thus, studying the impact of the religion of the ruler on the literacy of his subjects in these princely states provides a quasi-experiment as to what would have happened if the local rulers had not been deposed.

As per our conceptual framework (Section 3.2), deposing the ruler was essential to making locals resist western education. Hence, our framework predicts that we should not find a negative effect of the ruler's religion on the literacy of the subjects if local rulers are not deposed but remain the administrators in their respective kingdoms. Chaudhary and Rubin (2016) study the effect of the religion of the ruler on literacy rates of Hindus and Muslims in these princely states. They found that Muslim rulers had no impact on Muslim literacy but had a negative and significant impact on Hindu literacy. This result is in line with the intuitive notion that Muslim kings perhaps neglected the literacy of their Hindu subjects or the Hindus found education much less valuable as fewer opportunities were available to them in an administration governed by Muslims.

Importantly for the argument in this paper, these results indicate that the negative effect of the religion of the ruler on the literacy rate is unlikely due to the explanation that Muslims were already behind under Muslim kings, even before annexation took place, while Hindus were already behind under Hindu kings. On the other hand, the results in Chaudhary and Rubin (2016) strongly suggest the removal of the local ruler did play an essential role in how these communities responded to the new opportunities available under the foreign occupiers.

We also do other robustness checks. Given that pre-colonial India was in political turmoil, sometimes we could not classify whether a particular district was under the political control of a Hindu or Muslim king before the British took over. Moreover, kings sometimes neither belonged to the Hindu or Muslim religion. For example, Sikhs controlled most of the Punjab region before the British took over. To ensure these districts are not affecting our results, we test whether our main results are robust to excluding the category when the annexed ruler is of the "other" religion. Table C.11 and Table C.12 report the results. We find that both Muslim and Hindu literacy remains negatively and significantly correlated with the religion of the deposed ruler.

A small community which were earlier the ruling class might be 'directly' affected when removed from power as they may be imprisoned or exiled, affecting human capital formation within that community. Thus, we test whether the results are just driven by districts where the share in the population of a particular religion is small. We test this by removing the districts with a share of Muslim (Hindu) population of less than 1 %, 2%, 3%, and 4%. The results in Tables C.13 and C.14 indicate robustness to the exclusion of such districts.

3.6 Concluding Remarks

Citizens of a country often identify themselves with the state and are willing to pay an economic price to support its regime. For instance, Fouka and Voth (2016) found that after a political conflict erupted between the German and Greek governments during the Greek sovereign debt crisis, German car sales in Greece declined.[36] In the pre-modern era, when citizens were subjects, this 'self-identification' was closely related to the religious identity shared by the regime and the subjects. In this paper, we have demonstrated that deposing the ruler lowered the literacy outcomes of the subjects who shared their religious identity with the ruler in colonial India.

Importantly, we show that this is true for both the Hindu and the Muslim communities, despite the historians focusing on Muslims. This one-sided observation may have arisen because over 66% of the total Muslim population in our sample lived in regions where the deposed ruler was Muslim in 1911. On the other hand, only 26% of the total Hindus lived in regions ruled by Hindu kings. Thus, an observer who does not have access to district-level data may end up missing the effect on Hindus. Nonetheless, the empirical analysis supports the hypothesis that even Hindus resisted western education where they lost political power. Moreover, we show that this resistance was higher at the core of the kingdoms than at the periphery, consistent with the idea that subjects identify more with the ruler in the core of the kingdom than in the *periphery* region.

Though grounded in a historical context, these results can shed light on some contemporary world issues. For instance, anti-western sentiment in the Muslim world has been linked to military interventions in Muslim countries.[37] Our findings suggest that the policymakers, to ascertain the long-term effects of any intervention,

[36] Similarly, a survey conducted in India reported that many citizens claim they reduced the usage of Chinese products substantially after the escalation of border issues between the two countries in June 2020. For the full story please see https://economictimes.indiatimes.com/news/defence/a-year-after-india-china-faceoff-in-china-43-indians-stopped-buying-chinese-products-localcircles-survey/articleshow/83522565.cms

[37] see this report published by CTC, West Point. https://ctc.usma.edu/military-interventions-jihadi-networks-terrorist-entrepreneurs-islamic-state-terror-wave-rose-high-europe/

must consider how it garners the trust and support of the local regime and the population. If that is not the case, then even well-intentioned, welfare-improving interventions can backfire.

4 Private Returns to Bureaucratic Appointments: Evidence from Financial Disclosures

with Song Yuan

4.1 Introduction

What drives civil servants? Bureaucrats play an essential role in state capacity and public service delivery. To select effective bureaucrats and regulate their behaviour in office, it is important to understand the incentives they face. Bureaucrats typically face non-monetary and low-powered incentives that have less wage differentiation (Wilson, 1989; Holmstrom and Milgrom, 1991; Dewatripont et al., 1999; Besley and Ghatak, 2018). This is mainly because bureaucracies by their nature are mission-driven organizations and not designed to meet narrow goals based on financial criteria (Wilson, 1989; Tirole, 1994).[1] Moreover, the multi-dimensional goals of bureaucracy and complex tasks that bureaucrats need to complete make it difficult to measure performance and apply performance incentives (Dewatripont et al., 1999; Prendergast, 2007; Besley et al., 2021). Bureaucrats' remuneration is hence often fixed and follows rigid rules. Instead, bureaucracies use nonmaterial rewards to incentivize bureaucrats, including missions in a sense of duty and purpose (Besley and Ghatak, 2005; Prendergast, 2007; Ashraf et al., 2014; Khan, 2020), career concerns (Iyer and Mani, 2012), and idiosyncratic preferences such as working closer to their hometowns (Khan et al., 2019). Further, the selection of mission matched employees increases organizational efficiency and reduces the need for high-powered incentives (Besley and Ghatak, 2005).

Conventional wisdom about the non availability of large monetary incentives for bureaucrats is difficult to test. The wealth status of bureaucrats is seldom publicly available, although there are often rigid official salary rules. In addition, any change in officials' wealth may be due to other factors, such as unobserved abilities of officers.

In this paper, we examine the financial incentives for bureaucrats by looking at the economic returns of bureaucrats after reassignment to important posts in the elite civil service in India, the Indian Administrative Service (IAS). Our finding is not consistent with the literature and we find high private returns for bureaucrats. IAS officers perform the vital functions of civil administration and policy making in the Government of India. Throughout their careers, IAS officers are transferred between

[1]The notion of a mission is a catch-all for a range of outcomes that a bureaucracy might pursue.

posts frequently at the discretion of political executives and senior bureaucrats. We digitized over 31,000 reports of immovable property of more than 5,100 IAS officers in all states from 2012 to 2020. We combine these data with career histories, including postings, and demographic characteristics of IAS officers during the same period.

Our setting provides two sources of variation that we can use to identify the financial returns to bureaucratic transfers. The first variation is the frequent change of jobs of officers in posts at different levels of importance. Specifically, posts in some ministries or departments such as Finance and Urban Development are identified to be important positions by existing IAS officers because they provide opportunities to make influential policy decisions (Iyer and Mani, 2012). Important posts are desirable for officers and may bring private returns to officers, for example, bribes in exchange for better service delivery or economic benefits. Our analysis also leverages rich information on immovable properties acquired by IAS officers over time, such as houses and land. These assets usually represent the vast majority of the total wealth of bureaucrats (RBI, 2017). The immovable property records of officers allow us to track the dynamics of assets before and after transfer to an important post.

To estimate the effects of bureaucratic transfers on the asset accumulation of bureaucrats, we adopt a staggered difference in difference (DID) method and an event study approach. We compare the change in immovable assets of officers who experienced and did not experience the reassignment to an important post for the first time in our panel, before and after the transfer. In particular, the DID approach allows us to control for all the unobserved time-invariant individual characteristics such as intrinsic ability, family background and political connections that may affect transfer decisions and asset accumulation. The identification assumption states that, in the absence of bureaucratic reassignment, the difference in immovable assets between officers with and without transfers should be constant over time conditional on all controls. An officer may be transferred to an unimportant post after reassignment; however, the empirical strategy allows us to more flexibly take into account the lasting effects of working in important posts in the short run.[2] In our baseline estimations, we find that immovable assets increase after reassignment to an important post. The results suggest that transfers to important posts lead to a 10% higher annual growth rate for the value and 4.4% higher for the number of immovable properties of an officer than she would have otherwise.

We conduct heterogeneity analyses of the effects at the ministry and state levels, and find evidence that is consistent with rent-seeking behaviours being a mecha-

[2] In robustness, we employ different independent variables such as important post dummy for each year after the transfer (see table D.19) and cumulative years in important posts after the transfer (see Table D.18), and results are still robust.

nism that drives the results. Officers in important positions may seek or accept bribes from people as their jobs might have a relatively large impact on people's lives and economic activities (Wade, 1985; Banik, 2001). Hence, one would expect the increase in assets to be larger in ministries or posts that are more prone to corruption. We proxy corruption by focusing on posts that are documented to be most corruption-prone (Finance, Urban Development, and District Administration and Land Revenue) by Transparency International India (TII, 2018, 2017).[3] We find that the increase in immovable assets is mainly driven by reassignment to important posts that are corruption-prone. We then examine whether the asset impact of transfers is larger in more corruption-prone states. The second way to proxy for corruption is looking at states (Karnataka, Andhra Pradesh, Tamil Nadu, Maharashtra, Jammu & Kashmir, Punjab, Gujarat, and West Bengal[4]) that are found to be more corruption-prone as the percentage of households experiencing corruption in public services was more than the "combined state average", according to the Centre for Media Studies (CMS) in 2017 (CMS, 2017). The effects of bureaucratic transfers in corruption-prone states are more than 3.2 times larger in other states.

We also assess whether the returns to bureaucratic reassignments differ when officers are working in their home states. Officers working in their home states are more familiar with the local environment, culture and language, enabling them to exploit information and social networking advantages for private gains (Dessein, 2002; Ashraf and Bandiera, 2018; Xu et al., 2018). The increase in the number of immovable assets for officers working in their home states is 2.9 times larger than that of officers working in non-home states. We explore other potential mechanisms and find that the main results are not explained by the promotion and higher salary, life cycle decisions of officers after reassignment to an important post, election, job title changes, etc.

We subject our results to several robustness exercises. We show that the results are robust to using the change in immovable assets as the dependent variable and using cumulative years in important posts after the transfer as the independent variable. The baseline results also hold when using alternative event windows and performing Poisson regressions. We show that our results hold when we drop observations with the top 1% and top 5% of immovable assets. Finally, following our baseline empirical framework, we conduct a counterfactual analysis by estimating

[3]Transparency International India asked respondents "If you paid a bribe, which authority did you pay the most of it to in the last 1 year". These departments received the most amount of bribes.

[4]West Bengal is also included in the group of corrupt states as it is regarded as the worst performing state in reducing the corruption and both Transparency International India and Centre for Media Studies found that it had a rapid increase in corruption in 2017.

the effects of reassignment to unimportant posts. We find that being transferred to an unimportant post and serving in unimportant posts thereafter is correlated with officers having fewer immovable properties, confirming our baseline results.

Contribution to the Literature. This paper contributes to a number of distinct literature. The first considers the motivations of employees in public organizations, which are crucial for incentivizing the performance and behaviours of bureaucrats. The theoretical foundation were laid by Holmstrom and Milgrom (1991) and Dewatripont et al. (1999), who consider the normative rationale for providing low-powered incentives to bureaucrats. The existing work has explored the intrinsic motivations such as missions both theoretically (Besley and Ghatak, 2005; Bénabou and Tirole, 2006; Prendergast, 2007) and empirically Ashraf et al. (2014); Khan (2020). The performance-based monetary incentive is studied mainly through field experiments in public sector organisations where performance is easier to measure (Muralidharan and Sundararaman, 2011; Duflo et al., 2012; Olken et al., 2014; Leaver et al., 2021). The use of explicit, monetary incentives remains the exception rather than the norm (Besley et al., 2021). Bureaucracies have also relied on other, non-monetary means to induce performance such as prestige of postings (Iyer and Mani, 2012) and personal preference of work place (Khan et al., 2019). Our paper provides the first evidence on the monetary incentives for bureaucrats reflected in their wealth accumulation, using the whole sample administrative asset disclosure data.

Second, the paper speaks to the questions on how to measure corruption and rent-seeking. The illicit and secretive nature of corruption makes itself difficult to detect (Olken and Pande, 2012). One method is to estimate corruption by direct observation, for instance, Olken and Barron (2009) directly measure corruption by observing the illegal payments made by truck drivers to local police on their routes. A second approach is to estimate the leakage of government funds by comparing the official records of funds released with actual receipt by beneficiaries (Reinikka and Svensson, 2004; Fisman and Wei, 2004; Imbert and Papp, 2011; Niehaus and Sukhtankar, 2013; Banerjee et al., 2020). A third way is to measure the degree of rent seeking through market inference (Olken and Pande, 2012; Chen and Kung, 2019). For example, Khwaja and Mian (2005) find that politically connected firms borrow 45% more and have 50% higher default rates in Pakistan. Fang et al. (2019) show that the housing price paid by who are bureaucrats is significantly lower than that paid by buyers who are not in China. A closely related work by Fisman et al. (2014) indicates that one can use politicians' asset disclosures to examine wealth effects attributable to corruption. We present a new method to measure the potential rent-seeking behaviours of bureaucrats by comparing the assets of officials before and after the bureaucratic transfers across positions of different levels of importance.

The third strand of literature considers the corruption and patronage in the process of bureaucratic appointment. Existing studies demonstrate that officials appointed based on connections and bribery perform worse (Wade, 1985; Akhtari et al., 2017; Xu, 2018; Ornaghi, 2019; Barbosa and Ferreira, 2019). However, the private returns to bureaucratic appointments which would motivate corruption are not well understood. Xu (2018) shows that governors of colonies connected with the Secretary of State receive a 10% higher salary during the period of patronage. Weaver (2018) documents that employees who paid bribes to get their jobs in the public sector experienced a 40% salary increase in a developing country in his setting. We contribute to the literature by showing that the private returns to bureaucratic appointments could be reflected in the immovable properties of officials, implying that the returns might be underestimated if only salaries are counted since civil servants' salaries are often rigidly proscribed and the assets of officers are rarely publicly available. We provide evidence suggesting that the rent-seeking behaviours of officers could be an explanation for the private returns.

This paper also contributes broadly to the emerging literature on the wealth accumulation of officials. Past research mainly focuses on politicians and compares the change in their assets after elections or serving in the parliament (Eggers and Hainmueller, 2009; Fisman et al., 2014; Truex, 2014; Szakonyi, 2018). In a related study by Banerjee et al. (2020) examine the asset change of district level officials in a rural employment program in Bihar, India after implementation of the program from 2012 to 2014. We add to this literature in three ways. First, to our knowledge, we are the first to digitize the records of immovable assets of bureaucrats from all ministries in India. Second, rather than compare asset accumulations before and after elections, the panel structure of our data set and the permanent civil service nature of the IAS allows us to present the asset accumulation of bureaucrats over whole careers. Third, we document that there may also be private returns for bureaucrats after the bureaucratic transfers due to the rent-seeking behaviours of officers.

The remainder of this paper is organized as follows. Section 4.2 introduces background information on the Indian Administrative Service, transfers of officers, and the dataset we use. Section 4.3 describes the empirical strategy adopted to estimate the relationship between the reassignment and asset changes of bureaucrats. The main results are presented in Section 4.4. We discuss the underlying mechanisms in Section 4.5. Section 4.6 provides the discussions on robustness check of main results. Section 4.7 concludes.

4.2 Background and Data

4.2.1 Background

Indian Administrative Service

The Indian Administrative Service is the highest administrative civil service of the Government of India. The IAS is the successor to the Indian Civil Service (ICS), which was established during the colonial period, and keeps the traditions and structure of that organization. IAS bureaucrats have life-long careers and remain politically neutral. For example, they cannot join any political parties or take part in any political activities.[5] IAS officers are involved in civil administration and policy-making and staff the most important posts in the Government of India. In 2019, the IAS had around 5205 officers.[6] They lead government departments or ministries as secretariats in central and state governments, fill executive administrative roles in districts, oversee state-owned enterprises, and are deployed to international organizations.

The IAS officers are regularly recruited through nationwide examination (direct recruits), promotion from state civil service (promotees), and, in rare cases, selection from non-state civil service. In 2019, around 71.4% of the current officers were centrally recruited by examination. The competitive examination is conducted by the independent Union Public Service Commission once a year and has a success rate of less than 0.1%.[7] The highest-ranked test takers are selected into the IAS and undergo two years of training at the Lal Bahadur Shastri National Academy of Administration (LBSNAA). The officers recruited by promotion are usually the best performing civil servants from the lower state civil service.[8]

Upon selection into the IAS, the bureaucrats recruited by exam are assigned to one of the states, known as their cadres, in a quasi-random manner following a complicated rule.[9] The rule factors in the vacancies in states, the preference of officers, their rankings in the exam and other variables. In general, politicians and bureaucrats themselves have little decision power over the assignment process. The ratio of officers posted in their home states to non-home states is maintained at 1:2

[5] See *The All India Services (Conduct) Rules, 1968*

[6] According to Civil List of IAS Officers

[7] See the report by Baswan et al. (2016)

[8] LBSNAA also conducts a 6-weeks induction training programme for officers promoted to the IAS from the state civil service

[9] In August 2017, the central government introduced a new cadre allocation policy for the Indian Administrative Service, which incorporates the preference of new officers and vacancies in states. The new policy has little impact on our observations as the officers studied in this project are from 2011 to 2019.

to ensure that officers from different states are placed all over India. IAS officers spend most of their career in the state cadres they are initially assigned to, and transfers between states are very rare.[10]

Officials in the IAS start their careers at districts within their allocated states. They are firstly assigned as subdivisional officers and gradually assume greater responsibilities in the district administration until they become the district officers (e.g. as deputy commissioner or district magistrate) after obtaining 4 - 9 years experience. After this, officers typically move between district administration, state government, and central governments. About twenty years after they join the IAS, officers undergo a comprehensive career review conducted by senior officials to determine whether they are eligible to hold higher secretary or secretary-equivalent posts in the central government. This process is called empanelment. The retirement age is 60 for both male and female officials.[11] In the first few years IAS promotions are year-based, thereafter performance is also taken into account. Wages of bureaucrats are determined by the level of seniority or payscale and the number of years working at each payscale level.[12]

Transfers of IAS Officers

IAS Bureaucrats are transferred frequently during their careers. Most postings in the IAS have a minimum tenure of two years,[13] however, consistent with Iyer and Mani (2012) the average tenure of IAS officers is around sixteen months in our sample, indicating the posting changes are quite common during a year. The transfers of bureaucrats are usually across different districts and departments within the state and sometimes between the state and central government or companies. Interstate transfers are rare and subject to strict rules.

The transfers or appointments of IAS officers can be made by the central government or state government at any time irrespective of tenure, depending on the locations of positions. Transfers of officers involve factors such as vacancies, administrative exigency, the matching between posts and bureaucrats, promotion, deputation outside the state and so on. Officers may, on limited occasions, request to be transferred to particular positions; however, they have very little influence on outcomes. While state-level politicians cannot hire or fire IAS officers, they have the power to evaluate and transfer officers. Politicians tend to transfer officers who are later in their careers and use transfers as a control mechanism (Iyer and Mani,

[10] The transfers across states usually occur in case of marriage or health issues

[11] A very few officers are hired after retirement or extended for retirement

[12] The pay rules are adjusted to the inflation and economic development every ten years

[13] See *Indian Administrative Service (Fixation of Cadre Strength) Regulations, 1955.*

2012). Transfers of senior bureaucrats between the state government and the central government are sometimes politicized as they may lobby politicians for particular posts (Bhavnani and Lee, 2018).

To provide stability of tenure and insulate the bureaucracy from political interference, the process of assignment and tenure for IAS officers has been reformed recently. In 2013, the Supreme Court mandated a fixed tenure of at least two years for bureaucrats.[14] In 2014, a new order[15] issued by the central government required every state government to constitute a Civil Services Board (CSB), which consists of a chief secretary, senior-most additional chief secretary or an officer of equivalent rank and status, and the secretary of the Department of Personnel in the state government.[16] The CSB makes recommendations for all appointments of cadre officers and examines and seeks detailed justification in cases where officers are nominated for transfer before the minimum period of service is completed. Though the recommendations of the CSB could be overruled by the chief minister,[17] the recording procedure helps to ensure transparency and accountability. The fixed tenure rule could also reduce the influence of the political executives on the transfers of bureaucrats, alleviating concern about political connections or patronage being the defining factor in bureaucratic transfers.

Assets of Bureaucrats and Submission of Asset Report

To ensure the accountability of officials, there are strict rules about the economic activities of IAS officers.[18] Officials are prohibited from engaging directly or indirectly in any business or undertaking any other employment. Officers shall not exercise their influence to secure jobs for any family member in the private or the public sector. They may accept gifts from relatives and friends with no official dealing with them, but they need to report to the government if the value of gifts exceeds 5,000 Rupees (approximately US$100). Officials are expressly prohibited from giving or taking any dowry from the parents or guardians of a bride or bridegroom. Officers may only occasionally invest in stocks or shares through stockbrokers or equivalent. Frequent trade, speculation in stock markets, and having any other person acting on their behalf to make any investments are forbidden. All these measures imply

[14] The exceptions are promotion, retirement, deputation outside the State or training exceeding two months. See Rule 7 in *The Indian Administrative Service (Cadre) Rules, 1954* and the news at `https://www.thehindu.com/news/national/in-major-reform-sc-orders-fixed-tenure-for-bureaucrats/article5299939.ece`

[15] See Rule 7 in *The Indian Administrative Service (Cadre) Rules, 1954*

[16] In robustness, we restrict our sample to period from 2014 to 2019 and period 2015 to 2019. The main results are still robust. See Table D.29

[17] The highest elected governor of the state government in India

[18] See *The All India Services (Conduct) Rules, 1968*

that the salary paid by the IAS constitutes the vast majority of income for most officers.

To increase transparency in the public sector, IAS officers must disclose the status of their assets and liabilities since joining the service. These assets include both immovable properties, for instance, land and houses, and movable properties. In addition to reporting their own immovable properties, officers must disclose the immovable properties of family members too. By definition, from the government document,[19] family members include the spouse, the son or daughter of the officer, and any other person related to by blood or marriage and economically dependent on the officer.[20] The mandatory reports of properties are submitted annually. To ensure the accuracy of asset information, the Department of Personnel and Training (DoPT) checks the reports and compares the submitted value with the market price of the immovable properties. The Income Tax Department will also examine the under or misreporting of the assets by reviewing the tax records of officers. To facilitate the filing of the immovable asset reports, the Department of Personnel and Training (DoPT) introduced online filing of immovable property reports in 2017.[21] If an officer fails to submit the report before the specified date, they can be punished by being made ineligible for empanelment, deputation or applying to higher posts, and training programmes.[22]

4.2.2 Data

Data on Immovable Assets of Officers

The data set on the immovable properties of IAS officers comes from the Immovable Property Return (IPR) from 2012 to 2020. The IPR reports are submitted by IAS officers in 25 state cadres annually. The IPR reports are in either typed or handwritten, and examples can be seen in Figure D.1. To digitize the dataset, we converted the typed reports into text using optical character recognition techniques, then we extracted the nonstandard text information and converted it to a structured dataset. We manually entered the data from the handwritten reports. The submission rate of IPR reports increases rapidly over time though it remains below 100%, as shown in Figure D.3. We discuss in detail that the submission rate of IPR reports does

[19] See *The All India Services (Conduct) Rules, 1968*

[20] As shown in immovable property return reports submitted by bureaucrats, many of these persons are parents, grandparents, and siblings and so on.

[21] We can observe that the submission rate of the immovable property reports increases rapidly over time as shown in Figure D.3.

[22] See *Submission of Annual Immovable Property Return for the year ending 2020 (as on 01.01.2021)*, Ministry of Tourism, Government of India.

not respond to our independent variable *Important* in Section 4.3. Our dataset has 31,079 IPR reports submitted by 5,169 officers, and the bureaucratic assets correspond to the period 2011 to 2019. The IPR contains detailed information on all the immovable properties owned by an officer or any member of his/her family:[23] address, size, type (house/flat/land/site), cost, value, ownership, year, and mode of acquisition, and income from the property. We compute the total present value and the total number of immovable properties of an officer in a given year. For properties without information on present value, we use the cost of properties as the present value, if it is available.

Summary statistics of the immovable properties of bureaucrats are displayed in Table 4.1. The average number of immovable properties is 2.424 in our sample. The mean and median value of immovable properties are 11,519,000 Rupees (about US$ 230,380) and 5,200,000 Rupees (about US$ 104,000), respectively. In comparison, the average wealth per adult in India was 544,000 Rupees in 2015 (about US$ 10,885).[24] Though the statistics represent the total value of immovable properties for the family of an officer, the value is still large considering the average family size of 4.8 in India[25] and average annual salary of 900,794 Rupees[26] in the IAS. In the meantime, the median metropolitan house price was 1,500 thousand Rupees and in underdeveloped rural areas it was 200 thousand Rupees in 2016. There are very few IPR reports that include the information on movable properties. Immovable properties are a good proxy of the total assets of an IAS official. According to the *Indian Household Finance Report* by the Reserve Bank of India in 2017 (RBI, 2017), real estate consists of more than 77% of the total household assets in India. Fisman et al. (2014) show that immovable properties consist of around 75% of the total assets of a candidate in India. Since underreporting[27] of immovable properties is possible, the immovable properties recorded in the IPR reports are likely to reflect a lower bound of the wealth of officers.

Table 4.1: Summary Statistics - Immovable Properties

Variables	Mean	S.D.	P1	P10	P25	P50	P75	P90	P99	Obs.
Value	11,519.732	37,425.137	0	0	800	5,200	12,150	24,510	100,000	29,740
Number	2.424	2.495	0	0	1	2	3	5	12	31,079

Note. Value is in 1000 Rupees. 50 Rupees = 1 USD (average exchange rate between 2011 to 2019).

[23]The definition of a family member is in Section 4.2.1

[24]According to the statistics by Statista. See `https://www.statista.com/statistics/1248500/india-wealth-per-adult/`

[25]Data from *Census of India 2011*

[26]Based on our calculation.

[27]It is less likely for an officer to overreport her immovable assets as it may attract the investigation of corruption from the government.

We generate a number of variables using the data from the IPRs. We define our key dependent variable, *ln Value*, as the logarithm of 0.01 plus the value of immovable properties of an officer in a given year,[28] as the data of immovable assets is right-skewed; we also define *ln Number* as the logarithm of 0.01 plus the number of immovable properties of an officer in a given year. In our robustness checks, we define *share of income-producing properties* as the fraction of immovable properties generating rental or agricultural income. To measure the rate of appreciation of the properties, we create the variable *the Ratio of value to cost*. More detailed definitions of variables can be seen in Table D.1.

Data on Career Histories of Officers

The data on other individual characteristics of IAS officers is from the *Executive Record Sheet of IAS Officers* (ER Sheet). This dataset contains comprehensive resume information for IAS officers from 1947 to the present. Specifically, the ER Sheet has detailed information on the date of birth, allotment year, education, place of domicile, language spoken, posting history (designation, ministry/department, period, work location, and level of seniority), and training. We web scrape the data from the ER Sheet and use the information for officers from 2011 to 2019. We match the resume data with the immovable property data using the unique identity number for each officer. Since some officers joined or retired during this period, the dataset we assemble is an unbalanced panel.

For the empirical analysis, we leverage the rich information on individual officers and generate the independent variable of main interest, control variables and variables for robustness checks. We first, following Iyer and Mani (2012), classify the following posts[29] as important: positions in the Department of Excise and Sales Tax, Finance, Food and Civil Supplies, Health, Home, Industries, Irrigation, Public Works, Urban Development, district officer positions, and central government positions. The important posts are defined as ones that provide opportunities to make influential policy decisions. The classification of important posts is based on detailed interviews with several IAS officers by Iyer and Mani (2012). Overall, around 51.13% of our observations involve officers holding important positions. Our main independent variable is *Important*, a binary variable equal to 1 during and after the year that a bureaucrat was reassigned to an important post in our panel for the first time. Though a limited number of officers were transferred to unimpor-

[28]We conduct robustness checks of main results by taking log transformation of value and number of immovable properties with constant 0.1 and 1 as shown in Table D.17

[29]In the following, we will use the terms ministries or departments interchangeably

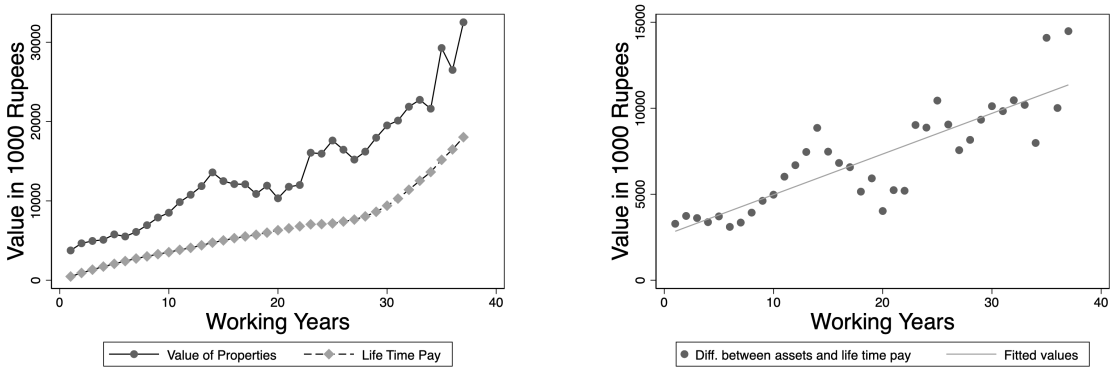
tant posts[30] after the reassignment described above, we still code the independent variable *Important* as 1 to capture the lasting impact of reassignment to important posts.

We create a number of other variables based on the information in the ER Sheet. To measure more formally whether the salary is an important determinant of wealth accumulation, we construct the predicted pay for each IAS officer in a given year based on the level of seniority or payscale of an officer and the pay matrix in different periods from *The Indian Administrative Service (Pay) Rules* from 1976 to 2016.[31] We also generate the variable *Life time pay* as the total salary since joining the service. We plot the lifetime pay and the value of immovable properties against working years for officers recruited by exam in the Panel (a) of Figure 4.1, and their difference in Panel (b). The patterns in the figure suggest that though both value of immovable assets and lifetime pay increase over time, the difference between them becomes larger the longer they work in the IAS. Note that the value of assets is the average across different cohorts, which may lead to a temporary declining trend during certain periods such as from 15 to 20 working years, as shown in both Panels. We measure the career investment in expertise by the total number of weeks spent in training. We define a dummy variable, *Home state*, if the work state cadre of an officer is the same as the state of domicile. The detailed definitions and summary statistics of variables are presented in Table D.1 and D.2.

[30]In our sample, more than 63% of officers always stayed in important positions after the reassignment, 72% of officers spent 80% of their time in important positions after the reassignment, and around 80% of officers spent 65% of their time in important positions after the reassignment. In robustness, we employ the cumulative number of years in important posts after the reassignment as the independent variable, and the main results are robust.

[31]The salary is a function of the level of payscale and working years in each payscale. The salary consists of the fixed grade pay and basic pay with an annual growth rate of about 3%, allowance and deduction(e.g. tax, etc.) at each level of payscale. The predicted pay of an IAS officer only includes grade pay and basic pay since the allowance and deduction are a tiny proportion of the total salary and almost cancel out.

Figure 4.1: Immovable Assets and Life Time Pay by Working Years



(a) Value of Properties and Life Time Pay (b) Diff. Between Properties and Life Time Pay

Note: Panel (a) in this figure shows the value of immovable properties and life time pay over working years, and panel (b) displays the difference between value of immovable properties and life time pay over working years.

Other Data sets

In order to understand mechanisms, we use several measures to proxy for opportunities for rent extraction. We first identify a post to be corruption-prone if the post is in the ministry/department of Excise and Sales Tax, Finance, Urban Development, or district administration. The variable is created based on a large scale study on corruption by Transparency International India in 2017 (TII, 2017). The national poll surveyed more than 100,000 respondents on their experience with corruption in public services. Departments or posts related to municipality, police, tax, land and house property had the highest percentage of respondents who experienced bribery and received most bribes. We then classify important posts to be corruption-prone posts [32] if they provide these services. Similar to our main independent variable *Important*, we define a binary variable *Reassignment to corruption-prone posts* whether during or after the year that a bureaucrat was for the first time reassigned to an important position that is corruption-prone in our panel. Reassignment to the remaining important posts is defined to be *Reassignment to non corruption-prone posts.* A similar corruption study by CMS (2017) and an online survey by *I Paid a Bribe*[33] have similar findings on the degree of corruption in departments. Since the classification above mainly focuses on people's experience with corruption in public

[32] The local district government broadly takes the responsibilities of land records, allotment of land and house, and land revenue collection and so on

[33] *I Paid a Bribe* is an online platform to collect people reported experience with bribery in India. It has been received more than 198,000 reports from people in 1081 Indian cities since 2010. Among all departments, the departments of Police, Stamps and Registration, Municipal Service, Customs, Exercise and Service tax, and Commercial Tax consist of the vast majority of all reports in terms of number and value. `http://www.ipaidabribe.com`

services, for robustness, we also treat posts in the department of Public Work and Industries as being corruption-prone, because they command a large share of budget and interact with the market. These posts leave more room for bureaucratic discretion and rent extraction in processes such as public project bidding, obtaining licenses and procurement (FICCI, 2013).

We generate an additional measure of rent-seeking opportunities at the state level based on a corruption study by the Centre for Media Studies (CMS) in 2017(CMS, 2017).[34] This study asked about people's experience with corruption, covering more than 3,000 households in both rural and urban areas of 20 Indian states 2015-2016. Among all surveyed states, Karnataka, Andhra Pradesh, Tamil Nadu, Maharashtra, Jammu & Kashmir, Punjab, and Gujarat were more corruption-prone as the percentage of households experiencing corruption in public services was more than the combined state average (CMS, 2017). Additionally, West Bengal was perceived as the worst-performing state in addressing corruption by both CMS (2017) and TII (2017). We define a binary variable, *Corruption-prone state*, to denote if a state cadre is one of the eight states listed above.[35]

4.3 Empirical Strategy

To test the average effects of the reassignment to important posts on the asset accumulation of IAS officers, we compare the change in the immovable properties of officers who were reassigned to important posts and those who were not, before and after the post changes. This allows us to control for the unobservable characteristics of officers that do not change over time and for unobserved variables in specific periods that affect all officers equally. In particular, we adopt a difference in difference approach with variation in treatment timing. Our baseline regression specification is the following:

$$\ln(0.01 + Assets)_{ist} = \beta Important_{it} + X_i' \times \delta_t + \eta_i + \delta_t + \lambda_{st} + \varepsilon_{ist} \tag{4.1}$$

where $\ln(0.01{+}Assets)_{ist}$ is the natural logarithm of 0.01 plus the value or number of immovable properties of bureaucrat i in state s in year t, which is either $\ln(Value)_{ist}$ or $\ln(Number)_{ist}$. $Important_{it}$ is a binary variable equal to 1 during and after the year that bureaucrat i was for the first time reassigned to an important post in

[34] We do not mainly use the findings on state-level corruption in TII (2017) as it only covered 12 states and asked questions about perceptions of people in states' progress in addressing the corruption.

[35] In robustness, we perform estimation with excluding five state cadres, Manipur, Tripura, Nagaland, Sikkim, Telangana, and Uttarakhand, that were not covered by CMS (2017)

our panel. The coefficient of main interest is β, which captures the average post-treatment effect of reassignment on immovable assets of bureaucrats in state s.

$(X_i' \times \delta_t)$ represents interactions of individual-specific time-invariant variables with year fixed effects. These are sex and education (having a graduate degree or not). We include these variables to account for the possibility that it is not reassignment to an important post that affects the immovable assets of bureaucrats, but that bureaucrats having specific characteristics such as master degrees may accumulate assets at a faster rate. Further, in some specifications, we control for the time-varying $Training_{it}$, which is the total number of weeks spent in training by an officer since joining the service. η_i and δ_t are officer fixed effects and year fixed effects. λ_{st} are state by year fixed effects. ε_{ist} is the error term clustered at the individual officer level.

We also estimate a more flexible event-study model, including dummy variables for each period. The flexible model allows us to examine the asset changes within a 16-year window and investigate the parallel trends assumption to ensure that treated officers are not on a diverging path to acquire more immovable assets prior to treatment. The regression specification is the following:

$$\ln(0.01 + Assets)_{ist} = \sum_{k=-7}^{8} \beta_k D_{t-k} + X_i' \times \delta_t + \eta_i + \delta_t + \lambda_{st} + \varepsilon_{ist} \tag{4.2}$$

where $\ln(0.01{+}Assets)_{ist}$ is one of the outcome variables $\ln(Value)_{ist}$ and $\ln(Number)_{ist}$ for bureaucrat i in state s in year t, which are the same as in equation (4.1). D_{t-k} is a dummy variable indicating the k year lead or lag of the first time officer i is reassigned to an important post in our panel. The omitted period is the first lead (one period prior to the reassignment), where $k = 1$. Our main parameter of interest is β_k, which captures the difference between treated and untreated officers compared to the prevailing difference in the omitted base period. The other variables are defined as above.

In terms of identification, the usual parallel trends assumption in the empirical frameworks (4.1) and (4.2) must be fulfilled. Specifically, the assumption is that the entire frequency distribution of immovable assets in the treated and untreated officers would move in parallel in the absence of the post reassignment. Adopting a difference in difference approach helps us control for all unobservable time-invariant individual characteristics of officers such as political connections and abilities that may affect both outcomes and treatment, by including individual officer fixed effects.

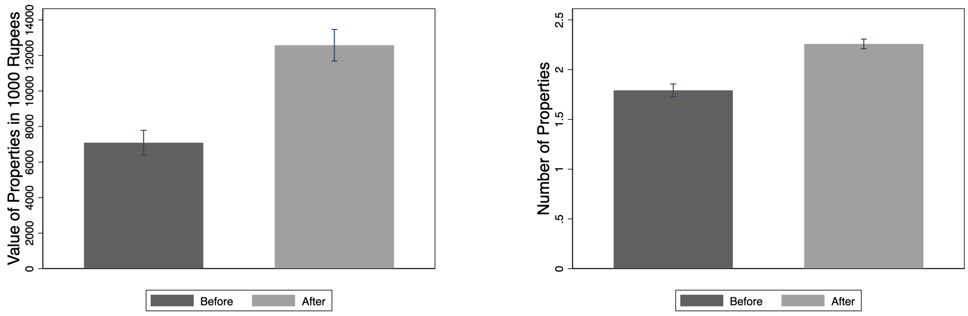
One concern for identification is the misreporting and underreporting of immovable properties by bureaucrats, especially when the reporting behaviours are different between treated and untreated officers. We first perform a bounding exercise by comparing the distribution of immovable properties of treated officers and untreated officers. Figure D.2 shows that the assets of these two groups of officers have very similar distributions before reassignment, implying that attrition bias is less of an issue for identification. We also demonstrate that the behaviour of non-submission of the IRP report does not respond to reassignment to an important post, as shown in Table D.3. Further, we proxy the misreporting with the share of properties without information on their present value and show that it is not significantly correlated with the treatment in Table D.4. To address the concern of reverse causality, we document that immovable properties do not predict the probability of reassignment to important posts, as displayed in Table D.5. As is standard, we also use the leading terms in specification (4.2) to assess pre-existing trends.

4.4 Bureaucratic Reassignment and Private Returns

4.4.1 Graphical Analysis

Before presenting the main results, we start with visual representation of the same trends that we uncover in formal estimations with the raw data. In Figure 4.2 we plot the average value and number of properties of officers before and after reassignment to important posts. Note that officers may be reassigned at different years, and there is not a common year of treatment. Therefore we will not be able to display the difference in assets of untreated officers between pre-event and post-event periods. Panel (a) displays the mean value of properties in 1000 Rupees, and Panel (b) displays the mean number of properties before and after the event. Though we cannot subtract the initial difference in assets between the treated and untreated officers, it is clear from the figure that there are significant increases in both value and number of properties after an officer is reassigned to an important post. The increase in the number of assets is more modest.

Figure 4.2: Properties Before and After the Reassignment



(a) Value of Properties (b) Number of Properties

Note: This figure shows the difference in assets before and after the reassignment to important posts for officers 2011-2019. The confidence interval is at 90% level.

4.4.2 Main Results

We now turn to the analysis of the patterns illustrated in Figure 4.2 on the basis of the empirical framework we developed in Section 4.3. We first look at the main results for the difference in difference estimation as shown in Table 4.2. We estimate the average effects of reassignment for two outcome variables, the logarithm of value and number of immovable properties of an officer in a given year. In column (1), we report sparser specifications with only individual officer fixed effects and year fixed effects. We find a statistically significant increase in the value of immovable properties. In column (2), we add the interaction term of state dummy and year fixed effects. In column (3), we control for the basic demographic variables: female dummy and graduate degree dummy, each interacted with year fixed effects, and the time-varying training of an officer. Across the first three columns, we observe a robust and significant increase in the value of immovable properties after an officer is reassigned to an important post. Another way to look at the asset accumulation of an officer is to count the number of immovable properties. Columns (4) to (6) display the results for the number of immovable properties of officers with the same control variables as in the first three columns. Similarly, reassignment to an important post significantly increases the number of immovable properties of officers.

In terms of magnitude of the treatment effects, focusing on column (3) in Table 4.2, the coefficient of 0.429 implies that after being transferred to an important post, the value of an officer's immovable properties increases by 53.5% on average over an eight-year post-event period, which also corresponds to an excess 10 percent compound annual growth rate.[36] The coefficient for the number of properties is 0.179

[36]The compound annual growth rate is computed with the formula $g_{compound} = \left(\frac{V_{final}}{V_{begin}}\right)^{1/t} - 1$, where V_{final} is (1 + average growth rate) i.e. (1 + 53.5%) , V_{begin} equals 1, and t is the average

in column (6), implying that the number of immovable properties increases by 19.6% after the reassignment, or an excess 4.4 percent compound annual growth rate.[37] The increase is larger for the value than for the number of properties, which might be explained by the price appreciation of real estate over time[38] or the possibility that the newly bought houses or lands are more expensive than properties one already owns. As a comparison, Banerjee et al. (2020) find that an e-governance reform that can reduce leakage in India led district officials' reported median personal wealth to fall by 36 per cent.

Table 4.2: Reassignment to Important Posts and Assets

Dep. Vars	ln Value			ln Number		
	(1)	(2)	(3)	(4)	(5)	(6)
Important	0.480***	0.495***	0.429**	0.193***	0.199***	0.179***
	(0.169)	(0.168)	(0.167)	(0.045)	(0.045)	(0.045)
Training	No	No	Yes	No	No	Yes
Female x Year FEs	No	No	Yes	No	No	Yes
Graduate x Year FEs	No	No	Yes	No	No	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	Yes	No	No
State x Year FEs	No	Yes	Yes	No	Yes	Yes
Observations	29,226	29.226	29,144	30,610	30,610	30,526
R^2	0.772	0.776	0.777	0.765	0.768	0.770
Mean dependent vars.	11.704	11.704	11.701	-0.179	-0.179	-0.180

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4.3 Results of Event Study Analysis

To evaluate the period-specific effects of reassignment on the immovable assets of bureaucrats, we now present results from the more flexible difference in difference event study estimation. Based on the empirical framework of specification (4.2), we perform the regression for both the value and number of immovable assets, including the entire set of control variables and fixed effects. We plot the coefficients of the first three leads and seven lags of the reassignment in Figure 4.3.[39] The omitted

length of period after reassignment i.e. 4.5 years.

[37] The compound annual growth rate is computed with the average growth rate of 19.6% for the number and average length of period after reassignment i.e. 4.5 years.

[38] In Table D.9, we show that the correlation between price appreciation and the value of properties is 6.5 times larger than the correlation between price appreciation and the number of properties.

[39] We do not plot the coefficients of the remaining four leads of the event because the number of observations for them is smaller than 200, which may lead to imprecise estimations of coefficients.

period is the first lead prior to the event. More detailed regression results can be found in Table D.15. Panel (a) displays the results for the value of properties. We can observe positive and significant effects of reassignment on the value of immovable assets, and the effects become larger over time. Specifically, at the year of transfer, the immovable assets increase by 21% compared to the year prior to the transfer. The effect continues to increase, and six years after the reassignment, the value of assets can grow by 163%. Panel (b) depicts a similar pattern for the number of properties. Officers own more immovable assets after the reassignment. At the year of transfer, officers, on average, have 12% more immovable properties in terms of number, and the increase becomes 24% after six years. In addition, the coefficients of all leads are not significant and close to zero. This suggests that our parallel pre-event trends assumption is satisfied.

After the first time being transferred to an important post, an officer may be transferred out to an unimportant post. In our data, more than 63% of officers always stayed in important posts after the reassignment, and 72% of treated officers spent 80% of their time in the panel in important positions after the reassignment. The steady increase in the coefficients of lags in Figure 4.3 implies that the impact of reassignment is not temporary and might grow over time. Officers may benefit from serving in important posts and build up political or economic connections during the period, which may bring financial returns over the years.

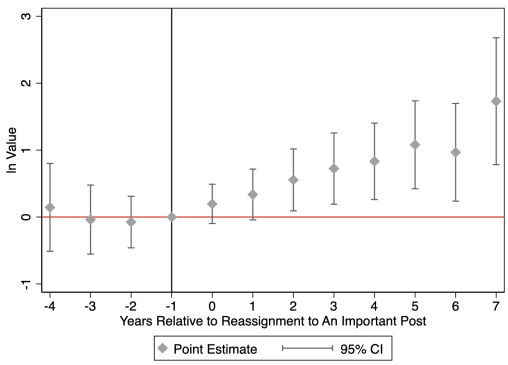
To further examine the persistence of the effect, we replicate our analysis by using the change in assets, measured by the first difference of *ln Value* or *ln Number*, as the dependent variable. The results are presented in D.16. Again, across all columns, we can find a consistent and robust positive effect of reassignment on the change in assets in both value and number. This confirms the possibility that economic returns to reassignment to an important post may last for years even after an officer is transferred out to an unimportant post.

4.5 Mechanisms

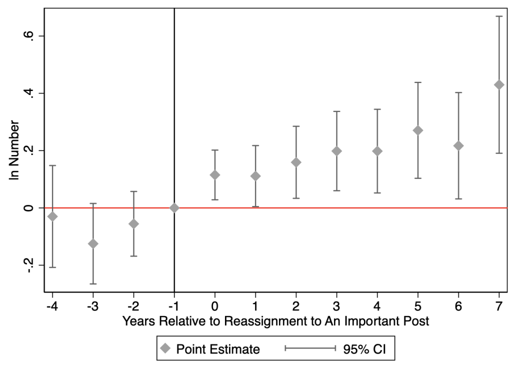
4.5.1 Rent Extraction Opportunities

To evaluate the mechanisms that might explain our results, we explore heterogeneity in the effects of reassignment, motivated by the background discussed in Section 4.2.1. Officers in important posts can make important policy decisions relevant to people's lives and the economic activities. This gives officers the opportunity to exercise power and seek bribes from people. People may also bribe officers in these positions to access better public services or in exchange for economic benefits. The difference in asset accumulation between transferred and non-transferred

Figure 4.3: Event Study Analysis



(a) ln Value of Properties



(b) ln Number of Properties

Note: This figure displays the coefficients of 4 leads and 7 lags of the event study analysis results for the estimation of specification (4.2). Panel (a) show the results for the value of immovable properties and Panel (b) show the results for the number of immovable properties.

officers thus could be explained by the rent-seeking behaviour of officers. We will examine the heterogeneity by the ministry-level and state-level measures of corruption.

Corruption-Prone Posts. We begin by testing the ministry or post-level heterogeneity. As discussed in Section 4.2.2, we classify the important posts into corruption-prone posts or ministries and non-corruption-prone posts. Similar to our baseline independent variable *Important*, we define two independent variables *Reassignment to corruption-prone posts* indicating whether an officer was for the first time reassigned to an important post that is corruption-prone, and *Reassignment to non corruption-prone posts* indicating whether an officer was for the first time reassigned to an important post that is non corruption-prone. The estimation is based on our baseline specification in equation (4.1) with the entire set of controls and the two independent variables we just defined above.

If the higher asset accumulation of officers with reassignment may be attributed to rent-seeking behaviour, we would expect a greater impact of reassignment to corruption-prone positions. We present the results in Table 4.3. In columns (1) and (2), we find a significant and positive effect of being transferred to a corruption-prone post on both value and number of immovable assets. Quantitively, reassignment to a corruption-prone post is correlated with 44% more immovable assets of an officer in value and 16% in number. In columns (3) and (4), we present results of the reassignment to a non corruption-prone important post. There is a negative but not significant response of immovable assets to the reassignment. Finally, we include both types of reassignment into the estimations; hence the control group are officers who were not transferred in the sample. The results in columns (5) and (6) display a consistent and positive impact of reassignment to a corruption-prone post on the asset accumulation of officers; its magnitude implies that immovable properties increase by 43% in value and 15% in number over an eight-year post-event period. Meanwhile, the effects of transfer to a non corruption-prone on immovable assets is not significant compared to officers who were not transferred to important posts. Overall, the results indicate that the rent-seeking behaviour of officers who were transferred to corruption-prone posts or ministries is a channel for higher asset growth of transferred officers.

Table 4.3: Reassignment to Corruption-Prone Posts and Assets of Bureaucrats

Dep. Vars	ln Value	ln Number	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)	(5)	(6)
Reassign. to CP posts	0.368**	0.149***			0.361*	0.147***
	(0.185)	(0.050)			(0.185)	(0.050)
Reassign. to non-CP posts			-0.265	-0.050	-0.255	-0.045
			(0.167)	(0.044)	(0.167)	(0.044)
Training	Yes	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No	No	No
Observations	29144	30526	29144	30526	29144	30526
R^2	0.777	0.769	0.777	0.769	0.777	0.769

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Reassign. to CP posts* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post that is corruption-prone in our panel. *Reassign. to non-CP posts* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post that is less corruption-prone in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Corruption-prone States. Another way to examine the heterogeneity by rent-seeking opportunities is to look at the state-level corruption. If the high immovable asset growth is explained by rent-seeking behaviour, we would expect to see that the effect of transfer on asset accumulation is more pronounced in states that are more prone to corruption.

We split the sample based on whether an officer works in one of the corruption-prone states as defined in Section 4.2.2. We then replicate the baseline difference in difference estimations for officers in corruption-prone states and non corruption-prone states, respectively. Subsample regressions allow all other control variables affecting the assets of officers in these two groups of states differently. The results are reported in Table 4.4. Columns (1) and (2) are the regression results for officers in corruption-prone states. The coefficients on *Important* are positive and significant at the 1 per cent level for both value and number of immovable assets. As shown in column (3), reassignment displays a positive but not significant effect on the value of immovable assets, and a positive and significant impact on the number of immovable assets. In comparison, the coefficient on *Important* in column (1) for officers in corruption-prone states is 2.8 times as large as that in column (3) for officers in non corruption-prone states. After performing a seemingly unrelated regression, the coefficient difference is significant at the 10 percent level. Similarly, the coefficient on *Important* in column (2) is 2.2 times as large as that in column (4) when the dependent variable is about the number of immovable properties. Quantitively, an officer in one of the corruption-prone states will see on average a 31% increase in the number of her immovable assets over an eight-year post-event period, however, the increase would be only 12% in non corruption-prone states. The significant differences in the effects of reassignment in corruption-prone and non corruption-prone states is therefore consistent with our conjecture that rent-seeking behaviour is a potential channel for the impact of bureaucratic appointments on asset accumulation. We next explore the asset change after reassignment to a corruption-prone post in corruption-prone states. Columns (5) and (6) present the results of our basic specification in equation 4.1 with the independent variable *Reassignment to corruption-prone posts*. The coefficients on *Reassignment to corruption-prone posts* are similar to that on *Important* in terms of significance and magnitude for the value and number of immovable properties. This confirms our findings in Table 4.3 that the main results are driven by transfers to corruption-prone posts.

Table 4.4: Reassignment to Important Posts and Assets by Corruption-prone States

Sample	Corruption-prone states		Non corruption-prone states		Corruption-prone states	
Dep. Vars	ln Value	ln Number	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)	(5)	(6)
Important	0.704***	0.270***	0.249	0.120**		
	(0.269)	(0.072)	(0.214)	(0.058)		
Reassign. to CP posts					0.658**	0.278***
					(0.292)	(0.079)
Training	Yes	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No	No	No
Observations	10945	11387	18199	19139	10945	11387
R^2	0.781	0.775	0.775	0.767	0.781	0.775
p-value difference			0.086	0.10		

Notes. The sub-sample *Corruption-prone states* include the states that are regarded to be more corruption-prone by CMS (2017). All remaining states are defined as *Non corruption-prone states.* The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *Reassign. to CP posts* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post that is corruption-prone in our panel. The *p-value difference* is the p-values of chi-square tests of the hypothesis of equal coefficients for *Important* compared to the estimates in column (1) for *ln Value* and column (2) for *ln Number.* Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5.2 Home Connections and Asset Accumulation

A different mechanism relates to whether bureaucrats work in their home states. Officers working in their hometown are more familiar with the local environment, culture and language. The greater social proximity between bureaucrats and the localities they serve may increase the collusion and enables bureaucrats to exploit the information and social networking advantages for private gains (Dessein, 2002; Ashraf and Bandiera, 2018; Xu et al., 2018). Working in one's home state may also affect the asset accumulation of officers in other ways. For officers working in their home states, transfers to important positions may increase the market value of the local houses and lands due to the better public services and goods provided by them. This is because the information and culture advantages allow bureaucrats to work more efficiently, and they have bigger incentives to perform better in their home areas (Bhavnani and Lee, 2018; Persson and Zhuravskaya, 2016); working in important positions also provides them with opportunities to make influential policies.

Table 4.5: Reassignment to Important Posts and Assets by Home State

Sample	Home state		Home state & Corrupt. state	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Reassign. to CP posts	0.948***	0.287***		
	(0.322)	(0.088)		
Important			0.995**	0.350***
			(0.466)	(0.133)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	9297	9731	3886	4047
R^2	0.784	0.773	0.779	0.774

Notes. The sub-sample *Home state* includes officers for whom the work state is the home state. The sub-sample *Home state & Corrupt. state* includes officers who work in their home states and their home states are corruption-prone states. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *Reassign. to CP posts* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post that is corruption-prone in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We begin by testing whether the effects of bureaucratic transfers on asset accumulation are different for officers working in home states and non-home states, respectively. We replicate our baseline analysis with specification (4.1) for these two groups of officers and report the results in Table 4.5. Comparing columns (1) and (3), we show that there is a significant increase in the value of immovable assets for officers working in their home states, and a positive but much smaller and insignificant increase in immovable assets for officers working in non-home states. Similarly, the coefficient on *Important* in column (2) is 2.5 times as large as that in column (4) when we look at the effects of reassignment on the number of assets. The difference in coefficients is significant at the 5 per cent level.

To understand whether the heterogeneity by home state is driven by the second hypothesis, we then test whether asset appreciation due to better performance by officials responds to the bureaucratic transfers of officers working in home states and non-home states respectively. We proxy asset appreciations by using the ratio of value to cost for an officer. The results are reported in Table 4.5. In columns (1) and (2), we show no significant increase for officers who work in either their home states or non-home states. Though we are not able to directly test the relationship between transfers and the performance of bureaucrats due to the lack of performance data, the results help us rule out the channel of asset appreciation due to officers delivering better local services and management. We further discuss the effects of home connections in corruption-prone states. We conduct subsample analyses by examining the effects of reassignment for officers working in their home states which are also corruption-prone states. The results in columns (7) and (8) show similar positive and significant asset changes as in columns (1) and (2). However, comparing with columns (1) and (2) in Table 4.4, the coefficients on *Important* increase by 41% for the value of properties and by 30% for the number of properties. This implies that home connections may increase the rent-seeking behaviours of officers. Overall, the results suggest that rent-seeking behaviours by officers working in their home states is likely to be a channel for the asset effects of bureaucratic transfers.

4.5.3 Alternative Mechanisms

Life Cycle Effects

Another hypothesis to explain our findings is that officers transferred to important posts might decide to buy immovable properties such as houses and flats since they may have better career prospects when working in important positions (Modigliani, 1986). The life cycle decisions of buying immovable properties are likely to be made during the first one or two years after the position change. More generally, it is likely to take place when an officer starts to buy her first house. This explanation is less plausible. First, the IAS service is a lifetime service, and IAS officers do not have to wait until they are promoted or transferred to important posts to be eligible for a housing loan. Second, the salary of officers follows rigid rules and depends mainly on the level of seniority and experience but not on the ministries they work in. Further, the heterogeneous asset effects of reassignment in corruption-prone states (posts) and less corruption-prone states (posts), as shown in Section 4.5.1, provide indirect evidence that life cycle effects are less likely, since the life cycle effects should be similar across states or important posts if they are the major driver of the asset change. Also, the estimates in event study analysis, as shown in Figure 4.3, indicate that the change in assets is less likely to be a temporary increase. We perform several estimations to rule out this explanation.

We begin by conducting subsample analyses by restricting observations to officers for whom the initial number of assets before the transfer is positive. This helps to take into account the possibility that the results are driven by the first house bought for their own use. For untreated officers or officers who are not transferred, the initial number of immovable properties takes on the value of the number of immovable properties at their first available year in the panel. For treated officers or officers experiencing reassignment, the initial number of immovable properties takes on the value of the number of immovable properties at the year before the transfer, because this can avoid treating the effects for officers with assets to be the effects for officers without any assets at their first available year, as some officers may have no assets in their first available year in the panel and accumulate assets before the reassignment.

Table 4.6: Reassignment to Important Posts and Assets by Initial Assets

Sample	Number of Properties = 0		Number of Properties ≥ 1		Number of Properties ≥ 2	
Dep. Vars	ln Value	ln Number	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)	(5)	(6)
Important	-0.333	0.154	0.426***	0.116***	0.368**	0.162***
	(0.397)	(0.102)	(0.140)	(0.039)	(0.147)	(0.042)
Training	Yes	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No	No	No
Observations	7217	7660	21927	22866	15246	15782
R^2	0.672	0.632	0.624	0.643	0.628	0.641

Notes. Initial assets are the number of immovable properties at the year before the reassignment to an important post for the first time for an officer; for untreated officers, we take on the number of properties at the first year for an officer in the panel. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We run regressions with the full set of baseline controls and present the results in Table 4.6. Columns (1) and (2) are the results for officers without any initial assets. We can see there are insignificant and mixed effects of reassignment on the value and number of assets. We then restrict to officers with at least one initial asset. The value and number of assets are positively correlated with reassignment, as shown in columns (3) and (4). Next, we restrict the sample to officers with at least two initial assets and present the results in the last two columns. We obtain consistent and positive effects of reassignment on assets. The results in Table 4.6 indicate that the impact of reassignment is probably not driven by buying one's first house after the transfer.

We also test the possibility that the effects are fully explained by purchasing a house at the first location after the transfer, implying after which assets stop increasing at least in the short run. We use first difference of logarithm of 0.01 plus the value or number of properties as the dependent variables, i.e. $\triangle$ *ln Value* or $\triangle$ *ln Number*. The dependent variables measure the additional change in the growth rate of assets. We then replicate our baseline regressions for the new dependent variables, controlling for lagged *ln Value* or *ln Number*. If assets remain unchanged after buying the first house, one would expect the coefficient on the variable of interest *Important* to be close to zero after we drop the first one or two years after the transfer.[40] The results, presented in Table D.7, show that the coefficients on *Important* are still positive and significant after dropping the first one or two years after reassignment, and the magnitude of the effects is similar to that in the full sample regressions. The results suggest that assets keep growing after the transfer and the main results are not likely to be fully explained by the purchasing behavior in the first location after reassignment.

Furthermore, we flexibly control for variables that are relevant to the life cycle decisions of officers such as promotion and job title change to address this concern in Section 4.5.3 and Section 4.5.3 respectively. The results indicate that life cycle effects are less likely to explain the main effects of reassignment.

Promotion and Salary

One potential channel of the main effects is promotion and salary. As an example, reassignment to important posts might be co-linear with the promotion and the associated pay increase. Therefore, it is likely that an officer may decide to buy the houses when they get promoted or receive a higher salary. To test this possibility, we control for the level of seniority fixed effects measuring promotion and log pay of officers in the baseline specification (4.1). Table 4.7 shows the estimation results. In columns (1) and (2), we check whether the pay of officers responds to reassignment, including level fixed effects. We find a significant increase in pay, with the magnitude of the effect being relatively small and about 0.7% after reassignment. We estimate the effects of pay and promotion in the remaining columns. Columns (3) and (4) don't include the level fixed effects and display a negative correlation between assets and pay. However, after controlling for promotion in columns (5) and (6), the coefficients on *ln Pay* become smaller in size and not significant. In the meantime, the coefficient on *Important* decreases by 23% for the value of assets and by 16% for the number of assets. Overall, the results imply that promotion and pay of

[40] We also conduct the analysis by dropping the first three or four years after the transfer, the results are still robust.

officers alone are not likely to explain the asset change after the transfer, though the magnitude of the effects may drop slightly.

Table 4.7: The Role of Promotion and Higher Pay

Dep. Vars	ln Pay		ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)	(5)	(6)
Important	0.006***	0.007***	0.419**	0.176***	0.329**	0.151***
	(0.002)	(0.002)	(0.167)	(0.045)	(0.164)	(0.044)
ln Pay			-1.047***	-0.275***	-0.228	-0.103
			(0.163)	(0.042)	(0.480)	(0.125)
Level fixed effects	Yes	Yes	No	No	Yes	Yes
Training	No	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	No	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	No	Yes	Yes	Yes	Yes	Yes
State x Year FEs	No	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	No	No	No
Observations	30524	30524	29142	30524	29142	30524
R^2	0.995	0.995	0.778	0.770	0.780	0.772

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *ln Pay* is the logarithm of the pay of an IAS officer in a given year. *Level fixed effects* are the fixed effects of level of seniority of officers. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Job Title Change

We consider another potential explanation, namely, that the main effects may be driven by the job title changes after the bureaucratic transfer. Officers with different job titles could obtain different private returns depending on their work contexts and may enjoy different working benefits. Therefore, it may not be important ministries but job titles that have an impact on the asset change. To test this possibility, we control for the job title fixed effects in the baseline specification. The results, summarized in Table 4.8, reveal that the coefficients on *Important* are still positive and significant for both the value and the number of immovable properties across all specifications. The size of coefficients on *Important* also change little. Overall, the results imply that job title changes are not likely to capture the effects of reassignment on assets. It is, however, the ministries that matters for the asset accumulations of officers.

Table 4.8: The Role of Job Title Change

Dep. Vars	ln Value		ln Number	
	(1)	(2)	(3)	(4)
Important	0.385**	0.397**	0.157***	0.159***
	(0.193)	(0.191)	(0.052)	(0.052)
Job title fixed effects	Yes	Yes	Yes	Yes
Training	No	Yes	No	Yes
Female x Year FEs	No	Yes	No	Yes
Graduate x Year FEs	No	Yes	No	Yes
State x Year FEs	No	Yes	No	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Observations	29105	29023	30491	30407
R^2	0.779	0.784	0.771	0.776

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *Job title fixed effects* are the fixed effects of job title of officers (even within the same department). Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Real Estate Market with High Growth Rate

We also test the possibility that the main effects are explained by the fast growth of real estate values in new locations after reassignment or places of domicile. For instance, it is likely that the important posts are located in cities in which housing prices rise quickly during the period in our panel. The real estate appreciation could increase the value of immovable properties owned by officers, and may also enable them to buy extra houses and land in their new cities or states of domicile. Unfortunately, we do not have the district and city level house and land price data. To take into account the impact of the real estate market, conditional on the baseline specification (4.1), we flexibly control for the state of domicile dummy interacted with the year fixed effects and the interaction term of working city and year fixed effects.

Table D.10 reports the results. In columns (1) and (2) we include the interaction term of domicile and year fixed effects for both value and number of immovable assets. In columns (3) and (4), we add the interaction term of working city dummy and year fixed effects. In the last two columns, we include both interaction terms in the baseline specifications. Across all columns, we find that the coefficients on *Important* for both the value and the number of immovable properties are similar across all specifications compared with Table 4.2. The results confirm that real estate appreciation is not likely to be a channel of the asset effects of reassignment.

Experience in Important Posts

Another potential channel of the effect is related to the experience in important posts before the reassignment. For example, experience in important posts might enable officers to build connections with political executives and senior bureaucrats, increasing the probabilities of being transferred to important posts or ministries during the period in our sample. Furthermore, experience in important posts in the past may continue to contribute to the asset accumulation after reassignment to unimportant posts.

Table 4.9: Reassignment and Immovable Assets with Controlling for Experience in Important Posts

Dep. Vars	ln Value	ln Number	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)	(5)	(6)
Important	0.057	0.083**	0.055	0.086**	0.181	0.119***
	(0.151)	(0.042)	(0.153)	(0.042)	(0.158)	(0.043)
Ever important	0.824***	0.203***				
	(0.235)	(0.062)				
ln lagged years in important posts			0.186***	0.044***		
			(0.048)	(0.013)		
IHS lagged years in important posts					0.639***	0.138***
					(0.161)	(0.041)
Level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Training	Yes	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No	No	No
Observations	29142	30524	29142	30524	29142	30524
R^2	0.780	0.772	0.780	0.772	0.780	0.772

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *Ever important* is a binary variable indicating whether an officer ever worked in important posts. *ln lagged years in important posts* is the logarithm of 0.01 plus the lagged total number of years in important posts since joining the service for an officer in a given year. *IHS lagged years in important posts* is the inverse hyperbolic sine transformation of the lagged total number of years in important posts since joining the service for an officer in a given year. *Level fixed effects* are the fixed effects of level of seniority of officers.Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To test whether our results are subject to this possibility, we begin by examining the role of experience in important posts in bureaucratic reassignment. We regress the baseline independent variable *Important* on a rich set of individual observables and fixed effects depending on the specifications. We report the results in Table D.5. Experience in important posts before the year of reassignment is negatively and significantly correlated with the probability of reassignment in our panel. This might be because the IAS service transfers officers to various departments to accumulate diverse experience.

To test whether our results are affected by this, we replicate our baseline analyses by controlling for the a dummy variable *Ever important* denoting whether an officer ever worked in an important post. We include level fixed effects to take into account the possibility that *Ever important* may capture unobserved abilities for outside earnings. We present the results in Table 4.9. We find that previous experience in an important post displays a significant impact on both value and number of immovable properties. The correlation between reassignment and immovable assets is positive for both the value and the number, but only significant for the number. Alternatively, we define two other proxy measures of experience in important posts: *ln lagged years in important posts* which is the logarithm of 0.01 plus the lagged total number of years in important posts since joining the service, and *IHS lagged years in important posts* being the inverse hyperbolic sine transformation of the lagged total number of years in important posts since joining the service. The results in columns (3) to (6) display similar patterns for experience to those in columns (1) and (2). Overall, the results suggest that experience in important posts has a long term effect on the asset accumulation of officers.

4.6 Robustness

In this section, we outline robustness exercises that we report in the appendix. We begin by showing that our results survive with different dependent variables, that is the change in the log of value or number of immovable properties in Table D.16. Since our data of immovable assets is right-skewed and contains many zeros, we then test if the main results are sensitive to the transformation of assets. We show the results with various transformations of assets in Table D.17. To be specific, the results are robust when we add a constant 0.1 or 1 when we take the logarithm transformation of the value or number of immovable properties. Alternatively, we generate the inverse hyperbolic sine of the value and the number of properties – *IHS Value* and *IHS Number* – and obtain similar results to our baseline analysis.

Because some officers may get transferred to unimportant posts after reassignment, we use alternative independent variables to test the robustness of our results. First, we use the cumulative years in important posts after the transfer and find a positive and significant effect of transfer on assets as shown in Table D.18. We also employ a flexible measure of reassignment *Important post dummy after reassignment*, denoting a given year to be 1 if an officer works in an important post after reassignment and 0 otherwise. This measure takes into account the possibility that an officer may get transferred to an unimportant post after reassignment, and then get transferred to an important post again. The results displayed in Table D.19 are consistent with our baseline analysis. Furthermore, we add the lagged cumulative years in important posts to the specifications in Table D.19, and present results in Table D.20. We find that working in an important post and past work experience in important posts positively affects assets. The results also indicate that there are likely to be lasting effects of being in an important post. Finally, We also define the variable *Important post dummy* to be a binary variable indicating whether an officer works in an important post in a given year without considering whether they are transferred or not. We replicate the baseline regressions and present the results in Table D.21. Again, the results are similar to our baseline results.

To check whether the main results are driven by extreme values, for instance, officers with many immovable assets, we conduct a subsample analysis by dropping the observations with the top 1% or top 5% of assets in terms of value. The results, displayed in Table D.23, show robust evidence that being transferred to an important post increases the assets of officials. For a similar reason, we also drop the observations of the first two years after reassignment. The results in Table D.24 are consistent with our baseline findings.

To further confirm our baseline findings, we conduct a counterfactual analysis by estimating the wealth impact of reassignment to unimportant posts. The independent variable *Unimportant* is a dummy indicating whether an officer is transferred to an unimportant post and stays in unimportant posts thereafter in our panel. We replicate the baseline regressions using the newly generated independent variable and present the results in Table D.25. We find that reassignment to unimportant posts decreases the number and value of assets. Restricting the sample to officers who experienced the reassignment, there is no significant increase in immovable properties. The results overall confirm our baseline findings.

Since 2014, every state government has been required to constitute a Civil Services Board to be responsible for the transfers of IAS officers. To check whether this policy change on bureaucratic transfers affect the main results, we restrict our sample to period 2014 to 2019 and the period 2015 to 2019. After replicating the baseline regressions, the results are consistent with the baseline findings, as shown in Table D.29.

Finally, we demonstrate that our results are robust to clustering standard errors at the state and ministry level (See Table D.26), using alternative event windows (see Table D.27), and employing Poisson estimation (see Table D.28).

4.7 Conclusion

We digitize the newly available immovable property reports for all the IAS officers from 2012 to 2020. We combine this with the career histories of officers, and study the economic returns from being transferred to important posts that enable officers to make influential policies.

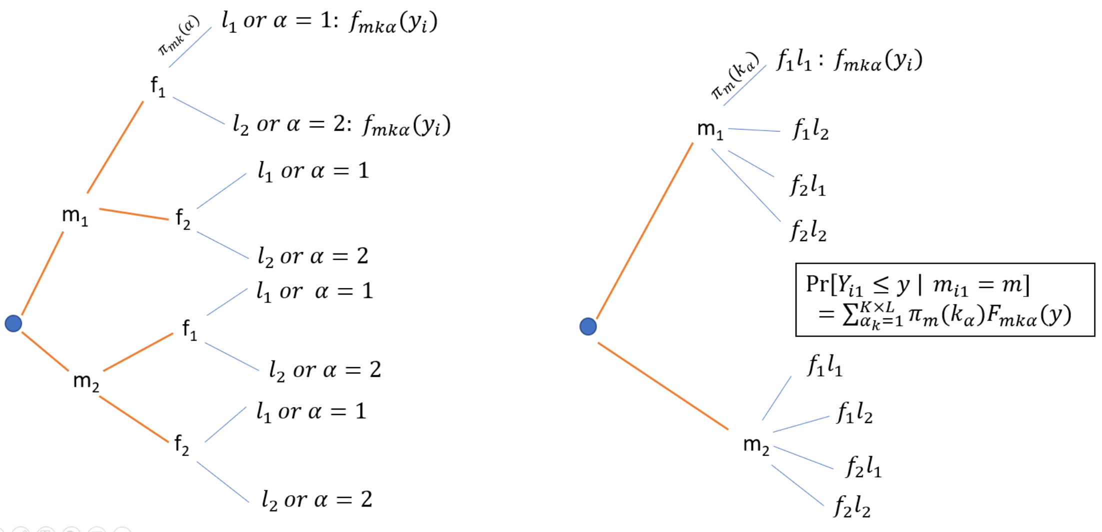
Our main findings suggest that over an 8-year period post the reassignment, officers who get transferred to an important post see a 10% higher annual growth rate for the value of their assets, and an increase of 4.4% for the number of immovable assets they hold. We argue that the main effects of reassignment are consistent with the explanation of rent-seeking behaviours of officials by showing that: the increase in assets is greater in more corruption-prone ministries, and in more corruption-prone states. Moreover, the effect is larger for officers working in their home states, where they can use their local information and cultural advantages to obtain private gains from their positions. We show that the results are less likely to be driven by the life cycle decision of buying their first house (in their life) at their new location after the transfers.

These findings imply that the non-salary financial returns could serve as one motivation for officers to seek more important positions in the government. The assets change of officers after the bureaucratic reassignment could be utilized to detect the rent-seeking behaviours of officials.

A Chapter 1 Appendix

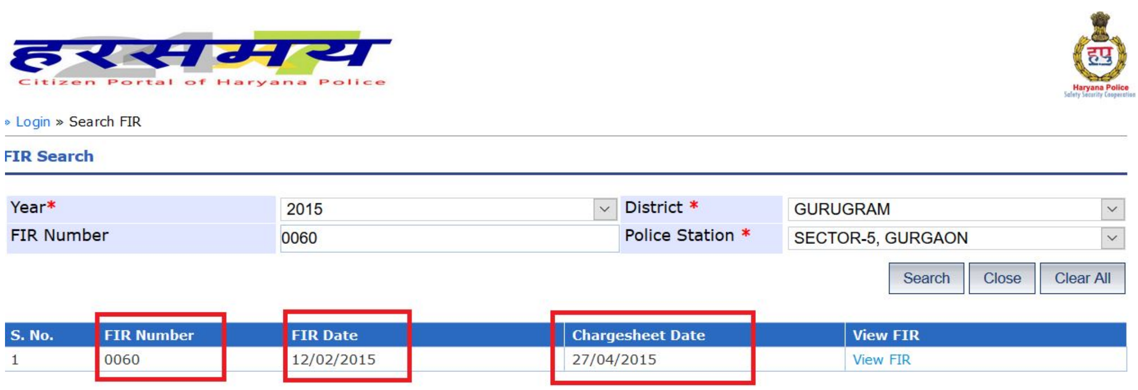
A.1 Figures

Figure A.1: Tree diagram of the distribution represented when together (No. of) manager classes (M) = 2, firm classes (K) = 2 and worker types (L) = 2 *(right)*. Tree diagram after combining the firm classes and worker type *(left)*



Note: I combine firm and worker class from figure in right to figure in left. For example, within manager class 1 (m_1), now there are four types of worker-firm classes namely k_1l_1, k_1l_2, k_2l_1 and k_2l_2.

Figure A.2: Charge sheet date sample from Haryana Police department webpage



S. No.	FIR Number	FIR Date	Chargesheet Date	View FIR
1	0060	12/02/2015	27/04/2015	View FIR

Figure A.3: Counterfactual allocation of workers using positive assortative matching

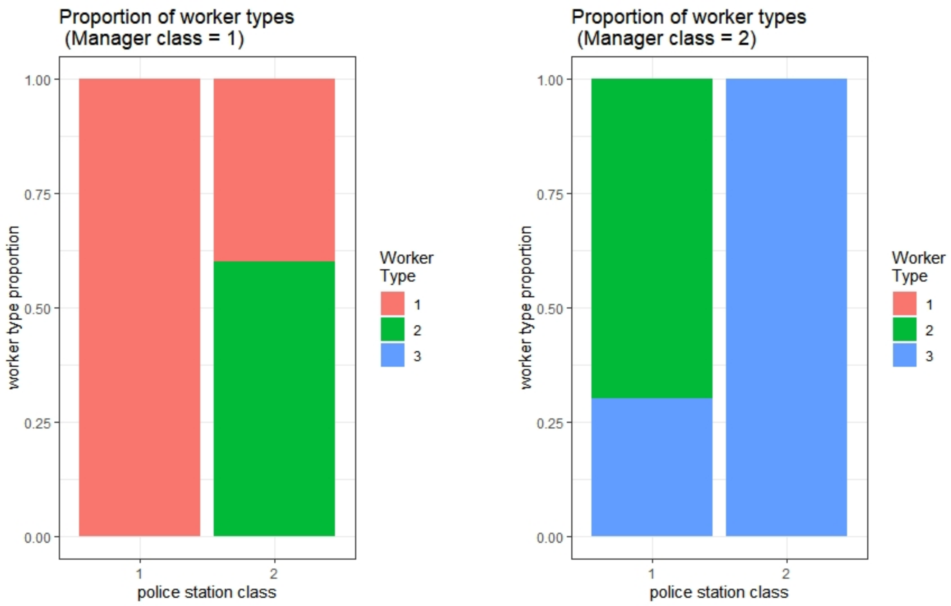


Figure A.4: Simulated data: Manager classes estimated by combining firm and worker classes together. ($K \times L$ or 2×2)

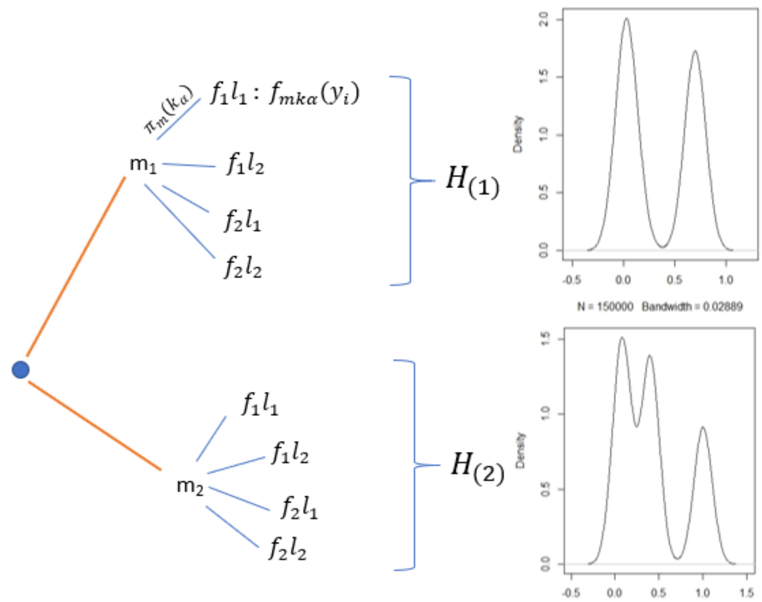


Figure A.5: simulated data: recovering the manager classes (Low misclassification rate (less than 1%))

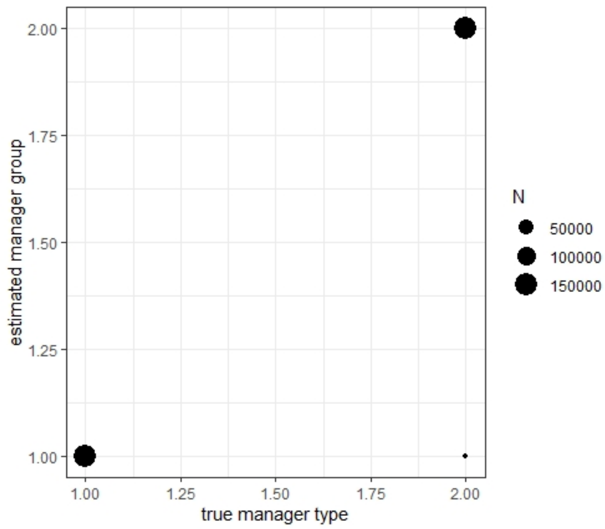


Figure A.6: Estimates of Step 2 on simulated data : Model parameters - Bold(circles) lines are true parameter values and dotted (triangles) are estimated values

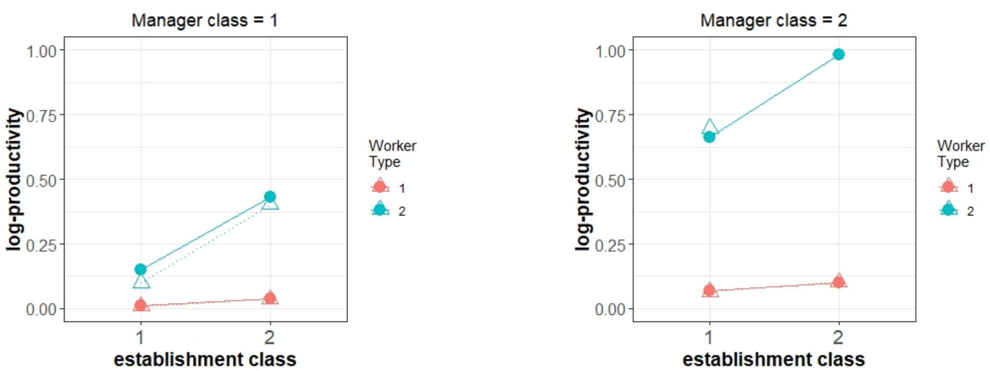


Figure A.7: Simulated data: estimating model parameters: recovering $\pi_{mk}(\alpha)$: worker proportions for manager class = 2

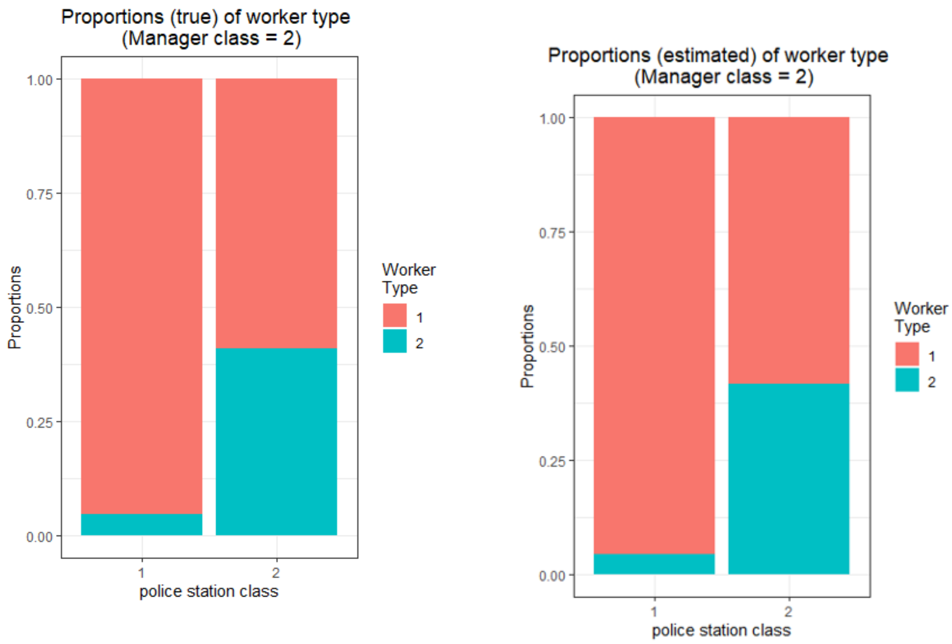


Figure A.8: Asymptotic properties: Monte Carlo simulations

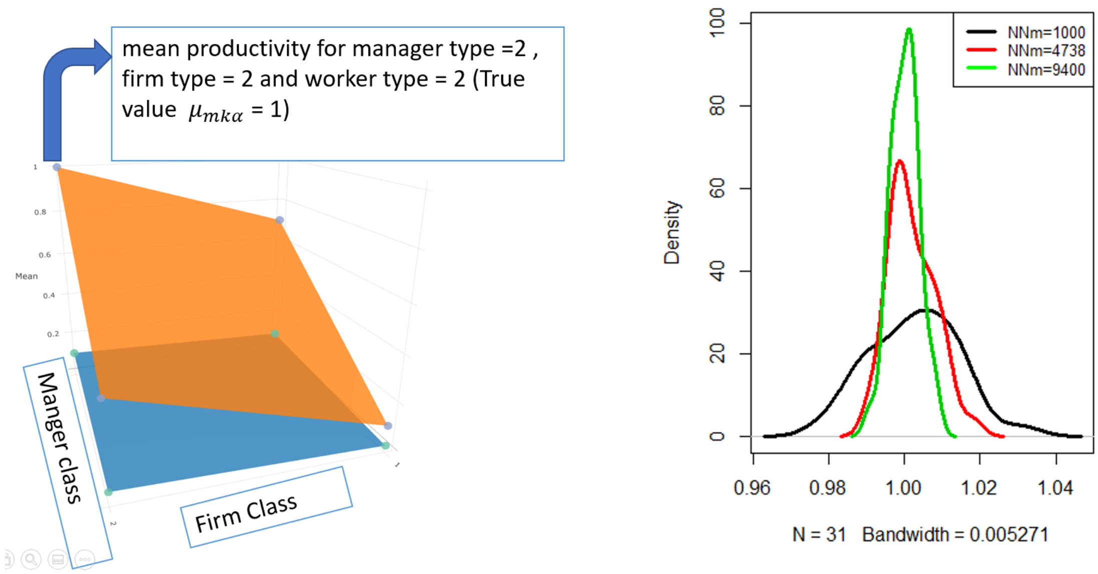
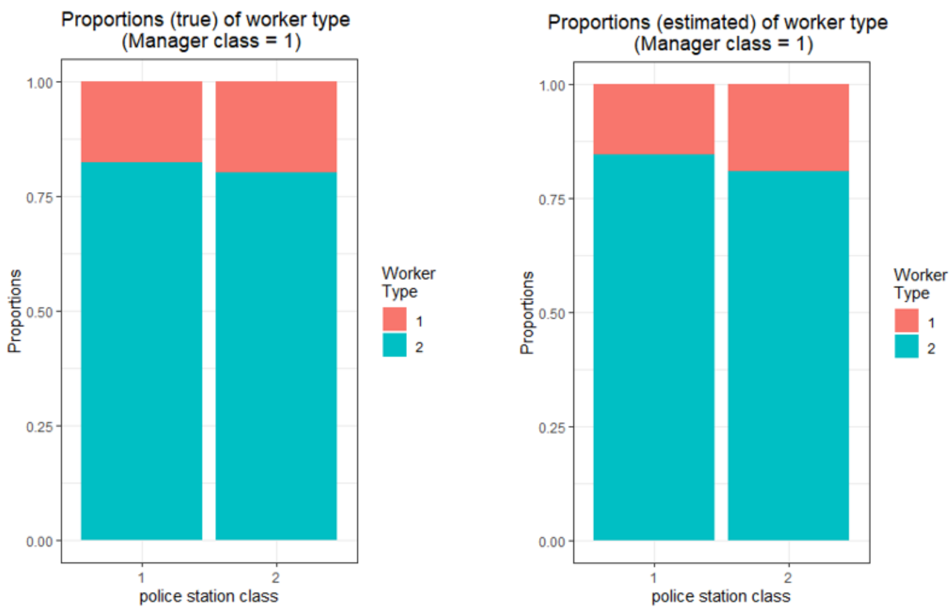


Figure A.9: Simulated data: estimating model parameters: recovering $\pi_{mk}(\alpha)$: worker proportions for manager class = 1



B Chapter 2 Appendix

B.1 Figures

Figure B.1: Rental indices from Zoopla data and the Office of National Statistics (ONS). Sources: (1) Zoopla Property Group PLC 2018, (2) Zoopla Historic Data (UK to 2017)

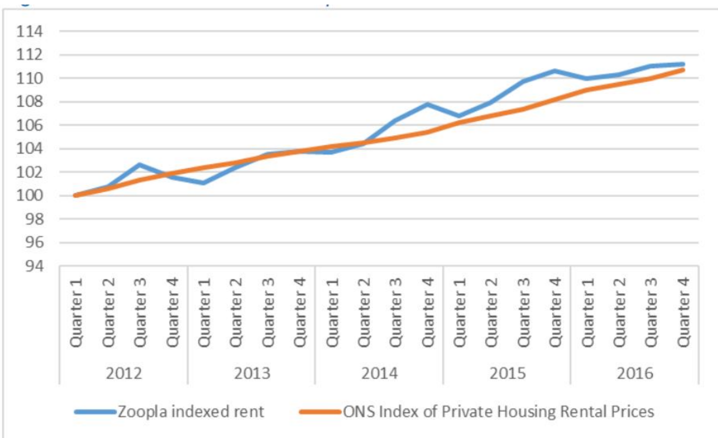
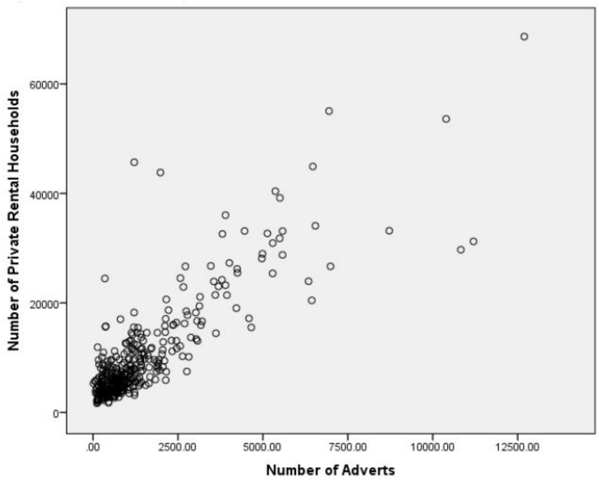


Figure B.2: Scatterplot Private rental households (Census 2011) by number of adverts (2012)



C Chapter 3 Appendix

C.1 Tables

Table C.1: Descriptive statistics of the Colonial India districts (1881)

	count	mean	sd	min	max
Muslim Literacy	182	0.03	0.02	0.01	0.16
Hindu Literacy	182	0.04	0.05	0.01	0.50
Literacy gap	182	0.01	0.05	-0.10	0.38
% Hindu	183	0.72	0.30	0.00	2.41
% Muslim	183	0.23	0.26	0.00	0.88
Normal rainfall	194	49.17	31.82	3.52	259.00
Latitude	194	24.83	4.43	13.06	33.57
Longitude	194	80.90	6.23	67.00	94.65
Year annexed by British	194	1809.70	32.47	1757.00	1871.00
Years of Muslim rule	190	79.39	39.67	-98.00	161.00
Distance from Junnar	194	1158.28	473.61	76.64	2292.32

Note: This table lists the districts of British India defined by 1881 Indian Census which were part of Mughal empire (1707) and ruled directly (excluding princely states).
[a] : Census document does not report the Literacy rate of Muslims in certain cities where there is negligible Muslim population. We do robustness checks excluding such sample completely.
[c] Years of Muslim rule is from the establishment of Muslim dynasty in India till the Annexation by British powers

Table C.2: Literacy gap

	Literacy gap(Hindu-Muslim)			
	(1)	(2)	(3)	(4)
Muslim ruler	0.0120	0.0175**		
	(0.00884)	(0.00758)		
Hindu ruler			-0.0579***	-0.0251***
			(0.00738)	(0.00741)
Geographic controls	NO	YES	NO	YES
Demographic controls	NO	YES	NO	YES
Economic controls	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
Observations	549	365	549	365

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.3: IV results for Muslim literacy

	Muslim Literacy	
	(1)	(2)
Distance from Junnar	0.000741***	
	(0.000180)	
Muslim ruler		-0.0691***
		(0.0240)
Geographic controls	YES	YES
Demographic controls	YES	YES
Economic controls	YES	YES
Year FE	YES	YES
N	365	365
Kleibergen-Paap Wald F statistics	17.0	

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.4: IV results for Hindu literacy

	Hindu Literacy	
	(1)	(2)
Hindu ruler		-0.0493***
		(0.0150)
Distance from Junnar	-0.000957***	
	(0.000167)	
Geographic controls	YES	YES
Demographic controls	YES	YES
Economic controls	YES	YES
Year FE	YES	YES
N	365	365
Kleibergen-Paap Wald F statistics	32.9	

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.5: OLS Muslim literacy with employment as control (1881)

	Muslim literacy	
	(1)	(2)
Muslim ruler	-0.00632*	-0.00865**
	(0.00330)	(0.00409)
muslimemp		-0.0294**
		(0.0137)
hinduemp		-0.0312**
		(0.0143)
Demographic (population)	NO	YES
Geographic controls	NO	YES
N	182	171

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.6: OLS Hindu literacy with employment as control (1881)

	Hindu Literacy	
	(1)	(2)
Hindu ruler	-0.0195**	-0.0156***
	(0.00836)	(0.00493)
hinduemp	-0.0347	-0.0460
	(0.0227)	(0.0479)
muslimemp	-0.0263	-0.0823*
	(0.0290)	(0.0428)
Demographic (population)	NO	NO
Geographic controls	NO	YES
N	171	171

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.7: OLS: Muslim literacy : Years since annexation

	Muslim literacy			
	(1)	(2)	(3)	(4)
Muslim ruler	-0.0248***	-0.0278***	-0.0243***	-0.0212***
	(0.00577)	(0.00483)	(0.00727)	(0.00793)
Geographic controls	NO	YES	YES	YES
Demographic controls	NO	NO	YES	YES
Economic controls	NO	NO	NO	YES
Year FE	YES	YES	YES	YES
N	547	547	365	365

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.8: OLS: Hindu literacy : Years since annexation

	Hindu literacy			
	(1)	(2)	(3)	(4)
Hindu ruler	-0.0267***	-0.0134***	-0.00965*	-0.0102**
	(0.00572)	(0.00438)	(0.00518)	(0.00502)
Geographic controls	NO	YES	YES	YES
Demographic controls	NO	NO	YES	YES
Economic controls	NO	NO	NO	YES
Year FE	YES	YES	YES	YES
N	563	563	365	365

Notes: Significance levels at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.9: Length of muslim rule : Muslim literacy

	Muslim literacy			
	(1)	(2)	(3)	(4)
Muslim ruler	-0.0144***	-0.0179***	-0.0175**	-0.0152*
	(0.00523)	(0.00604)	(0.00871)	(0.00879)
Years of muslim rule	-0.00897***	-0.00714***	-0.00666**	-0.00680**
	(0.00120)	(0.00203)	(0.00309)	(0.00283)
Geographic controls	NO	YES	YES	YES
Demographic controls	NO	NO	YES	YES
Economic controls	NO	NO	NO	YES
Year FE	YES	YES	YES	YES
N	547	547	365	365

Notes: Significance levels at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.10: Length of muslim rule : Hindu litearcy

	Hindu literacy			
	(1)	(2)	(3)	(4)
Hindu ruler	-0.0161***	-0.0164**	-0.0118**	-0.0105**
	(0.00608)	(0.00816)	(0.00495)	(0.00493)
Years of muslim rule	0.00576***	0.000785	-0.00222	-0.000394
	(0.00187)	(0.00396)	(0.00220)	(0.00234)
Geographic controls	NO	YES	YES	YES
Demographic controls	NO	NO	YES	YES
Economic controls	NO	NO	NO	YES
Income control	YES	YES	YES	YES
Year FE	563	182	365	365

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.11: Muslim Literacy: Excluding religions 1)Gurkhas 2)Mixed/Tribal 3)Neo-Hindu/Tai 4)Sikhs 5)Uncertain

	Muslim Literacy				
	(1)	(2)	(3)	(4)	(5)
Muslim ruler	-0.0138*	-0.0195**	-0.0216***	-0.0181**	-0.0213***
	(0.00729)	(0.00809)	(0.00824)	(0.00875)	(0.00805)
Geographic controls	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES
Economic controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	359	361	358	318	357

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.12: Hindu Literacy: Excluding religions 1)Gurkhas 2)Mixed/Tribal 3)Neo-Hindu/Tai 4)Sikhs 5)Uncertain

	Hindu Literacy				
	(1)	(2)	(3)	(4)	(5)
Hindu ruler	-0.0105**	-0.0105**	-0.0106**	-0.00786*	-0.0129**
	(0.00496)	(0.00501)	(0.00503)	(0.00472)	(0.00515)
Geographic controls	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES
Economic controls	YES	YES	YES	YES	YES
Income control	YES	YES	YES	YES	YES
Year FE	359	361	358	318	357

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.13: Muslim literacy: Excluding district with low muslim population share (1)<1%, (2)<2%, (3)<3%, and (4)<4%

	Muslim Literacy			
	(1)	(2)	(3)	(4)
Muslim ruler	-0.0166**	-0.0117*	-0.0132**	-0.0138**
	(0.00697)	(0.00627)	(0.00611)	(0.00690)
Geographic controls	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES
Economic controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	356	341	339	320

Notes: Significance levels at * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

Table C.14: Hindu literacy: Excluding district with low hindu population share (1)<1%, (2)<2%, (3)<3%, and (4)<4%

	Hindu Literacy			
	(1)	(2)	(3)	(4)
Hindu ruler	-0.0106**	-0.0106**	-0.0106**	-0.0106**
	(0.00498)	(0.00498)	(0.00498)	(0.00494)
Geographic controls	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES
Economic controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	365	365	365	364

Notes: Significance levels at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses corrected for district-level clustering.The Muslim ruler dummy (Hindu ruler Dummy) is assigned as one when the religion of last ruler whose territory British annexed is Muslim (Muslim). Demographic controls include population shares of different religions, population shares of different castes, average household size. Geographic controls: coastal dummy, major census city in colonial India, altitude, latitude, and longitude. Economic controls which include occupation classes (industry, agriculture etc.), port city and urbanization.

D Chapter 4 Appendix

D.1 Figures

Figure D.1: Immovable Property Return Reports

2019-2010106-1488303900862086

STATEMENT OF IMMOVABLE PROPERTY RETURN FOR THE YEAR 2018 AS ON 01st January 2019

1. Name of Officer (in full) : [redacted]
2. Service to which the Officer belongs : IAS
3. Cadre & Batch : PUNJAB - 2010
4. Present Pay :

SL NO.	Name of Khasra No., Village/City, Taluk, Sub-Division, District in which property is situated (full location & postal address)	Name & Details of Property (Description)	Cost of construction/Acquirement (and year when purchased) including of land in case of house	Present value*	If not in own name, state in whose name held and his/ her relationship to the Govt. Servant	How acquired whether by purchase, lease**, mortgage inheritance, gift or otherwise with date of acquisition and name with details of person(s) from whom acquired.	Annual income from property	Remarks
1	2	3	4	5	6	7	8	9
1	PUNJAAB Patiala Patiala Patiala Patiala Patiala City 147001	House 190 Sq. Yards	20 Thousand Aprox 1954	20 Lacs	No Tejpal Singh Father 1/2 share in property which is presently owned by my father	Purchase n.a. n.a. - 01/01/1954	0	no
2	PUNJAAB Patiala Patiala Patiala Theri Village Theri Near Urban Estate, Patiala 147002	House 285 Sq. Yards Residential House	12 Lacs 2003	50 Lacs approx	Yes Sole No	Purchase Army Welfare Housing Organization IAWHO) Army Welfare Housing Organization IAWHO) - 28/10/2003	0	No
3	PUNJAAB Patiala Patiala Rawaas Brahmna Village Rawaas Brahmna, Patiala 147001	Land 2 Bigha (2000 Sq. Yards) , Rural Cultivating Land	687500 2010	687500	Yes Sole Through Transfer deed from Father	Inheritance Tejpal Singh Father - 03/03/2010	15000	No

(a) Typed Report

STATEMENT OF IMMOVABLE PROPERTY FOR THE YEAR 2018 (as on 01.01.2019)

1. Name of Officer (in full) and service to which the officer belongs [redacted]
2. Cadre & Batch: Karnataka - 2018 (in case of IAS officers)
3. Present post held: Officer Trainee
4. Present Pay Rs 57800/-

	Name of District, Sub-Division, Taluk & Village or in which property is situated (full location & Postal address)	Name & Details of Property, Housing and other buildings	Cost of construction/ Acquirement (and year when purchased) including of land in case of house	Present Value*	If not in own name, state in whose name held & his/her relationship to the Govt. Servant	How acquired whether by purchase, lease**, mortgage, inheritance, gift or otherwise, with date or acquisition and name with details or person(s) from whom acquired	Annual Income from the Property	Remarks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1.	Anand Nagar BIDAR	H.NO 19-2-62 Plot - 58	- 1990. -	Sale Deed 5000	Shankar Rao Shinde (Father)	- Parents property -	Residence	-
2.	Anand Nagar BIDAR	Sy. 46/1 plot - 59.	- 2006 -	Sale Deed 47000/-	Shankar Rao Shinde (Father)	- " -	Open plot -	-
3.	Gauspur Bidar	24/1 & 31/1	- 1994	Sale Deed 15000/- 20000/-	Vandana Shinde (Mother)	- By purchase - (parents property)	05000/- 420000/-	agriculture land

Signature: Rahul

Name: Rahul Shinde

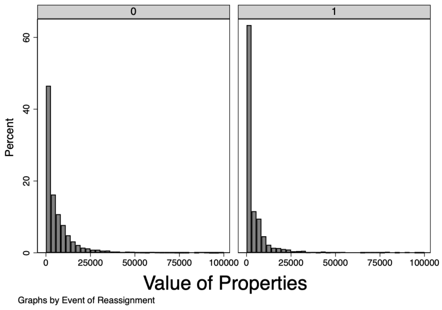
Designation: IAS - OT

Date: 13-12-2018

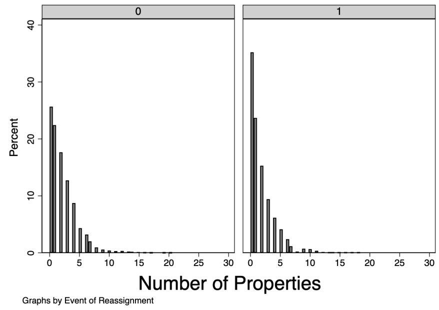
(b) Handwritten Report

Note: This figure shows two examples of Immovable Property Return Reports. Panel (a) is a report with typed text, and panel (b) is a handwritten report.

Figure D.2: Distribution of Properties by Reassignment



(a) Value of Properties



(b) Number of Properties

Note: This figure shows the distribution of properties in terms of value and number by reassignment dummy. Reassignment dummy is a binary variable equal to 1 if an officer experiences reassignment in our panel.

D.2 Tables

D.2.1 Summary Statistics

Table D.1: Data Sources and Description of Main Variables of Interest

Variable Description and Data Sources
Immovable properties
Value of immovable properties: the value of immovable properties owned by an IAS officer or any member of his/her family in a given year. Source: *Immovable Property Return (IPR).*
Number of immovable properties: the number of immovable properties owned by an IAS officer or any member of his/her family in a given year. Source: *Immovable Property Return (IPR).*
ln Value of immovable properties: the natural logarithm of 0.01 plus the value of immovable properties. Source: *Immovable Property Return (IPR)*
ln Number of immovable properties: the natural logarithm of 0.01 plus the number of immovable properties. Source: *Immovable Property Return (IPR).*
Ratio of value to cost: the ratio of value to the cost of immovable properties owned by an IAS officer or any member of his/her family in a given year. Source: *Immovable Property Return (IPR).*
Share of income-producing properties: the share of immovable properties producing rental income or agricultural income. Source: *Immovable Property Return (IPR).*
IAS officers
Important post: a post that provide opportunities to make influential policy decisions as defined by Iyer and Mani (2012). Important posts include the posts in ministry of Home, Finance, Industries, Public Works, Water Resources, Urban Development, Central Government, Health & Family Welfare, Consumer Affairs, Food & Public Distribution, Land Revenue Management and District Administration, and central government. Source: *Executive Record Sheet of IAS Officers.*
Important: a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Source: *Executive Record Sheet of IAS Officers.*
High perceived corrupt ministry: ministries that are more prone to corruption as reported in India Corruption Survey 2017 by Transparency International India.

Continued on next page

Table D.1 – continued from previous page

Variable Description and Data Sources
Training: total number of weeks spent in training since working in IAS. Source: *Executive Record Sheet of IAS Officers.*
Working years: number of years working in IAS in a given year. Source: *Executive Record Sheet of IAS Officers. Experience in important posts*: the cumulative years in important posts for the whole career of an officer in a given year. Source: *Executive Record Sheet of IAS Officers.*
Level of seniority: the level of seniority corresponding to payscale for an IAS officer in a given year. There are 7 levels of seniority in total for IAS officers. Source: *Executive Record Sheet of IAS Officers.*
ln Pay: the natural logarithm of the annual pay of an IAS officer. The pay is calculated by authors based on the pay rule and payscale of each officer. Source: *Executive Record Sheet of IAS Officers.*
Age: the age of an IAS officer in a given year. Source: *Executive Record Sheet of IAS Officers.*
Female: a binary variable equal to 1 if an IAS officer is female. Source: *Executive Record Sheet of IAS Officers.*
Graduate: a binary variable equal to 1 if an officer has a graduate degree. Source: *Executive Record Sheet of IAS Officers.*
Recruited by exam: a binary variable equal to 1 if an officer was recruited by civil service exam, 0 if recruited by selection or promotion from state administrative service. Source: *Executive Record Sheet of IAS Officers.*
Home state: a binary variable equal to 1 if the work state is the home state of an IAS officer. Source: *Executive Record Sheet of IAS Officers.*
Working city: The city of work for an IAS officer in a given year. Source: *Executive Record Sheet of IAS Officers.*
Other variables
Economic development: the GDP per capita of a cadre state in 2010. Source: *Ministry of Statistics and Programme Implementation, India.*
Corruption-prone state: a binary variable equal to one if the cadre state is one of states Karnataka, Andhra Pradesh, Tamil Nadu, Maharashtra, Jammu and Kashmir, Punjab, Gujarat, and West Bengal. Source: CMS (2017).

Continued on next page

Table D.1 – continued from previous page

Variable Description and Data Sources

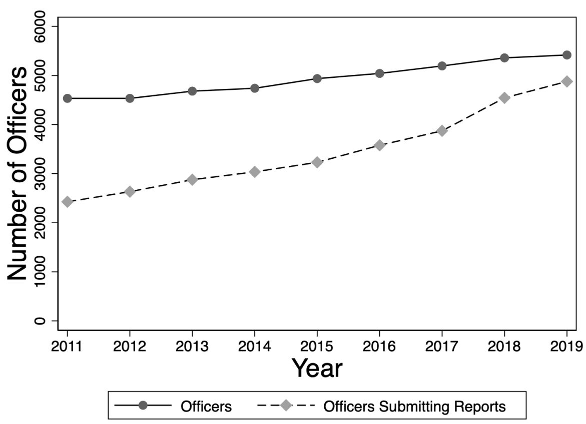
Table D.2: Summary Statistics - Other Variables

Variables	Mean	Min	Max	S.D.	Obs.
Important	0.214	0.00	1.00	0.41	31079
Working years	14.045	1.00	38.00	9.23	31076
Age	43.237	23.00	60.00	9.78	30995
Female	0.197	0.00	1.00	0.40	31079
Graduate	0.657	0.00	1.00	0.47	30995
Recruited by exam	0.822	0.00	1.00	0.38	31079
Home state	0.318	0.00	1.00	0.47	31079
Pay	900.794	0.00	3245.29	655.96	31079
Training	0.350	0.00	8.00	1.23	31079
Experience in important post	7.594	0.00	33.00	7.27	31079

Note. The number of officers is 5169 in the sample. The pay is in 1000 Rupees.

D.2.2 Submission of IPR

Figure D.3: Officers and Submission of Property Reports



Note: This figure shows the number of IAS officers and number of IAS officers who submitted property reports during 2011 - 2019.

Table D.3: Determinants of Submission of IPR Reports

Dep. Vars	Submit		
	(1)	(2)	(3)
Important	-0.014	0.001	0.001
	(0.009)	(0.005)	(0.005)
Training	0.024***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)
ln Pay	0.085***	-0.002	-0.002
	(0.016)	(0.004)	(0.004)
Working years	0.002		
	(0.001)		
Age	-0.026***		
	(0.001)		
Female	-0.022**		
	(0.010)		
Graduate	0.130***		
	(0.008)		
Recruited by exam	0.024		
	(0.025)		
Home state	0.050***		
	(0.009)		
Working city FEs	Yes	Yes	Yes
Female x Year FEs	No	No	Yes
Graduate x Year FEs	No	No	Yes
State x Year FEs	No	No	Yes
Officer FEs	No	Yes	Yes
Year FEs	Yes	No	No
Observations	44173	43195	43195
R^2	0.436	0.870	0.870

Notes. The dependent variable *Submit* is a binary variable equal to 1 if an officer submitted the Immovable Property Return report in a given year. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.4: Determinants of Missing Information on Property Value

Dep. Vars	% properties with value info. missing		
	(1)	(2)	(3)
Important	0.014*	-0.004	-0.004
	(0.008)	(0.008)	(0.008)
Training	-0.003***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
ln Pay	-0.004	0.020***	0.020***
	(0.010)	(0.007)	(0.007)
Working years	-0.000		
	(0.001)		
Age	-0.003**		
	(0.001)		
Female	-0.011		
	(0.009)		
Graduate	-0.003		
	(0.007)		
Recruited by exam	-0.024		
	(0.020)		
Home state	0.010		
	(0.008)		
Working city FEs	Yes	Yes	Yes
Female x Year FEs	No	No	Yes
Graduate x Year FEs	No	No	Yes
State x Year FEs	No	No	Yes
Observations	24947	24390	24390
R^2	0.102	0.645	0.645

Notes. The dependent variable *% properties with value info. missing* is the share of immovable properties without the information on present value for an officer in a given year. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.5: Determinants of Reassignment

Dep. Vars	Important					
	Full sample		Year of reassignment		Year of reassignment 2	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Age	-0.004		0.081***	0.080***	-0.005	0.003
	(0.005)		(0.006)	(0.006)	(0.004)	(0.005)
Lag Age squared	0.000		-0.001***	-0.001***	-0.000	-0.000**
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Female	0.007		-0.013	-0.003	-0.001	-0.003
	(0.013)		(0.012)	(0.013)	(0.009)	(0.010)
Graduate	-0.010		-0.022**	-0.025**	0.015*	0.010
	(0.011)		(0.009)	(0.010)	(0.008)	(0.009)
Recruited by exam	0.226***		0.504***	0.450***	0.095***	0.091***
	(0.034)		(0.031)	(0.035)	(0.022)	(0.026)
Home state	-0.009		-0.019**	-0.036***	-0.004	-0.013
	(0.013)		(0.010)	(0.013)	(0.008)	(0.011)
Lag Working years	0.023***		0.051***	0.051***	0.007***	0.007***
	(0.002)		(0.002)	(0.003)	(0.002)	(0.002)
Lag Experience in important posts	-0.029***	-0.052***	-0.047***	-0.044***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Lag Training	-0.005***	0.001	0.003	0.005	0.003	0.002
	(0.001)	(0.001)	(0.003)	(0.004)	(0.003)	(0.003)
Lag ln Value	-0.001	0.000	0.001	0.001	-0.000	-0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Lag ln Pay	-0.012***	-0.003	-0.022***	-0.023***	-0.000	0.002
	(0.003)	(0.003)	(0.005)	(0.007)	(0.006)	(0.007)
Lag Level FEs	Yes	Yes	Yes	Yes	Yes	Yes
Domicile FEs	Yes	No	No	Yes	No	Yes
Working city FEs	Yes	Yes	No	Yes	No	Yes
State FEs	No	No	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	No	No	No	No
Officer FEs	No	Yes	No	No	No	No
Year FEs	Yes	No	Yes	Yes	Yes	Yes
Observations	30078	29635	4979	4979	4977	4977
R^2	0.226	0.755	0.584	0.656	0.734	0.751

Notes. The sub-sample *Year of reassignment* includes the year of reassignment for officers who experienced job reassignment and the first year in the panel for officers who did not experience job reassignment. The sub-sample *Year of reassignment 2* includes the year of reassignment for officers who experienced job reassignment and the last year in the panel for officers who did not experience job reassignment. The dependent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. All continuous variables take on the lagged value. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.2.3 Other Explanations

Table D.6: Other Explanations: Elections

Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.424**	0.175***	0.463**	0.174***
	(0.170)	(0.046)	(0.190)	(0.051)
Important x Election year	0.021	0.017		
	(0.141)	(0.038)		
Important x Transfer at elect. year			-0.143	0.020
			(0.388)	(0.106)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	29144	30526	29144	30526
R^2	0.777	0.770	0.777	0.770

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *Election year* is a binary variable equal to 1 if the year was the year of State Assembly Election in the state an officer worked in. *Transfer at elect. year* is a binary variable equal to 1 if an officer was for the first time reassigned to an important post at the year of State Assembly Election in the state an officer worked in. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.7: Change in Asset Growth Rate and Drop the First Two Years after the Transfer

Sample	Full sample		Drop first year post event		Drop first two years post event	
Dep. Vars	△ ln Value	△ ln Number	△ ln Value	△ ln Number	△ ln Value	△ ln Number
	(1)	(2)	(3)	(4)	(5)	(6)
Important	0.287*	0.105**	0.452**	0.104*	0.612***	0.148**
	(0.164)	(0.047)	(0.189)	(0.053)	(0.223)	(0.062)
Lagged ln Value	Yes	No	Yes	No	Yes	No
Lagged ln Number	No	Yes	No	Yes	No	Yes
Training	Yes	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No	No	No
Observations	23721	25399	22317	23829	21138	22555
R^2	0.370	0.375	0.383	0.389	0.384	0.388

Notes. The dependent variable △ *ln Value (Number)* is the first difference of the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.8: Other Explanations: Higher Share of Income-Producing Properties

Dep. Vars	% Income-producing properties		ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.002	0.003	0.421***	0.175***
	(0.007)	(0.007)	(0.161)	(0.044)
% Income-producing properties			4.949***	1.195***
			(0.232)	(0.059)
Training	No	Yes	Yes	Yes
Female x Year FEs	No	Yes	Yes	Yes
Graduate x Year FEs	No	Yes	Yes	Yes
State x Year FEs	No	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	No
Observations	30610	30526	29144	30526
R^2	0.664	0.669	0.791	0.781

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *% Income-producing properties* the share of immovable properties producing rental income or agricultural income for an officer in a given year. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.9: Other Explanations: Local Management and Asset Appreciation

Dep. Vars	Ratio of value to cost		ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	-0.005	-0.004	0.396**	0.100**
	(0.044)	(0.043)	(0.168)	(0.044)
Ratio of value to cost			0.342***	0.053***
			(0.034)	(0.009)
Training	No	Yes	Yes	Yes
Female x Year FEs	No	Yes	Yes	Yes
Graduate x Year FEs	No	Yes	Yes	Yes
State x Year FEs	No	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	No
Observations	28482	28403	28403	28403
R^2	0.596	0.601	0.783	0.809

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *Ratio of value to cost* is the ratio of present value to the purchasing cost of all immovable properties winsorized at the 1 and 99 percentiles. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.10: Other Explanations: Real Estate Market with High Growth Rate

Dep. Vars	ln Value	ln Number	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)	(5)	(6)
Important	0.440***	0.179***	0.480***	0.202***	0.474***	0.199***
	(0.167)	(0.045)	(0.183)	(0.049)	(0.183)	(0.049)
Domicile x Year FEs	Yes	Yes	No	No	Yes	Yes
Working city x Year FEs	No	No	Yes	Yes	Yes	Yes
Training	Yes	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No	No	No
Observations	29138	30520	26598	27966	26589	27957
R^2	0.780	0.772	0.816	0.807	0.818	0.809

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. *Domicile* is the state of domicile of an officer. *Working city* is the working city of an officer in a given year. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.2.4 Heterogeneity

Table D.11: Reassignment to Important Posts and Assets by Education

Sample	Graduate		Non-graduate	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.192	0.128**	0.784***	0.260***
	(0.195)	(0.053)	(0.302)	(0.080)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	19158	19984	9986	10542
R^2	0.766	0.767	0.795	0.774
p-value difference			0.098	0.168

Notes. The sub-sample *Graduate* includes officers with graduate degrees. The sub-sample *Non-graduate* includes officers without graduate degrees. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. The *p-value difference* is the p-values of chi-square tests of the hypothesis of equal coefficients for *Important* compared to the estimates in column (1) for *ln Value* and column (2) for *ln Number*. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.12: Reassignment to Important Posts and Assets by Economic Development

Sample	Initial development above median		Initial development below median	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.228	0.125**	0.599**	0.224***
	(0.233)	(0.063)	(0.240)	(0.064)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	13898	14432	15246	16094
R^2	0.792	0.787	0.764	0.754
p-value difference			0.267	0.271

Notes. The sub-sample *Initial development above median* includes states for which the initial GDP per capita was above the median in 2010. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. The *p-value difference* is the p-values of chi-square tests of the hypothesis of equal coefficients for *Important* compared to the estimates in column (1) for *ln Value* and column (2) for *ln Number*. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.13: Reassignment to Important Posts and Assets by Recruitment Type

Sample	Recruited by Exam		Recruited by other ways	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.452**	0.189***	-0.302	-0.058
	(0.179)	(0.048)	(0.285)	(0.087)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	24176	25360	4964	5160
R^2	0.777	0.766	0.681	0.711
p-value difference			0.023	0.012

Notes. The sub-sample *Recruited by Exam* includes officers who were recruited by national exam. The sub-sample *Recruited by other ways* includes officers who were recruited by selection or promotion from state administrative service. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. The *p-value difference* is the p-values of chi-square tests of the hypothesis of equal coefficients for *Important* compared to the estimates in column (1) for *ln Value* and column (2) for *ln Number*. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.14: Reassignment to Important Posts and Assets by Sex

Sample	Female		Male	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.924**	0.256**	0.308*	0.160***
	(0.402)	(0.106)	(0.181)	(0.049)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	5757	6025	23387	24501
R^2	0.801	0.784	0.770	0.764
p-value difference			0.158	0.407

Notes. The sub-sample *Female* includes all female officers. The sub-sample *Male* includes all male officers. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. The *p-value difference* is the p-values of chi-square tests of the hypothesis of equal coefficients for *Important* compared to the estimates in column (1) for *ln Value* and column (2) for *ln Number*. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.2.5 Robustness

Table D.15: Reassignment to Important Posts and Assets - Event Study

Dep. Vars	ln Value	ln Number
	(1)	(2)
Lead 8	-0.655	-0.163
	(1.818)	(0.455)
Lead 7	-1.436	-0.298
	(1.261)	(0.293)
Lead 6	-0.590	-0.314*
	(0.692)	(0.182)
Lead 5	-0.361	-0.166
	(0.484)	(0.123)
Lead 4	0.144	-0.030
	(0.335)	(0.091)
Lead 3	-0.038	-0.125*
	(0.263)	(0.072)
Lead 2	-0.075	-0.056
	(0.197)	(0.058)
Lag 0	0.197	0.115***
	(0.150)	(0.044)
Lag 1	0.337*	0.111**
	(0.194)	(0.054)
Lag 2	0.555**	0.159**
	(0.236)	(0.064)
Lag 3	0.723***	0.198***
	(0.272)	(0.071)
Lag 4	0.832***	0.198***
	(0.291)	(0.074)
Lag 5	1.079***	0.271***
	(0.335)	(0.085)
Lag 6	0.967***	0.217**
	(0.372)	(0.095)
Lag 7	1.730***	0.430***
	(0.484)	(0.122)
Observations	29144	30526
R^2	0.778	0.770

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Lead #* is a year dummy indicating # years before the year of reassignment to an important post. *Lag #* is a year dummy indicating # years after the year of reassignment to an important post. *Training*, *Female* $\times$ *Year FEs*, *Graduate* $\times$ *Year FEs*, *Graduate* $\times$ *Year FEs*, *State* $\times$ *Year FEs* and officer fixed effects are included in all columns. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.16: Alternative Dependent Variables - Change in Assets

Dep. Vars	$\triangle$ ln Value		$\triangle$ ln Number	
	(1)	(2)	(3)	(4)
Important	1.239***	1.225***	0.348***	0.337***
	(0.204)	(0.202)	(0.052)	(0.052)
Training	No	Yes	No	Yes
Female x Year FEs	No	Yes	No	Yes
Graduate x Year FEs	No	Yes	No	Yes
State x Year FEs	No	Yes	No	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Observations	28453	28374	30609	30525
R^2	0.130	0.144	0.112	0.116

Notes. The dependent variable $\triangle$ *ln Value (Number)* is the first difference of the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.17: Alternative Transformations of Assets

Dep. Vars	ln(0.1 + Value)	ln(0.1 + Number)	ln(1 + Value)	ln(1 + Number)	IHS Value	IHS Number
	(1)	(2)	(3)	(4)	(5)	(6)
Important	0.369**	0.087***	0.309**	0.018*	0.327**	0.024*
	(0.148)	(0.026)	(0.129)	(0.011)	(0.135)	(0.014)
Training	Yes	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No	No	No
Observations	29144	30526	29144	30526	29144	30526
R^2	0.779	0.798	0.781	0.832	0.780	0.831

Notes. The dependent variable *ln (0.1 (1) + Value (Number))* is the logarithm of 0.1 (1) plus the value (number) of immovable properties owned by an IAS officer in a given year. The dependent variable *IHS Value (Number)* is the inverse hyperbolic sine transformation of the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.18: Alternative Independent Variables - Cumulative Years in Important Posts

Dep. Vars	ln Value		ln Number	
	(1)	(2)	(3)	(4)
Years in important posts	0.212***	0.215***	0.057***	0.057***
	(0.058)	(0.058)	(0.015)	(0.015)
Training	No	Yes	No	Yes
Female x Year FEs	No	Yes	No	Yes
Graduate x Year FEs	No	Yes	No	Yes
State x Year FEs	No	Yes	No	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Observations	29226	29144	30610	30526
R^2	0.772	0.778	0.765	0.770

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The dependent variable $\triangle$ *ln Value (Number)* is the first difference of *ln Value (Number)*.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.19: Alternative Independent Variables: Important Post Dummy After Reassignment

Dep. Vars	ln Value	ln Number	$\triangle$ ln Value	$\triangle$ ln Number
	(1)	(2)	(3)	(4)
Important post dummy after reassignment	0.267*	0.139***	0.874***	0.250***
	(0.143)	(0.038)	(0.166)	(0.043)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	29144	30526	28374	30525
R^2	0.777	0.769	0.143	0.115

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The dependent variable $\triangle$ *ln Value (Number)* is the first difference of *ln Value (Number)*.The independent variable *Important post dummy after reassignment* is a binary variable equal to 1 if an officer worked in an important post after he was for the first time reassigned to an important post in our panel in a given year. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.20: Important Post Dummy after Reassignment and Cumulative Years in Important Posts after Reassignment

Dep. Vars	ln Value		ln Number	
	(1)	(2)	(3)	(4)
Important post dummy after reassign.	0.267*	0.166	0.139***	0.119***
	(0.143)	(0.140)	(0.038)	(0.038)
Lag Experience in important posts after reassign.		0.224***		0.047***
		(0.063)		(0.016)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	29144	29144	30526	30526
R^2	0.777	0.778	0.769	0.770

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important post dummy after reassignment* is a binary variable equal to 1 if an officer worked in an important post after he was for the first time reassigned to an important post in our panel in a given year. *Lag Experience in important posts after reassignment* is lagged cumulative number of years working in important posts after reassignment. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.21: Alternative Independent Variables - Important Post Dummy

Dep. Vars	ln Value		ln Number	
	(1)	(2)	(3)	(4)
Important post dummy	0.311***	0.270***	0.117***	0.107***
	(0.095)	(0.094)	(0.025)	(0.025)
Training	No	Yes	No	Yes
Female x Year FEs	No	Yes	No	Yes
Graduate x Year FEs	No	Yes	No	Yes
State x Year FEs	No	Yes	No	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Observations	29226	29144	30610	30526
R^2	0.772	0.777	0.765	0.770

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important post dummy* is a binary variable equal to 1 if the ministry an officer worked in is an important post in a given year. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.22: Reassignment and Assets by Experience in Important Posts

Sample	Experience in important posts		No experience in important posts	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.390**	0.171***	0.960*	0.303**
	(0.176)	(0.048)	(0.533)	(0.138)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	25600	26824	3543	3701
R^2	0.777	0.768	0.798	0.794

Notes. The sub-sample *Experience in important posts* includes officers who have work experience in any important posts before 2011. The sub-sample *No experience in important posts* includes officers who have no work experience in any important posts before 2011. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.23: Drop Sample with Top 1% and Top 5% Assets

Sample	Drop top 1%		Drop top 5%	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.424**	0.106**	0.465***	0.116***
	(0.168)	(0.043)	(0.170)	(0.043)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	28834	28834	27648	27648
R^2	0.778	0.805	0.780	0.807

Notes. The sub-sample *Drop top 1%* drop the observations with top 1% value of properties in the whole sample. The sub-sample *Drop top 5%* drop the observations with top 5% value of properties in the whole sample. The sub-sample *6 Periods* and the sub-sample *4 Periods* are 3 and 2 years before and after the reassignment respectively. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.24: Life Cycle Effects: Drop the First Two Years after the Transfer

Sample	Drop the first year post event		Drop the first two years post event	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.536***	0.168***	0.654***	0.183***
	(0.207)	(0.054)	(0.243)	(0.063)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	27730	29011	26544	27744
R^2	0.776	0.772	0.776	0.773

Notes. The first two columns in the table exclude the first year after the reassignment to an important post for officers. Columns (3) and (4) exclude the first two years after reassignment. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.25: Reassignment to Unimportant Posts and Assets

Sample	Full sample				Treated officers			
Dep. Vars	ln Value		ln Number		ln Value		ln Number	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unimportant	-0.497***	-0.469***	-0.152***	-0.149***	0.079	0.124	0.010	0.013
	(0.165)	(0.166)	(0.043)	(0.042)	(0.173)	(0.175)	(0.046)	(0.046)
Training	No	Yes	No	Yes	No	Yes	No	Yes
Female x Year FEs	No	Yes	No	Yes	No	Yes	No	Yes
Graduate x Year FEs	No	Yes	No	Yes	No	Yes	No	Yes
State x Year FEs	No	Yes	No	Yes	No	Yes	No	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No	Yes	No	Yes	No
Observations	29226	29144	30610	30526	7773	7742	8037	8006
R^2	0.772	0.777	0.764	0.769	0.746	0.757	0.751	0.762

Notes. The first four columns are results for full sample, and the column (5) - (8) are results for officers who experienced the reassignment to unimportant posts. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Unimportant* is a binary variable equal to 1 during and after the year that a bureaucrat was reassigned from an important to an unimportant post and stay in unimportant posts thereafter in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.26: Standard Errors Clustered at Different Levels

Dep. Vars	ln Value		ln Number	
	(1)	(2)	(3)	(4)
Important	0.480	0.429	0.193	0.179
Clustered SE (State)	(0.222)**	(0.211)*	(0.063)***	(0.061)***
Clustered SE (Ministry)	[0.207]**	[0.199]**	[0.048]***	[0.046]***
Training	No	Yes	No	Yes
Female x Year FEs	No	Yes	No	Yes
Graduate x Year FEs	No	Yes	No	Yes
State x Year FEs	No	Yes	No	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Observations	29226	29144	30610	30526
R^2	0.772	0.777	0.765	0.770

Notes. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.27: Alternative Window Lengths of DID

Window	8 Periods		6 Periods		4 Periods	
Dep. Vars	ln Value	ln Number	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)	(5)	(6)
Important	0.413**	0.183***	0.367**	0.174***	0.263*	0.110**
	(0.164)	(0.044)	(0.159)	(0.044)	(0.151)	(0.044)
Training	Yes	Yes	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No	No	No
Observations	26969	28269	25910	27148	24195	24343
R^2	0.794	0.781	0.800	0.786	0.808	0.800

Notes. The sub-sample *8 Periods* include 4 years before and 4 years after the reassignment to an important post for first time. The sub-sample *6 Periods* and the sub-sample *4 Periods* are 3 and 2 years before and after the reassignment respectively. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year.The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.28: Poisson Estimation

Dep. Vars	Number of properties		
	(1)	(2)	(3)
Important	0.021	0.020	0.037*
	(0.019)	(0.019)	(0.019)
Working city	No	No	Yes
Training	No	Yes	Yes
Female x Year FEs	No	Yes	Yes
Graduate x Year FEs	No	Yes	Yes
State x Year FEs	No	Yes	Yes
Officer FEs	Yes	Yes	Yes
Year FEs	Yes	No	No
Observations	28305	28226	28076
Pseudo R^2	0.355	0.357	0.360

Notes. Poisson estimates. The dependent variable *Number of properties* is the number of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.29: Restrict Sample to After 2013 and After 2014

Sample	Period 2014-2019		Period 2015-2019	
Dep. Vars	ln Value	ln Number	ln Value	ln Number
	(1)	(2)	(3)	(4)
Important	0.509**	0.207***	0.660***	0.238***
	(0.211)	(0.059)	(0.230)	(0.067)
Training	Yes	Yes	Yes	Yes
Female x Year FEs	Yes	Yes	Yes	Yes
Graduate x Year FEs	Yes	Yes	Yes	Yes
State x Year FEs	Yes	Yes	Yes	Yes
Officer FEs	Yes	Yes	Yes	Yes
Year FEs	No	No	No	No
Observations	21461	22612	18498	19565
R^2	0.825	0.804	0.842	0.818

Notes. The first two columns are results for observetions 2014-2019, and column (3) - (4) are results for observations 2015 - 2019. The dependent variable *ln Value (Number)* is the logarithm of 0.01 plus the value (number) of immovable properties owned by an IAS officer in a given year. The independent variable *Important* is a binary variable equal to 1 during and after the year that a bureaucrat was for the first time reassigned to an important post in our panel. Standard errors clustered at the individual officer level are reported in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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