Are Criminal Politicians More Corrupt?: Evidence from Bihar's Public Distribution System

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Abstract

Do criminal politicians under-provide public services? I investigate this question by examining corruption in the distribution of publicly subsidized grain in the Indian State of Bihar. Subsidized grain often fails to reach its intended beneficiaries in Bihar. Using a multilevel hurdle I find that households in districts controlled by criminal politicians are 41 percent more likely to receive at least part of their subsidized grain entitlement.

Keywords:

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1 Introduction

Do criminal politicians under-provide public services? I investigate this question by examining corruption in the distribution of publicly subsidized grain in the Indian State of Bihar. Bihar's Public Distribution System (PDS) is responsible for providing below poverty line (BPL) households with 25 kgs of subsidized wheat and rice each month. However, PDS entitlements often fail to reach their intended beneficiaries with only 18 percent of BPL households receiving their full entitlement (Khera 2011).

At the same time, Bihar has witnessed a steady increase in the number of State Legislators who have been accused of criminal misconduct over the past two elections in 2005 and 2010 (Association for Democratic Reform, 2010). While most studies attempt to explain the increasing "criminalization" of Indian politics, I test whether criminal politicians promote (or inhibit) the provision of publicly subsided grain relative to clean politicians.[1] I combine household surveys with administrative and electoral data to estimate the impact of criminal politicians on the distribution of. Specifically, I employ a mixed, multilevel model to examine the consumption of publicly subsidized grain as a function of household covariates (ethnicity, land-ownership, rural residence) and district-level political variables (political competition and the share of politicians in the district with a criminal record) in Bihar from 2009 to 2011.

I find that households in majority criminal districts are 8 percentage points more likely to receive some PDS entitlement in the previous month than those in "clean" political districts. This translates to an extra 5,633 calories per BPL household per month, a non-trivial amount in a state where over half of children under 5 are malnourished. In turn, this provides one potential expla-

[1]To clarify, I refer to politicians facing criminal charges at the time of election as âĂIJcriminal politicians.âĂİ Politicians convicted of crimes are not allowed to hold office. However, politicians can contest elections while cases are pending trial. Some cases remain on the dockets for years. It is possible that charges could be politically motivated and do not represent actual crimes and thus not a direct indicator for criminality. However for charges to be filed there needs to be sufficient evidence for a judge to have deemed the case worthy of proceeding to trial (similar to an indictment in the U.S.) (Vaishnav, 2011). I restrict my analysis to only serious charges to help alleviate concerns that criminal charges are politically motivated.

nation for the recent ascendancy of criminal politicians in India. Voters may be willing to accept candidates with sordid criminal histories if it means increased access to targeted goods.

Secondly, this paper contributes to the current policy debate between reforming the Public Distribution System and replacing it with a direct-cash transfer. Gulati and Saini (2015) estimate that up to 47 percent of PDS grain at the all India leaks out of the distribution system. Khera and Dreze (2015) have countered, that previously problematic states (especially Bihar) have seen dramatic improvement in the provision of PDS grain in recent years. However, no study has considered sub-state variation in the provision of grain and whether certain types of politicians are better at ensuring benefit delivery. I demonstrate that significant variation exists both across districts and beneficiary demographics in the receipt of PDS entitlements. Scheduled caste, rural and landed households are all positively correlated with consumption of PDS grain.

1.1 Undernourishment and the PDS

Despite recent economic growth, malnutrition rates are staggeringly high in India. In fact, Indian children face malnutrition rates "five times [higher] than in China, and twice those in Sub-Saharan Africa" (World Bank 2013). As documented by Amartya Sen (1981) in his seminal work "Poverty and Famines", India has a history of food shortages due to a failure of distributing available food where it is needed most. To combat this public health crisis and to ward off recurring famines, the Government of India (GOI) instituted the Public Distribution System in 1957. The PDS supplies poor households with subsidized food goods, mainly wheat and rice[2]. Since it's incarnation, the PDS has undergone a number of reforms, eventually transitioning from a universal to targeted program, culminating in the Targeted Public Distribution System in 1997. Today, the PDS represents one of largest anti-poverty programs in India, and accounts for around 1 percent of Indian GDP, or $13.6 billion (New York Times 2012).

When functioning properly, the Public Distribution System provides vital food security to impoverished households. However, in a country where an estimated 21 percent of Indians remain

[2] In Bihar the TPDS also delivers subsidized sugar and kerosene

malnourished, corruption and leakage in PDS entitlements present an obvious cost (ICPRI 2012). A central government sponsored performance evaluation of the PDS in 2005 concluded that "only about 42% of subsidized grains.... reaches the target group." Jha and Rhamwani (2010) estimate a similar amount of diversion finding that for every dollar spent on the PDS 43 percent is illegally diverted. However, these noticeable shortcomings at the all-India level mask significant state and sub-state level variation in the successful procurement and distribution of PDS grains.

1.2 PDS in Bihar

Some states have nearly perfected the delivery of grain to below poverty line households. In a nine-state survey of PDS consumption Khera (2011) notes that "respondents received 84-88 percent of their entitlements", with Himachal Pradesh, Andhra Pradesh and Orissa nearing 100% . On the other hand, Bihar lagged far behind, with beneficiaries receiving only 45% of their entitlement.

While the TPDS is a centrally sponsored scheme, individual states are responsible for lifting grain from central government storehouses and subsequent distribution to below poverty line households. The federal government allocates 35 kg grain (25 Kg rice and 10 Kg wheat) to each BPL household in a given state. [3]

After lifting grain from the central government, the Bihar State Food Corporation stores food goods in one of 45 "godowns" (warehouses). Village-level Fair price shop dealers are required to pay for lifting and transportation of grain from these state run warehouses. In Bihar there are 42,900 PDS shops each serving one to several villages. Ostensibly, dealers then sell the subsidized wheat and rice to households that have procured the necessary BPL ration card. Anecdotal evidence suggests that diversion occurs most heavily during the last node in the distribution chain, when grain is lifted from state godowns by individual PDS dealers, (Justice Wadhwa 2013, Khera

[3] The central government has set the number of below poverty line (BPL) households in Bihar at 6,523,000. However, the State of Bihar believes this number to severely underestimate the true population of BPL households. Based on its own survey in 2008, Bihar claims there are in fact 13,000,000 BPL households. To correct this discrepancy in centrally provided grain Bihar spreads the PDS grain more thinly than the Center's household. While the Center issues 35kg of grain per BPL households, the State of Bihar allocates only 25kgs of grain (15 kg wheat and 10kg) rice to each BPL family per month. The criteria for determining BPL status are routinely debated and in the process of being updated. I discuss BPL criteria more thoroughly below.

2011). Still, it is impossible to rule out the potential for leakage to occur further up the distribution chain (e.g. when grain is lifted from central godowns and transferred to state godowns).

1.3 How Politicians Influence PDS Delivery

To determine if criminal politicians differ from clean politicians in the delivery of PDS grain it is first necessary to understand how Members of Bihar's Legislative Assembly can exert influence over PDS distribution. First, MLAs are responsible for appointing part of the district-level PDS monitoring committee. If MLAs staff the monitoring committee with ineffective cronies, then lax monitoring may in turn promote diversion of grain from intended targets to the open market.[4] [5] As the main body tasked with "keeping a vigil on the lifting and distribution of food grain by the FPS dealers" the monitoring committee plays an important role in the smooth functioning of PDS distribution (Wadhwa 2010). Second, MLAs retain power over the suspension and transfer of bureaucrats. Politicians can use this leverage over bureaucratic employment throughout the distribution chain from district level PDS supply officers and managers to local ration shop dealers. While local, village-level politicians may also impact the distribution of PDS grain, they lack the same political clout to transfer bureaucrats.[6]

2 Literature Review and Theoretical Arguments

2.1 Criminality and Public Service Delivery in India

Several authors have discovered a bizarre trend in Indian politics where criminal candidates are actually "rewarded" for their checkered past (Aidt et al 2011, Vaishnav 2011, Tiwari 2014). Over the last decade India has witnessed a rise in criminal politicians at both the National and State level. Thirty-four percent of the current Members of Parliament faced criminal charges during the 2014

[4]Support for electoral impacts on patronage can be found in Pakistan where doctors are more likely to be absent in politically safe constituencies (Callen et al 2013).

[5]During field interviews I conducted in the summer of 2013, at least 1 PDS dealer acknowledge he obtained his license via a family member who happened to be a local politician.

[6]In addition there is no available data on criminal charges for Mukhiyas or other lower-level politicians. I leave the diversion of PDS grain by village politicians and the local level political economy as a black box for future research.

elections, up from 24 percent in 2004. The charge sheets of Bihar's State Assembly Members are even longer. In 2010, 58% of Bihar's Members of the Legislative Assembly (MLAs) faced criminal charges, with 34% of these charges considered "serious" (e.g. murder, kidnapping, extortion, theft-related etc). In this paper, I code criminal politicians as those facing serious charges.[7]

While scholars remain perplexed by the success of criminal candidates, few have studied the impact of criminal politicians on public service outcomes in India.[8] Put differently, is there evidence that criminal candidates are actually more corrupt once elected? The question is largely empirical. If "criminal"[9] politicians are more likely to engage in patronage, their constituencies may suffer from a disproportionate amount of PDS leakage. To clarify, in so far as criminal accusations serve as a proxy for "corruption" or ties to criminal organizations, criminal politicians may be more likely to staff their bureaucracy with loyal compatriots leading to lax monitoring and poor enforcement of service delivery.

H1a: Districts governed by criminal MLAs will be associated with lower levels of PDS grain delivery

On the other hand, Milan Vaishnav (2011) has argued that criminal politicians use their "reputation as a badge of honor-a signal of their credibility to protect the interests of their parochial community." In short, in settings where public service delivery is poor, criminal politicians cast themselves as "community warriors"[10] protecting constituents from a corrupt and intransigent bureaucracy. Criminal politicians have several tools at their disposal that makes them uniquely suited (relative to non-criminal politicians) for the role of "community warriors." First, illegal rents bol-

[7]This helps alleviate concerns that criminality is only capturing trumped up, politically motivated charges. In addition, serious charges are often violent in nature and more reflective of organized crime, in general. Thus, serious charges are theoretically closer to my argument about how criminal politicians may use their violent reputations to intimidate bureaucrats and reduce PDS grain diversion. However, some of these serious crimes may still reflect political motivations especially those related to rioting. I am currently in the process of combining specific charges with qualitative information to reduce bias from potentially politically motivated accusations.

[8]See Chemin 2012 for a notable exception.

[9]I use criminal here, and throughout the rest of the paper to distinguish between politicians who have been accused, but not convicted, of serious criminal misbehavior.

[10]The term community warriors is borrowed from Milan Vaishnav (2012).

ster criminal politicians personal coffers allowing them to develop voting blocs via personal transfers to voters. When citizens are unable to pay a fee (or bribe) to access state resources, criminal politicians can more easily dip into their own pockets. Second, criminal politicians are more likely to have access to physical muscle and a reputation for violence. Criminal politicians can use this muscle power to intimidate bureaucrats into diverting benefit flows to their voting blocks or protect their favored constituents from extortion at the hands of the bureaucracy, police or other criminal cadres (Vaishnav 2014). For example, Pappu Yadav, a Bihari Member of Parliament "known for flexing his muscle" issued a self-imposed order limiting doctors' fees for poor households (Yahoo News India, 2014). Where public service delivery is erratic or corrupt, criminal politicians can deploy multiple strategies (legal or extralegal) to deliver targeted benefits.

H1b: Districts governed by criminal MLAs will be associated with higher levels of PDS grain delivery

2.2 Information and Electoral Accountability

Government responsiveness (e.g. better service delivery, reduced leakage) may largely depend on the electoral incentives politicians face at the polls. Several authors have argued that government performance depends on institutional structures of accountability (Besley 2007, Adsera et al 2003). Politicians face greater pressure to be responsive when facing intense competition and an electorate who is informed about their background and policy choices in office. Adsera et al (2003) test Besley's principal agent model on both large cross-national and panel data. They find that democratic institutions (proxied by Polity scores) have small, but negative effects on corruption. In addition, the frequency of newspaper readership produces a large reduction in corruption.

Similarly, the public distribution system in India has proven responsive, at the state-level, to changes in electoral turnout and voter information levels (as proxied by newspaper circulation and literacy rates) (Besley and Burgess 2001). Thus, it is plausible that sub-state distribution of PDS grain may respond to similar political incentives. Lacking a direct measure of information flows at the district level I proxy for voter awareness of entitlements and politician behavior with literacy rates (however, I am still awaiting data on household education and literacy so will not be able to fully test this hypothesis at this time).

I analyze political competition during the 2005 and 2010 Bihar State Legislative elections. As previously discussed, state legislators may potentially facilitate (or inhibit) PDS distribution primarily through their control over bureaucrats' career trajectories. MLA's embroiled in tight, electoral contests should face incentives to limit grain diversion and staff bureaucracies with competent technocrats, as a large swath of voters would benefit from a fully functioning PDS.

H2: Districts with greater levels of political competition, on average, will have higher levels of PDS delivery.

2.3 Ethnic Heterogeneity

A multitude of studies link ethnic heterogeneity to the under-provision of public goods (e.g. Alesina et al., 2004, Barr et al. 2012). In fact, there is evidence from North India suggesting that ethnic heterogeneity inhibits access to public goods. Using World Bank survey data, Nagavarapuy and Sheetal (2013) demonstrate that "households that share the same 'broad' caste as" the local distributor receive more grain, relative to those who tried to obtain grain from a bureaucrat of a different caste. Similarly, caste differences act as a barrier to groundwater markets in rural Uttar Pradesh and Bihar (Anderson 2011). However, Dunning and Nilekani (2013) provide evidence from Northern India that complicates the "caste impedes public goods" narrative. Instead, they claim that belonging to the same political party as the Pradhan (a village-level politician responsible for the allocation of public goods) determines access to publicly provided benefits. In short, when partisan ties cut across castes, party affiliation determines access to state benefits. More recently, scholars have begun to study why ethnic diversity may inhibit public goods provision. Experimental evidence from Kampala demonstrates that co-ethnics can more easily identify and sanction group members (Habyarimana et al 2007).

H3: Districts with greater ethnic heterogeneity will be associated with lower levels of PDS grain delivery

2.4 Ethnic Reservations

A similar logic applies to the reservation of political and bureaucratic offices for ethnic groups. The Government of India has mandated political reservations for state legislators. In 2005 and 2010, 16 percent of Bihar's 243 legislative constituencies were reserved for scheduled caste candidates.[11] Previous scholarship has demonstrated that political reservations can increase public good distribution to the reserved group (Chattopadhyay and Duflo 2004). Considering that scheduled caste populations are typically poorer and disproportionately benefit from anti-poverty programs like the PDS, increasing political reservations for this marginalized group could improve PDS delivery.[12]

H4a: Districts with a higher proportion of reserved constituencies will be associated with higher levels of PDS grain provision, especially among scheduled caste households

In a similar fashion, BPL households that share the same caste as the PDS dealer may be more capable of sanctioning dealers who divert grain away from the community and towards the private market. Thus, leakage should be lower in villagers were PDS dealers and consumers are co-ethnics. In fact, in an attempt to reduce PDS leakage, the central government mandated that 16% of new PDS dealer licenses be reserved for scheduled castes and 1 percent for scheduled tribes.[13] This leads to the following testable hypothesis:

H4b: Districts with a higher proportion of scheduled caste PDS dealers will be associated with higher levels of PDS grain provision, especially among scheduled caste households

[11] A further 2 constituencies were reserved for scheduled tribes in 2010

[12] Average Monthly Per Capita Expenditure is 970 Rs for Scheduled Caste/Tribe respondents and 1,271 Rs for other caste groupings.

[13] A further 18 percent were set aside for the most backward class and 3 percent for women of a backward class.

3 Data Description and Summary Statistics

Household data comes from two NSSO survey waves (2009-2010, and 2011-2012) across Bihar's 38 districts. This data can be thought of as repeated cross sections with 18,297 households nested within 38 districts and two time periods. I supplement survey data with originally collected administrative, census and election data aggregated to the district level. MLAs compete in one of Bihar's 243 assembly constituencies. In other words, constituencies are further nested within districts. However, the NSSO household surveys lack identifying information below the district level making it impossible to map households to their respective constituencies. Instead, I aggregate political constituency variables to the district level. For example *Serious Criminal* represents the percentage of the district's MLAs that have a serious criminal record.

3.1 Dependent Variable

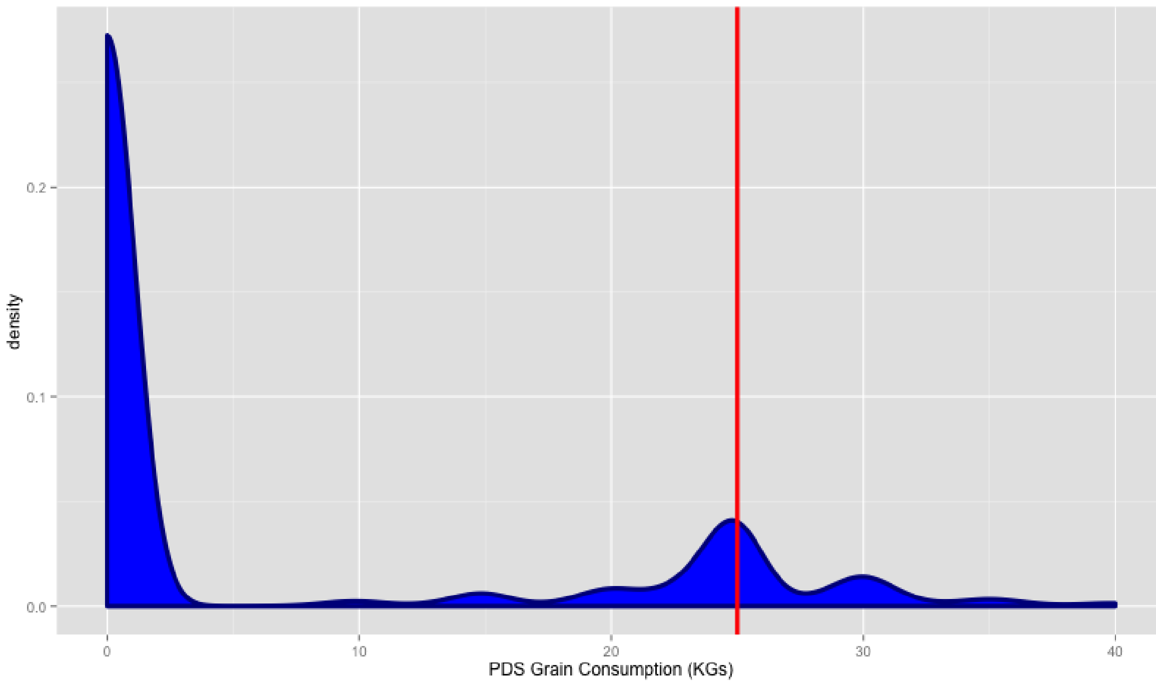
My outcome of interest is the kilograms of PDS grain consumed by an household in the previous month. Self-reported data on grain consumption in Bihar comes from two rounds of India's National Sample Survey conducted between 2009-10 and 2011-12. I focus exclusively on the 7,774 respondent households that fall below an imputed poverty line.[14]

Overall, only 26 percent of surveyed, below-poverty-line households consumed *any* PDS grain in the prior month. This is particularly disheartening considering the PDS is one of India's largest anti-poverty programs. Figure 1 provides a density plot of PDS grain consumption in the previous month for 7,774 below-poverty-line households. Restricting the analysis to BPL households provides estimates of grain consumption for intended beneficiaries. In actuality, households above

[14] I classify households that fall below Bihar's rural and urban poverty thresholds based on reported Monthly Per Capita Expenditure. However, Bihar determines BPL and ration card status based on a "system that assigned "scores" to each household on the basis of 13 questions...including questions on food security, sanitation, literacy status, means of livelihood, status of labour including women and children, indebtedness, and migration. The response to each question [are] scored on a scale of 0 to 4 and thereafter aggregated" (Roy 2011). Lacking data on most of these dimensions, I include households that do not own any land and/or are members of a Scheduled Caste or Scheduled Tribe community as landless and marginalized communities tend to fall below the poverty line. In the data appendix, I run robustness checks including all surveyed households.

the poverty line often illegally obtain access to this targeted anti-poverty program. Moreover, including richer households that are ineligible for the program would artificially inflate the number of households reporting zero consumption of PDS grain.

Figure 1: Density of Household PDS Grain Consumption



Even after restricting the sample to poor households, the distribution of PDS grain demonstrates a severe number of excess zeroes and skewness. The red line in Figure 1 indicates the monthly 25 kg quota guaranteed to every BPL household. Only 16 percent of BPL households receive their full entitlement. Conversely, some households report receiving more than the 25 kg allotment. Over-consumption could result from: 1) recall error, 2) an additional allotment to compensate for a previous month's shortage, or 3) excess distribution often resulting from collusion between the local ration-shop dealer and local elites.

The excess zeroes represent both eligible poor households who desire to purchase PDS grain but fail to receive their entitlement and poor households who opt out of the program due to taste or other preferences.[15] The zero-inflated and skewed distribution suggests that a standard OLS model would provide a poor fit. Instead, I employ a two step multilevel "hurdle" model, described below.

3.2 Predictors

3.2.1 Household Level Covariates

I include the following household level predictors to model PDS grain consumption:

Scheduled Caste and Scheduled Tribe (SCST) is an indicator variable for ethnic group membership. It takes a value of 1 for households that belong to traditionally marginalized groups in India (e.g. Scheduled Caste or Scheduled Tribe). While members of Scheduled Castes and Scheduled Tribes tend to be poorer and thus more likely to utilize the PDS program they may also be systematically excluded from the distribution of subsidized grain. I also use this variable in cross-level interactions with ethnic reservation variables (i.e. interactions between measures of district level and household level ethnicity) to test the ethnic reservation hypotheses.

Land is an indicator for land-ownership. Larger land-owners have traditionally held more power in villages and thus may be more capable of accessing limited state resources.

Rural is an indicator variable for whether the household is located in an rural or urban area. *Ceteris paribus*, delivery to remote areas may be more difficult.

Table 1 provides the summary statistics for all household-level variables included in the model.

[15] I can not completely rule out the case of some households self-selecting out of the PDS but restricting the analysis to BPL households helps alleviate this concern. My qualitative fieldwork along with a survey conducted by Muralidharan et al (2011) in Bihar indicates that quality of PDS grains is similar to market grains. All else equal, BPL households should prefer the cheaper PDS grain.

Table 1: Summary Statistics Household Variables

	PDS Grain Kgs	PDS Grain > 0	Land	SCST	Rural
Min	0.00	0.00	0.00	0.00	0.00
Max	65.00	1.00	1.00	1.00	1.00
Median	0.00	0.00	1.00	0.00	1.00
Mean	6.43	0.26	0.90	0.26	0.64
Std Dev	11.46	0.44	0.30	0.44	0.48
Obs	7268	7268	7772	7767	7774

3.2.2 Distirict-Level Covariates

My main predictor of interest is *Serious Criminal*. This variable is an indicator for districts where over half of the MLAs faced serious criminal charges (e.g. murder, rape, robbery, extortion)[16] when standing for elections. In some specifications *Serious Criminal* enters as the *percentage* of a district's Members of the Legislative Assembly who face serious criminal charges.

Margin of Victory measures the difference in vote share between the winning MLA candidate and the runner up. Thus, lower values indicate greater political competition. This variable is aggregated to the district-level and proxies for the average level of political competition in the district.

SC/ST Pop measures the percentage of a district's population that belongs to a Scheduled Caste or Scheduled Tribe. Since *SC/ST Pop* ranges from 7% to 30% an increase in SC/ST population share corresponds to an increase in ethnic heterogeneity. In reality this is a poor proxy for ethnic heterogeneity as their are multiple caste identities even within scheduled caste populations. Unfortunately, I lack finer grained data on caste membership.

SC Reserved measures the percentage of MLA seats reserved for only Scheduled Caste candidates. This variable (by itself and in interactions with household ethnicity) tests whether caste-based reservations for politicians improves PDS delivery. Districts with a greater share of reserved seats

[16]Criminal charges are similar to indictments in the U.S. and require sufficient evidence to initiate court proceedings. Still, I can not rule out the fact that some charges are politically motivated and do not represent actual crimes.

may witness an increase in PDS benefit delivery given that scheduled caste persons disproportionately benefit from the program.

SC Dealers measures the percentage of a districts village PDS dealers that are assigned to scheduled caste persons. This variable tests whether caste reservations for bureaucrats improves PDS delivery.

PDS Lifting measures the percentage of federally allotted PDS grain lifted by a district's PDS distribution center. Some district's lack the necessary bureaucratic capacity to acquire their full monthly allotment, with tons of grain left in federal warehouses. This variable controls for within-district bureaucratic efficiency in PDS delivery during the first step in the distribution chain.

Table 2 provides summary statistics for district-level variables.

Table 2: Summary Statistics District Variables

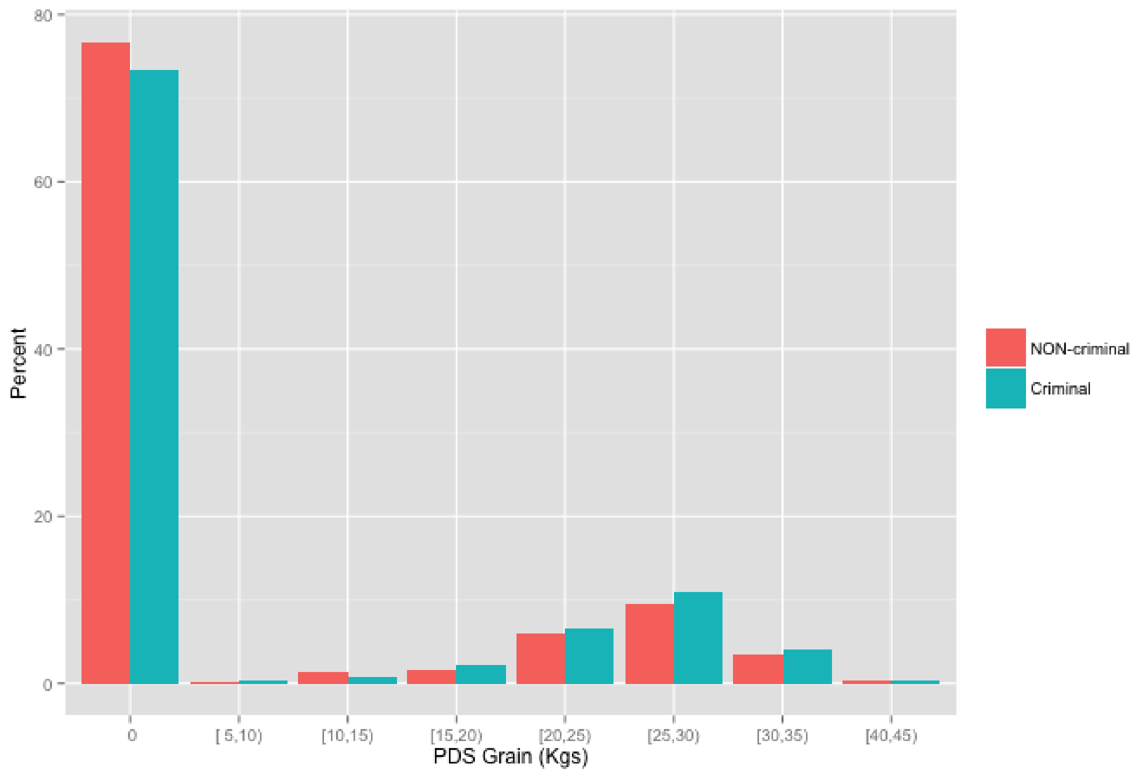
	Ser Crime	Ser Crime %	Mar. Vic	SC/ST Pop	SC Reserved	SC Dealers	Lift Percent
Min	0.00	0.00	0.21	6.69	0.00	8.70	32.79
Max	1.00	83.0	25.25	30.39	50.00	32.40	126.39
Median	0.00	25.0	10.03	15.31	14.29	17.10	80.37
Mean	0.22	29.0	11.14	15.79	15.60	17.02	76.68
Std Dev	0.42	22.0	5.16	4.75	9.29	5.06	21.49
Obs	7774	7774	7774	7774	7774	7774	7774

4 Method: Multilevel Hurdle Model

4.1 Bivariate Relatioship between Criminality and PDS Consumption

Figure 2 displays the unconditional distribution of PDS grain within criminal and clean districts. Bars indicate the percentage of households that fall into 5kg bins of reported PDS consumption. Two points are worth noting. First, 30 percent of households in criminal districts receive at least part of their PDS entitlement, compared to only 24 percent in clean districts. Second, conditional on receiving some positive amount of grain, the modal outcome is for households to receive their full 25kg entitlement. However there is evidence of potential under-weighting or under-provision even among households that receive some grain. Of course criminal MLAs may win in constituencies that correlate with observed (e.g. urban, ethnically homogeneous) or unobserved covariates (bureaucratic talent) that facilitate the delivery of subsidized grain.

Figure 2: PDS Grain Consumption in Criminal and Clean Districts by 5kg Bins



The rest of this section uses a hierarchical hurdle model to explore the correlation between criminal candidates and PDS delivery, while controlling for alternative hypotheses. To recapitulate, households are nested within in 38 districts and across two survey waves (2009 and 2011). Failing to account for this nested data structure would "violate assumptions about independent errors" and underestimate standard errors (Solt 2008). Given that the outcome of interest has excess zeroes, I fit a two step (or hurdle) model. The first step fits a logistic regression for the *Pr (PDS Grain > 0)*. That is, the probability that households consumes some, non-zero amount of PDS grain. Conditional on positive consumption, the second step fits a linear model to the natural logarithm of *PDS Grain*.

4.2 Logistic Multilevel Model

For the first stage (i.e. the probability that a household receives any grain,) I fit a multi-level logistic regression, allowing intercepts to vary across both districts and survey-waves. The varying-intercept model with both household and district-level predictors can be expressed as

$$\begin{aligned} Pr(PDSGrain_{itj} = 1) = logit^{-1}(\beta_0 + +\beta_1\mathbf{X}_{itj} + \beta_2 Criminal_{tj} + \beta_3\mathbf{Z}_{tj} + \beta_3\mathbf{D}_j + \mu_t + \mu_j) \\ \mu_t \sim N(0, \sigma^2_{\mu 1}) \\ \mu_j \sim N(0, \sigma^2_{\mu 2}) \\ e_{itj} \sim N(0, \sigma^2_e) \end{aligned}$$

Where *i* indexes households, *t* indexes survey-waves, and *j* indexes districts. The main parameter of interest is β_2 which captures the effect of a district where the majority of MLAs are serious criminals on the probability that a household receives any PDS grain. **X** and **Z** are sets of household district level predictors, respectively. Predictors sub-scripted *tj* are district level variables that vary over time. **D** is a set of predictors at the district level that are stable over time. The district-level intercepts μ_j and survey-wave intercepts μ_t are modeled as random draws from a normal distribution with mean 0 and variance $\sigma^2_{\mu 1}$ and $\sigma^2_{\mu 2}$.

4.2.1 Results from Household Predictors: Land, Caste and Rural Areas

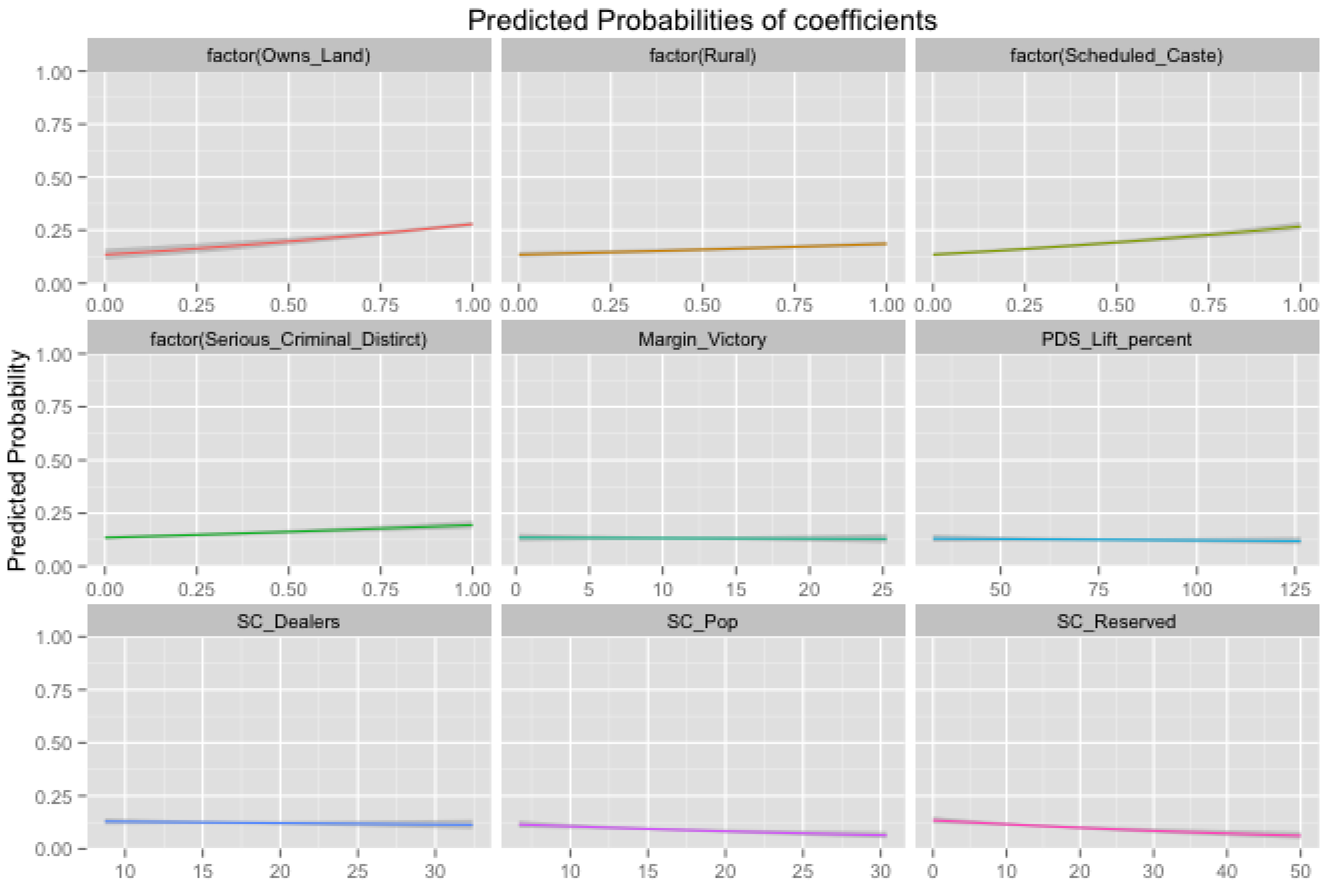
The second column of Table 3 provides the parameter estimates for the varying intercept model including only household-level predictors. Owning land, belonging to a Scheduled Caste or Tribe and living in a rural environment are all associated with a higher probability of consuming PDS grain. Column 3 provides the fully specified model with both household and district level predictors. As a robustness check, In column 4, I replace the *Serious Criminal* indicator variable with the

Table 3: Multilevel Logistic Regression with Varying Intercepts

	Dependent variable: PDS Grain = 1					
	1	2	3	4	5	6
Household Predictors						
Land		0.914^{***}	0.907^{***}	0.913^{***}	0.906^{***}	0.912^{***}
		(0.134)	(0.134)	(0.134)	(0.135)	(0.134)
SCST		0.846^{***}	0.851^{***}	0.850^{***}	0.405^{***}	0.408^{*}
		(0.067)	(0.067)	(0.067)	(0.132)	(0.230)
Rural		0.382^{***}	0.380^{***}	0.372^{***}	0.378^{***}	0.383^{***}
		(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
District-Level Predictors						
Serious Criminal	0.447^{***}	0.476^{***}	0.438^{***}		0.423^{***}	0.444^{***}
	(0.120)	(0.123)	(0.140)		(0.141)	(0.141)
Serious Criminal %				0.007^{**}		
				(0.003)		
Mar Victory			−0.002	−0.009	−0.001	−0.002
			(0.010)	(0.009)	(0.010)	(0.010)
SC Reservation			-0.017^{**}	-0.017^{**}	-0.0289^{***}	-0.017^{**}
			(0.008)	(0.008)	(0.009)	(0.008)
SC/ST pop			−0.027	−0.026	−0.027	−0.028
			(0.023)	(0.023)	(0.024)	(0.023)
PDS Lifting			−0.001	0.00005	−0.001	−0.001
			(0.003)	(0.003)	(0.003)	(0.003)
SC Dealers			−0.006	−0.010	−0.005	−0.014
			(0.021)	(0.020)	(0.021)	(0.021)
SCST * SC Reservation					0.0291^{***}	
					(0.007)	
SCST * SC Dealers						0.026^{**}
						(0.013)
Std. Dev Varying Intercepts						
District	0.55	0.58	0.61	0.60	0.63	0.62
Survey-Wave	0.70	0.79	0.81	0.80	0.81	0.81
Constant	-1.407^{***}	-2.782^{***}	-1.857^{**}	-1.895^{**}	-1.707^{**}	-1.710^{**}
	(0.501)	(0.582)	(0.786)	(0.776)	(0.796)	(0.792)
Observations	7,268	7,261	7,261	7,261	7,261	7,261
Bayesian Inf. Crit.	7,561.740	7,284.890	7,319.520	7,325.130	7,312.910	7,324.370

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 3: Predicted Probabilities for Model 3



percentage of a district's MLAs who face criminal charges. Columns 5 and 6 include interactions between household caste identification and political and bureaucratic reservations for scheduled caste groups, respectively. The parameter estimates for household predictors are similar across all specifications. To ease interpretation of logistic coefficients, figure 3 provides (marginal) predicted probabilities for each coefficient from Model 3. Parameter estimates are discussed below.

Interpreting the coefficients from Model 3, below-poverty-line households that own land are 10 percentage points more likely to have consumed PDS grain in the previous month compared to landless households, while holding other predictors at their median. Similarly, Scheduled Caste and Tribe households are 16 percentage points more likely to consume some PDS grain relative to households who are members of OBC or "higher" castes, after controlling for other predictors. Rural households are 5 percentage points more likely to consume PDS grain than their urban counterparts, again controlling for other predictors. This suggests that last-mile delivery is particularly inefficient in urban areas.

4.2.2 District Predictors: Comparing Criminal and Clean Districts

The multilevel model also allows the inclusion of district level variables that are time invariant or slowly changing. Most of these second-level predictors have large standard errors, indicating that these coefficients are not precisely estimated. However, several results are noteworthy. First, districts with a majority of MLAs are positively associated with PDS grain provision across all specifications. In criminally governed districts, households are 8 percentage points more likely to receive PDS grain than households in clean districts (predicted probability of 0.185 vs 0.261). This finding provides support for the hypothesis that Criminal MLAs act as community warriors. To be clear a substantial amount of grain still leaks in majority criminal districts. In expectation, households have an 26.1% probability of receiving some grain in majority criminal districts relative to the low base of 18.5% in clean districts. In other words, this result simply implies that there is a minimal improvement in districts governed by mostly criminals relative to cleaner political districts.[17]

Second, of the remaining district-level predictors, only *SC Reservation* and the interaction terms attain conventional levels of statistical significance. The negative coefficient on *SC Reservation* suggests, that households in districts with a greater share of MLA seats reserved for Scheduled Caste persons are less likely to consume any PDS grain. Thus, caste based reservations are associated with lower provision of PDS grain, in general. However, the reservation hypothesis actually claims that benefits in the reserved constituency will accrue to the reserved group (e.g. Scheduled

[17]These results could also be the product of an ecological fallacy. Recall that I am unable to identify which households belong to which political assembly constituency and thus must aggregate the political constituency predictors to the district level. In short it is possible that PDS consumption in clean constituencies could be very high and low in criminal constituencies but that this outcome is masked when aggregated to the district level.

Caste members). Models 5 and 6 include interactions between the percent of MLA seats and village PDS shops reserved for scheduled caste persons and household caste membership. Political reservations reduce the probability that non-scheduled caste households receive any PDS grain. On the other hand, more reservations for scheduled caste politicians are associated with higher levels of PDS provision among scheduled caste households (albeit the effect is extremely small). Likewise, increasing the number of PDS dealers who belong to scheduled caste groups is associated with a higher probability of scheduled caste households receiving PDS grain. These results provide some evidence in favor of reservations as a useful tool to improve public goods delivery to reserved groups.

Finally, I lack power to fully examine how political competition or ethnic heterogeneity alter the distribution of subsidized grain. These imprecisely estimated coefficients may result from substantial measurement error. Both *Margin of Victory* and *Scheduled Caste Population* are imperfect proxies for the theoretical mechanisms of political competition and ethnic heterogeneity. Recall that margin of victory is just the average level of competition across the district and thus may suffer from an ecological fallacy that masks the impact of competition at the constituency level. Second, Bihar is incredibly diverse with multiple caste identities even within the scheduled caste identifier. Lacking finer grained data on ethnic heterogeneity, results remain inconclusive.

4.2.3 Temporal and Spatial Variation

Now consider the standard deviation estimates for the varying intercept components. The district level errors (μ_j) have an estimated standard deviation of 0.6. This corresponds to districts differing by approximately $\pm$ 15% in the probability that households receive any portion of their entitlement. Considering that only 26 percent of sampled households report receiving any grain, there is indeed substantive variation among districts in the chance that BPL households access their entitlements. However, there is even greater variation in PDS outcomes over time. The differences among survey-wave intercepts (μ_t) are approximately $\pm$ 17% on the probability scale.[18]

[18]Coefficient interpretation follows Gelman and Hill, 2006

4.3 Log-Normal Multilevel Model

The second step of the model fits a multilevel linear regression to predict the amount of PDS grain consumed (in Kg) by a household, conditional on household consumption of *PDS Grain > 0*. The model includes the same predictors as the first step logistic regression and allows intercepts to vary across districts and survey-waves. Results for the second step are provided in Table 4. The fully specified second step can be written as:

$$
\begin{aligned}
ln(PDSGrain_{itj}) = \beta_0 + \beta_1\mathbf{X}_{itj} + \beta_2 Criminal_{tj} + \beta_3\mathbf{Z}_{tj} + \beta_3\mathbf{D}_j + \mu_t + \mu_j) \\
\mu_t \sim N(0, \sigma^2_{\mu 1}) \\
\mu_j \sim N(0, \sigma^2_{\mu 2}) \\
e_{itj} \sim N(0, \sigma^2_e)
\end{aligned}
$$

The parameters for the log-normal portion of the model are not precisely estimated, with some predictors switching signs. In short, most of the predictive power of the model comes from the first step in predicting whether or not a household receives any PDS benefit. Given the drastic reduction in sample size (from 7,261 to 1,859 households), the uncertainty in these estimates is hardly unexpected.

Using both parts of the hurdle model I estimate the expected kilograms of PDS grain for a household in a majority criminal district relative to a household in a clean district. For example, to estimate the expected PDS grain consumption for a household in an average, majority criminal district I calculate the $Pr(PDSGrain > 0|Criminal, X) * E[PDSGrain|Criminal, X]$, with other covariates (X) held at their median.[19] I estimate that households in majority criminal districts consume 6.02 kg of PDS grain per month, on average. Households in clean districts only consume

[19] This estimation takes the predicted values from each step of the hurdle model given covariates X. Predicted values of grain consumption are based on marginal effects of explanatory values and do not condition on the random intercepts across districts or over time.

Table 4: Multilevel Lognormal Model

	Dependent variable:PDS Grain (Kg)	
	(1)	(2)
Land		0.031
		(0.032)
SCST		0.004
		(0.014)
Rural		−0.006
		(0.014)
Serious Criminal	−0.013	−0.024
	(0.021)	(0.023)
Mar. Victory		−0.002
SC Reservation %		−0.001
		(0.001)
SC Population |		(0.003)
PDS Lifting		0.001
		(0.001)
SC Dealers		0.003
		(0.002)
Constant	3.200^{***}	3.000^{***}
	(0.059)	(0.093)
Observations	1,860	1,859
Note:		*p<0.1; **p<0.05; ***p<0.01

4.38 kg, while controlling for other variables in the model. An additional 1.68 kg of PDS grain in criminal strongholds translates to an extra 5,633 calories per household per month. [20][21] While not an astronomical increase, considering the high rates of malnutrition in Bihar, especially among children and women, every calorie counts. For example, 56% of children under 5 and 45% of women are undernourished (Menon et al 2009, IIPS 2007). Given the severe level of undernourishment in Bihar, an extra 3 days of food is not inconsequential.[22] However, these calculations do not account for uncertainty in the estimated regression coefficients for either the logistic or log-normal portions of the model. More generally, I use predictive simulations to account for the uncertainty in both steps of the model.

Figure 4 uses predictive simulation to summarize inferences from the two step hurdle model. Figure 4 estimates mean predicted PDS grain consumed by a household as a function of their caste and the percentage of Criminal MLAs in their district (Gelman and Hill, 2006).[23] The red line indicates expected PDS Grain consumption among Scheduled Caste households across the percentage of MLAs with serious charges in a district. The blue-line indicates the same for other caste identities. Among, non-Scheduled Caste households if we compare a district with only clean MLAs (e.g. Lakishari) to a distrcit where 83 percent of MLAs face serious charges (e.g. Gopalganj), households in the criminalized district can expect about 2.3kgs more PDS grain, on average. Similarly, comparing the intercept shift for Scheduled Caste and Tribe households to other caste groupings corresponds to about an extra 4 kg difference, on average across the range of criminal political districts.

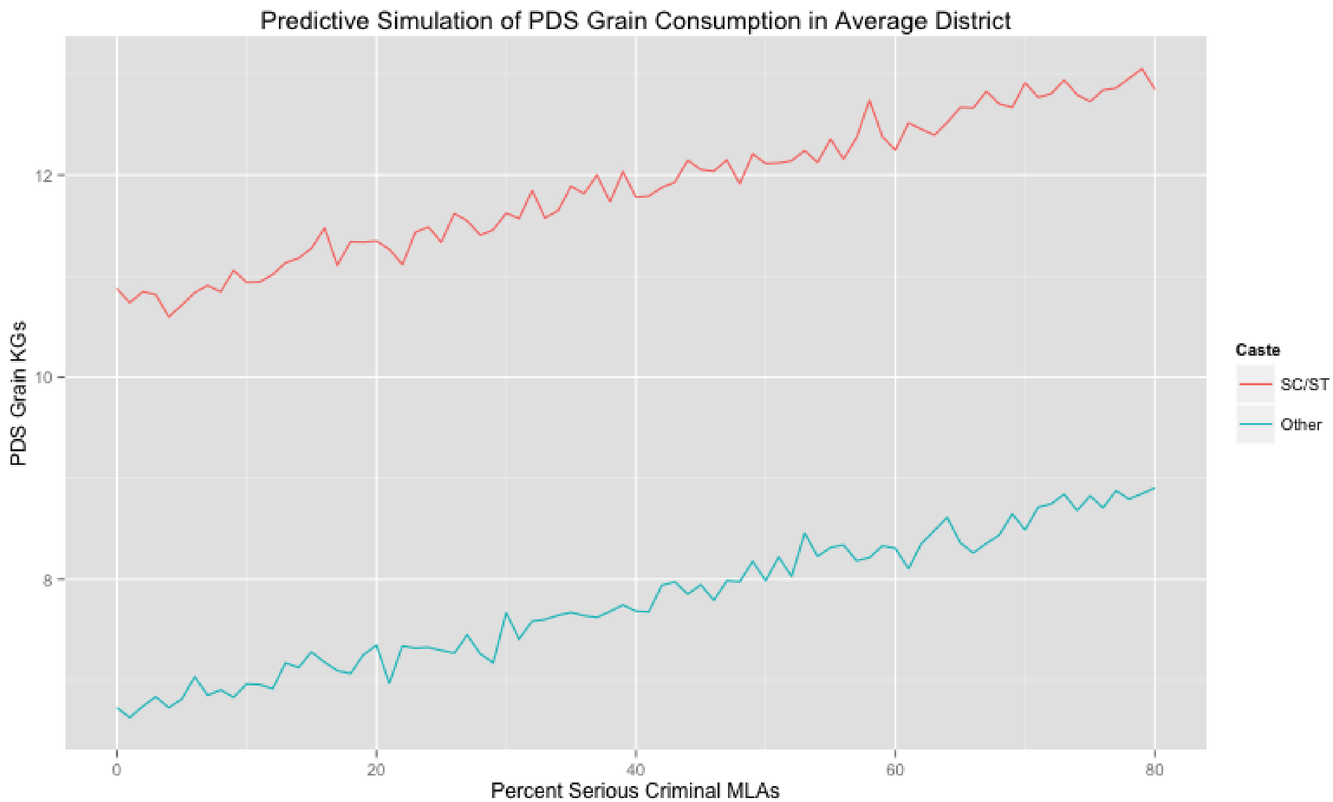
[20] Conversions from Kilograms of PDS Grain to calories are taken from the National Sample Survey Organization (2007). On average, BPL households consume 1780 calories per person per day, see Sen (2005)

[21] This is fairly close to the unconditional difference in mean PDS consumption between criminal and non-criminal districts. BPL households consume 7.5kgs of grain in criminal districts, on average, and only 6 Kgs in clean districts.

[22] This calculation is based on average calorie consumption in BPL Households in Bihar of 1,780 calories per person per day.

[23] Inferences for Figure 4 were created using predictive simulation from the ARM package in R with all other covariates held at their median, see Gelman and Hill, 2006

Figure 4: Predictive Simulation



Estimates of PDS Grain were calculated using 10,000 simulations from ARM package in R. The simulation takes random draws of parameter estimates (i.e. β and σ) from both steps of the fully-specified, multilevel model. The model used to create this figure replaces the binary indicator for criminal with the percent of criminal MLAs in a district (e.g. coefficients for the logistic first step correspond to column 4 of Table 3. Coefficients for the log-normal portion of the model were estimated using the same covariates. The simulation does not include the random intercepts for districts or survey-waves, instead using the intercept estimated from the pooled data Results can be interpreted as the expected household PDS grain consumption in the "average" Bihari district.

5 Discussion

Recent experimental evidence claims that information deficits explain why Indian voters favor criminal politicians at the ballot box. For example, Green et al. (2014) randomized whether survey respondents heard a speech that denoted a candidate as having a criminal record or the same speech without the information on criminal background. Respondents strongly favored the clean candidate. Another experiment in Delhi's slums found that having a criminal charge did not effect an incumbent's vote share (Banerjee et al 2010). On face, these studies seemingly conflict with the empirical reality of the increasing criminalization of Indian politics and the fact that criminal politicians are elected at higher rates than those without a criminal record (Vaishnav 2011).

This paper offers one way to reconcile this apparent contradiction. Voters may still penalize criminal politicians for their sullied record but weight other characteristics of criminal candidates more positively. For example, if criminal politicians are better at providing voters with targeted benefits- either via personal resources or by contesting a malfunctioning bureaucracy- this positive inducement may outweigh any distaste for criminal charges. I find that districts with criminal politicians are 8 percentage points more likely to receive PDS entitlements, even after controlling for household demographics, political competition and ethnic heterogeneity. This association provides one potential explanation for the recent ascendancy of the criminal political class. Put simply, voters may trade past accusations of criminal wrongdoing for increased service delivery. Recent survey evidence of voter preferences in Bihar corroborates this narrative. When Bihari citizens were asked why they vote for candidates with serious criminal records, 67 percent responded because the "candidate does good work." Alternatively only 20 percent cited caste or religion as motivating support for criminal candidates (Association for Democratic Reform 2014). Future work should focus on why voters favor criminal candidates at the polls and whether the association between between criminality and targeted goods is robust across India and other public benefits.

India faces some of the highest malnutrition rates for children under 5 in the world (World Bank

2013). Hunger is especially acute in Bihar. To combat this problem, India passed the National Food Security Act in 2013. The act enshrines the PDS as a central cog "[guaranteeing] cheap food grain to nearly 70% of India's 1.2 billion people" (Wall Street Journal, 2013). It is therefore vital to ensure that subsidized PDS grain reaches its intended beneficiaries. However, recent estimates have placed the all-India leakage rate at somewhere between 32 and 42 percent (Dreze and Khera 2015). Amidst this backdrop, Indian policymakers and scholars continue to debate the merits of reforming the PDS or replacing it with direct cash transfers (see Khera 2011, Dreze and Khera 2015 , Gulati and Saini 2015, and Government of India 2015). Both sides have focused on the headline estimates of leakage at the all-India level and recent improvements in historically under-performing states like Bihar. However, these aggregate numbers ignore variation in benefit delivery within states and across demographic groups. In Bihar, I find that landless, non-scheduled caste and urban households are all less likely to receive any portion of their monthly PDS entitlement. Finally, Scheduled Caste and Scheduled Tribe persons were not less likely to receive PDS grains among below poverty line households. It is encouraging that these marginalized groups are not excluded from this anti-poverty program. Still, 74 percent of BPL households failed to receive any grain significantly questioning the continued use of the targeted PDS in Bihar. Given the high stakes of this debate, policymakers should consider sub-state and demographic variation in PDS provision when weighing the relative merits of replacing an in-kind transfer of grain with direct cash payments.

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7 Appendix

I first fit a naive logistic regression ignoring the hierarchical structure of the data. The naive model can be expressed as:

$$Pr(PDSGrain_i = 1) = logit^{-1}(\beta_0 + \beta_1 Land_i + \beta_2 SCST_i + \beta_3 OtherRice_i + \beta_4 Rural_i + \beta_5 Serious_i + \beta_6 MarVictory_i + \beta_7 SCRes_i + \beta_8 LiftPercent_i)$$

7.1 Naive Logistic Model Analysis and Diagnostics

Table 3 provides coefficients for the naive logistic regression fit to the pooled data. The first column includes only the district level predictor for percentage of criminal MLAs in a given district. Counter-intuitively, having a greater proportion of criminal MLAs is strongly associated with households consuming some PDS grain. Columns 2 and 3 include individual and district level controls respectively. Almost, all predictors are statistically significant. However, before interpreting the sign and magnitude of coefficients, I first check the residual diagnostics of these complete

Table 5: Linear Model for Positive Consumption of PDS Grain

	Dependent variable:PDS Grain		
	OLS		*coefficient test*
	(1)	(2)	(3)
Land	-3.600^{**}	-3.400^{**}	-3.400^{***}
	(1.500)	(1.500)	(1.100)
SCST	0.120	0.035	0.035
	(0.340)	(0.340)	(0.320)
Market Rice	-0.020^{*}	-0.018	-0.018
	(0.012)	(0.012)	(0.015)
Rural	-0.220	-0.230	-0.230
	(0.360)	(0.350)	(0.640)
Serious Criminal	0.210	0.015	0.015
	(0.710)	(0.720)	(1.100)
Mar. Victory		0.006	0.006
		(0.030)	(0.041)
SC Reserved		0.006	0.006
		(0.019)	(0.037)
Lift Percent		0.040^{***}	0.040^{**}
		(0.009)	(0.015)
Constant	26.000^{***}	22.000^{***}	22.000^{***}
	(0.460)	(0.920)	(1.000)
Observations	1,764	1,764	
R^2	0.006	0.017	
Adjusted R^2	0.003	0.013	
Residual Std. Error	6.600 (df = 1758)	6.600 (df = 1755)	
F Statistic	2.100^{*} (df = 5; 1758)	3.900^{***} (df = 8; 1755)	

Note: *p<0.1; **p<0.05; ***p<0.01

pooling models.

Table 6

	Dependent variable: PDS Grain > 0			
	logistic			*District Clustered S.E.'s test*
	(1)	(2)	(3)	(4)
Land		−3.200***	−3.200***	−3.200***
		(0.320)	(0.320)	(0.430)
SCST		0.400***	0.390***	0.390***
		(0.070)	(0.071)	(0.110)
Market Rice		−0.077***	−0.075***	−0.075***
		(0.003)	(0.003)	(0.006)
Rural		0.330***	0.360***	0.360***
		(0.070)	(0.070)	(0.099)
Serious Criminal	0.420***	0.380***	0.200	0.200
	(0.120)	(0.140)	(0.150)	(0.480)
Mar. Victory			0.024***	0.024
			(0.006)	(0.019)
SC Reserved			−0.010***	−0.010
			(0.004)	(0.008)
Lift Percent			0.011***	0.011***
			(0.002)	(0.004)
Constant	−1.200***	0.740***	−0.240	−0.240
	(0.045)	(0.098)	(0.170)	(0.350)
Observations	7,268	6,549	6,549	
Log Likelihood	−4,128.000	−3,026.000	−2,991.000	
Akaike Inf. Crit.	8,259.000	6,063.000	6,000.000	
Note:				*p<0.1; **p<0.05; ***p<0.01

Figure 5: Binned Residual Plots for Complete Pooling Logit Models