ESSAYS ON THE ECONOMICS OF LABOR MARKET INSTITUTIONS AND POLITICAL ECONOMY

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This dissertation compiles three empirical studies in Labor Economics and Political Economy. Overall, the manuscript focuses on policy evaluation, and in understanding the hurdles in policy implementation in developing countries. The first study estimates the effects of minimum wage on employment in India, filling an important gap in the empirical minimum wage literature by accounting for the imperfect nature of law enforcement rampant in developing countries. The results are consistent with a model of imperfect competition and imperfect enforcement. The second study employs a semi-structural model using a 13-year firm-level panel dataset from India, and estimates the contemporaneous and lagged productivity effects of firms hiring contract workers. Results indicate that although firms benefit from hiring contract workers through increased productivity in the current period, lagged productivity effects are negative, reflecting the tradeoff in hiring workers on temporary contracts. The last study, a joint paper with two coauthors, develops a model on political clientelism to show that politicians may not only target swing voters to buy support, as shown in previous studies, but can additionally simultaneously target politically active households who can inturn indirectly influence other swing voters. Our empirical results based on a household survey in a southern Indian state, are consistent with these predictions.

BIOGRAPHICAL SKETCH

Vidhya Soundararajan is an applied microeconomist whose work primarily examines the impact of labour market institutions and regulations on employment, wages, and productivity in low-wage labour markets. Improving overall employment levels and worker welfare, and understanding and alleviating impediments to workplace productivity growth are running threads in her research. Another strand of Vidhya's work examines the political economy of institutions and program implementation in developing countries. Her work employs both reduced-form and semi-structural econometric approaches focussing on causal estimations, and uses observational data at the firm or household level. Prior to pursuing a PhD at Cornell University, Vidhya worked at the World Bank, the International Food Policy Research Institute, and the Planning Commission of India, where her work centered on understanding agricultural value chains and evaluating rural development programs in India. More details on Vidhya's work is available on her website, www.vidhyasrajan.com. She holds an M.S. degree in Economics from Madras School of Economics, and a B.Tech. degree in Information Technology from Anna University.

To my parents, for encouraging all my endeavours in all situations

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CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

My dissertation has two disctinct strands. The first strand examines the challenges and ramifications surrounding two types of labor regulations in a developing country, namely employment protection regulations and the minimum wage regulation. These two themes are addressed in chapters 2 and 3. Another strand in my dissertation explores the challenges besetting policy and program implementation at the ground level. The challenges could be multifold such as poor enforcement of laws (dealt with in the second chapter), corruption in implementing public programs, socio-cultural aspects that may prevent the adoption of a particular policy, and so on. I address one aspect of this, -political clientelism in the implemetation of public programs-, in chapter 4. Thus, overall, my dissertation not only offers insights on policy effectiveness, but by engaging with and delineating the appropriate challenges, also potentially helps improve their delivery and management.

The minimum wage is often violated as a result of poor enforcement, especially in developing countries. The resultant non-compliance poses a challenge both by itself and in effectively evaluating the effects of the minimum wage. I address the latter issue in the first chapter, and fill an important gap in the empirical minimum wage evaluation literature which currently does not effectively account for the imperfect nature of law enforcement.

In many developing and industrialized countries, costly employment protection regulations protecting regular or permanent workers, has led to the rise of contract workers who are usually employed on fixed term contracts without any job security. Despite the flexibility gains for firms in employing contract workers, such work arrangements could prevent the accumulation of firm specific human capital, consequently affecting firm productivity. The second chapter explores these relationships and delineates the static and dynamic effects of contract workers on productivity using a semi-structural production function approach.

In the last chapter, along with my coauthors Nancy Chau and Yanyan Liu, I examine the nature of political clientelism under a popular decentralized public works program in India. It is well known that in economies with high poverty and inequality, the influence of political economy on decentralized resource allocation is strong. However, the nature of patronizing reltionships that emerge in these settings are poorly understood. Interstingly, our paper sheds new light on how incumbent politicians use vote buying not only as a means to mobilize support directly from swing voters (which is already known and understood), but also to influence the behavior of political activists and the tenor of political campaigns which indirectly fetches them more support from other voters.

Minimum Wage Effects at Different Enforcement Levels

This chapter presents the first set of estimates on the effects of an imperfectly enforced minimum wage on wages and employment in the construction industry in

India. An effect of a minimum wage hike is a central policy issue in many countries and not surprisingly contributed to a vast empirical literature. The premise and the conclusion of these studies often espouse a competitive labor market, wherein a minimum wage hike produces a uniform negative effect on employment (Neumark and Wascher 1992). However, a growing number of empirical studies find positive or no effect on employment, consistent with models of imperfect competition (Stigler, 1946; Card and Krueger 1993; Dube, Lester and Reich, 2010).

I make three contributions to the literature. First, this paper addresses a key weakness in the above literature - the lack of studies accounting for the imperfect nature of labor enforcement and non-compliance with labor laws (Ronconi, 2010). Second, only few studies estimate minimum wage effects throughout the minimum wage distribution although theories predict non-linear effects (e.g. Stigler, 1946). This paper, in that spirit, without binding relationships to be linear, employs flexible form models. Moreover, I directly test the implications of a theoretical model developed by Basu, Chau and Kanbur (2010) (BCK) who show that, in an imperfectly competitive labor market model, a imperfectly instituted minimum wage hike produces either a positive, negative or mute response depending intricately on the interaction between minimum wage and enforcement. Third, the nature of minimum wage effects (sign and significance of coefficients) observed in my paper can point towards the nature of the underlying labor market (competitive or otherwise).

To estimate responses to minimum wages, I take advantage of state-time variation in minimum wage and enforcement (number of inspectors) and use five years of repeated cross-section data on construction workers from the National Sample Survey. A candidate measure for the level of enforcement of minimum wages is the number of inspectors at the state level under The Minimum Wages Act, 1948 but this measure is possibly endogenous because factors determining labor market outcomes may also affect how strictly states enforce the minimum wage law. To address the endogeneity, number of inspectors under The Factories Act, another state-level regulation but whose machinery works independently, is used as an instrument. Instrumental variables estimate reveal a hump-shaped relationship between employment and minimum wage at median and higher enforcement levels, but a negative relationship at lower levels of enforcement, consistent with BCK.

Results point to construction industry labor markets' monopsonistic nature (employers have market power) which is consistent with anecdotal evidence. The main policy take away is that employment could be increased if poorly enforced states perhaps strengthen their law enforcement machinery and/or states with exorbitantly high levels of minimum wage correct them downwards.

Productivity Effects of Contract Work

Firms hire contract workers or temporary agency workers through third-party labor market intermediaries (staffing companies) to obtain flexibility in labor markets. While much of the literature on contract work focuses on the socio-economic mobility and wage penalty of these workers (Jahn 2010), little effort has been made to analyze their effects on workplace productivity. The second chapter in my dissertation provides the first piece of evidence on the static and dynamic workplace productivity impacts of employing contract workers at the firm level in any developing country.

Results indicate that on average, contemporaneous productivity effects of employing contract workers are positive, reflecting high motivation and effort levels of these workers. However, lagged productivity effects are negative indicating poor firm-specific human capital accumulation among these workers because they are usually employed on temporary/fixed-term contracts. In most industries, productivity increases with an increase in lagged contract mandays share (as a proportion of total mandays), but starts decreasing after a threshold indicating potential undesirable effects in employing excessive contract workers.

Findings explain why despite the flexibility gains from employing contract workers, firms choose to employ a core set of regular workers who can contribute to the firm's pool of human capital. Due to the temporary nature of such work, neither firms nor workers have the incentives to invest in firm-specific knowledge and skills. Employment protection laws, in protecting regular workers, create a separate pool of workers (contract workers) who are unable to invest in and contribute greatly to firms they work in, simply because they do not stay long enough.

Consistent estimates of production function and productivity are obtained using the semi-structural production function approach employing proxy variables, proposed by Olley and Pakes (1996) (OP). In addition, this paper extends the OP methodology in two important ways. One, it relaxes their assumption of exogenous productivity growth (markov process) and explicitly allows productivity to grow endogenously. Productivity now evolves as a controlled process, depending on lagged productivity and contract labor share in the last period, in addition to being influenced by contract share in the current period (Doraszelski and Jaumandreu 2013 endogenized productivity evolution similarly using firm R&D). Second, to avoid the collinearity problem (elaborated in Ackerberg et al. 2003), I assign a functional form to productivity. Since static inputs (proxy variables) are determined as a result of single period optimization problem in a competitive market, an appropriate demand function for those inputs can be derived using the lagrangian function of the static cost minimization problem. This parametric demand function is then inverted to yield a parametric form for productivity, aiding identification.

Generalized Method of Moments estimates, using a vector of moments (production inputs and/or their lags, lagged rainfall shocks representing temporary demand shocks, and labor regulation index), are reported for the production function and productivity evolution equation separately for 5 industry groups in India, employing a 13-year firm level panel data set from the Annual Survey of Industries (ASI).

Political Economy of Decentralized Public Programs

Political parties in developing countries have been noted to strategically favor households and direct public resources to expand or retain their party base. This political behavior is termed as vote-buying and more generally clientelism in a large and long standing body of work. The debate on clientelism until recently focussed on whether politicians target swing voters or loyalists with voters being passive recipients of transfers and information. However, a number of recent studies investigate the role of voter information in their targeting (Grossman and Helpman 1996, Wantchekon 2003), by uncovering cases where politicians alter their vote buying patterns to target voters who attended education programs about the practice of vote buying (Vincente 2014), and voters who received information about the qualification of candidates (Banerjee et al, 2011).

We develop a simple model and argue that households that are politically active produce a public good that can change the information voters have about incumbent and rival politicians and set the tenor of political campaigns in their style. Our model then allows politicians to buy support not only from swing voters with relatively mild political attachments (this has been shown before), but also from voter-cum-activists who spearhead political campaigns, so long as the transfers engender support from other swing voters, if not the activists themselves.

We take the model predictions to data and study the nature of clientelism under the Mahatma Gandhi Rural Employment Guarantee Scheme, a public works program operating at high budget in India. We use household survey data from the state of Andhra Pradesh in the year 2006 and ask how political affiliation measured in 2006 affects MNREGS work and payments received cumulative in 2006 and 2007. Our main contribution to the empirical literature is in tackling the issue of reverse causality by exploiting the timing of our survey which captures political affiliation just around the time or before the MNREGS program started based on the year MNREGS was introduced in the district.

Tobit regression results indicate that village level leaders affiliated to the state-ruled coalition during the study period (the United Progressive Alliance), venture expanding their support base by offering more MNREGS jobs and higher payment to opposition party affiliates and unaffiliated households compared to their own. Village leaders offer more benefits to active households compared to inactive households. In exploring the mechanisms, we note that both UPA rival and unaffliated households in villages with high level of political activism overall - proxied by the fraction of politically active households in among those included in our survey-, tend to receive higher days of work and payment. Other voters in villages with high proportion of active households tend to receive significantly less work and payment. These provide suggestive evidence that politicians target "informed" voters, consistent with Banerjee et al. (2011) and Vincente (2013), where "informed" refers to residing in villages with an overall high level of political activism.

CHAPTER 2

MINIMUM WAGE EFFECTS AT DIFFERENT ENFORCEMENT LEVELS: EVIDENCE FROM EMPLOYMENT SURVEYS IN INDIA

2.1 Introduction

How do the effects of minimum wages on the labor market vary according to the level of enforcement? To date, no empirical study in the minimum wage literature has addressed this question. Empirical studies consistent with the standard competitive neo-classical model and monopsonisitc or oligopsonistic models assume perfect enforcement of the minimum wage legislation (Card and Krueger, 1994; Card and Krueger, 2000; Neumark and Wascher, 2000; Machin and Wilson, 2004; Dube, Lester and Reich, 2010). However, this assumption does not accord with the growing empirical evidence of non-compliance of labor regulations (including minimum wage) in both developed and developing countries. Important studies in this regard include Ashenfelter and Smith (1979) who found that compliance with the minimum wage law during the early 1970s in the United States was just 64%. Also, Ronconi (2010) reports that compliance with employment regulations in Argentina between 1995 and 2002 was just 48.26%.This evidence underscores that the enforcement of the minimum wage legislation is as important as the level of minimum wage itself.

With perfect enforcement, the standard competitive labor market model predicts that the response of employment to a binding minimum wage hike is uniformly negative. Contrarily, models of imperfect competition predict a positive response of employment, as long as the minimum wage is below a threshold (Stigler, 1946). However, recent theoretical work by Basu, Chau and Kanbur (2010), henceforth BCK, incorporating elements of imperfect enforcement in an imperfectly competitive labor market model predicts that the equilibrium response to minimum wages depends intricately on the interaction between enforcement and the minimum wage.

The above discussed theoretical results have empirical implications that beg to be tested, and the present study precisely investigates those implications in the Indian context. Specifically, it asks two questions: First, how does a minimum wage affect the level of employment, wage, and days of work across the minimum wage distribution? Second, do these relationships vary across the level of enforcement? Using a repeated-cross sectional dataset from the nationally representative employment surveys of India (administered by the National Sample Survey) for the years 2004, 2004-05, 2005-06, 2007-08, 2009-10, and 2011-12, this study estimates the interactive effect of minimum wages and enforcement on employment, wages and days of work in the construction industry.

This paper contributes to the minimum wage literature in three key ways. First, evidence in the empirical minimum wage literature supports competitive labor market models as well as imperfectly competitive models and the issue still remains open for debate. Many recent and older studies based on developed countries and developing countries find negative employment effects supporting the competitive theory (Burkhauser, Couch and Wittenburg, 2000, Neumark and Wascher, 2000, Neumark, Schweitzer and Wascher, 2000, for the US; Machin, Manning and Rahman, 2002, for the UK; Abowd et al., 2000, for France; Bell (1997) for Mexico and Colombia, Montenegro and Pagés (2004) for a group of Latin American countries). Positive or insignificant employment effects, supporting imperfectly competitive models, are also found in a number of old and new studies alike, both in developed and in developing countries (see Card and Krueger (1994) and Dube et al (2010) for United States, Lemos (2004) for Brazil; Dickens, Machin and Manning (1999) for the United Kingdom; Abowd et al., 2000, for United States). The nature of minimum wage effects (sign and significance of coefficients) on employment observed in this paper can point towards one labor market model versus the other, contributing directly to the above debate.

Second, this paper addresses a key weakness in the above literature - the lack of studies accounting for the imperfect nature of labor enforcement and non-compliance with labor laws. In developing countries, and to an extent in developed countries, there is high non-compliance with labor laws, and the de facto level of regulation is lower than the de jure level of regulation (Ronconi, 2005). Studies find non-compliance in United States (Ashenfelter and Smith, 1979), Argentina (Ronconi, 2010), South Africa (Bhorat, Kanbur, and Mayet, 2012), Brazil (Lemos, 2004, 2006), Costa Rica (Gindling and Terrell, 1995), Mexico (Bell, 1997), Trinidad and Tobago (Strobl and Walsh, 2001), Chile (Kanbur, Ronconi, and Wedenoja, 2013) and a selection of Latin American countries (Maloney and Nunez, 2004). The present study directly addresses this above weakness by controlling for enforcement and enforcement interacted with minimum wage in its empirical models.

Third, only few studies estimate minimum wage effects throughout the minimum wage distribution (Neumark, Schweitzer and Wascher, 200; Dickens, Machin and Manning, 1999) although theories predict non-linear effects (e.g. Stigler, 1946). This paper, in that spirit, without binding relationships to be linear, employs flexible form models to estimate minimum wage effects throughout the distribution.

Gauging the effects of minimum wage increase throughout the minimum wage distribution at different levels of enforcement presented a few empirical challenges. First, the level of enforcement at the state level is possibly endogenous because factors determining labor market outcomes may also affect how strictly states enforce the minimum wage law. A candidate measure for the level of enforcement of minimum wages is the number of inspectors at the state level under The Minimum Wages Act, 1948. To address the endogeneity in this variable, number of inspectors under The Factories Act, another state-level regulation, is used as an instrument. The Factories Act, 1948, concerns health and safety violations in factories in the registered manufacturing industry. This is a relevant instrument because both factories and the minimum wage divisions, falling under the same state labor department, are subjected to similar shocks. Also, exclusionary criteria are plausibly satisfied because factories inspectors check health and safety violations of factory workers and do not deal with minimum wages in the construction industry.

The second challenge is in estimating non-linear minimum wages effects and interactive effects of minimum wages and enforcement as suggested by theories. Non-linear effects, particularly hump-shaped effects of minimum wages on employment, are suggested by Stigler (1946)'s model of imperfect competition. The interaction effects capturing cross elasticities of labor market outcomes with respect to minimum wages and enforcement, are suggested by BCK who incorporated imperfect enforcement in Stigler's model of imperfect competition. BCK show that the effects of minimum wage depends intricately both on the level of minimum wage and its interaction with the level of enforcement. In this paper, I capture non-linear minimum wage effects by dummy variables representing various quartiles of minimum wages and interactive effects by explicitly interacting the minimum wage dummy variables with the continuous enforcement variable.

The present study focuses on the construction industry in India, the second largest employer (after agriculture) employing 32 million workers in 2009-10. It is a dynamic industry that contributed to 8% of the country's Gross Domestic Product in 2012-13 (approximately $124 billion) and grew at 14.58% on average between 2000-01 and 2011-12 (a rise of $104 in the current U.S dollars or 6475 billion Indian rupees). Despite the growth and employment generation in the construction industry, a majority of workers receive wage payments below the minimum wage. In 2009-10, 52% of the construction workers nationwide received wages below the minimum and state specific noncompliance varied from as low as 4% to as high as 90%. There is qualitative evidence that contractors employing workers exert considerable monopsony power in payment of wages (Self-Employed Women's Association, 2005).

Studying minimum wage effects across enforcement regimes in the Indian context, is worthwhile for a number of reasons. First, there is state-time variation in minimum wages in India. Minimum wages, under the Minimum Wage Act, 1949, are set and revised by the state governments and revisions occur once or at most twice every year. Second, there is evidence of imperfect enforcement in India. A comparison of minimum wage violations estimated from worker reported National Sample Survey data and government reports on detection of violation reveals the starkness of this phenomenon. According to the National Sample Survey, 37% of the workers working in all industries throughout India received wages below the minimum wage in 2009-10. In contrast, only 2.1% of inspections lead to discoveries of violations in the same year. Remarkably, only about one-fifth of violations are detected by the government. Further, enforcement also varies across state and time, a setting unique to India which provides a platform to study the interactive effects of minimum wages and enforcement.

Ordinary Least Squares regression and Instrumental Variables two-stage least squares regression methods are employed. Additionally, Probit and Instrumental Variable Probit regressions are employed to model binary employment outcomes. Two sets of results are striking. First, there is a hump-shaped relationship between employment (as measured by participation in the construction industry) and minimum wage at median and higher levels of enforcement (at the 50th and 75th percentiles). However, at lower levels of enforcement (the 25th percentile), there is a negative relationship between employment and minimum wage. Second, there is a positive and an increasing relationship between wages and minimum wages at median and higher levels of enforcement (at the 50th and 75th percentiles). However, at low levels of enforcement (the 25th percentile), there is a positive effect on wages but only at the upper tail of the minimum wage distribution. The non-linearly in the minimum wage effects and the role of enforcement in above estimated relationships is striking, particularly for employment effects.

The empirical results are largely consistent with a model of imperfect competition and imperfect enforcement (BCK) and contrary to the neoclassical model which predicts a uniform negative effect on employment. Stigler's model predicts that employment responses to minimum wage are positive until a threshold (the competitive wage equilibrium in this case) and negative beyond that. BCK's model of imperfect competition and imperfect enforcement, built on Stigler's model, predicts that the turnaround threshold of the minimum wage at which employment response changes from positive to negative,changes based on the level of enforcement. The lower the level of enforcement, the smaller the threshold. This theory has clean testable implications. At high levels of enforcement, the upward sloping part of the employment response to minimum wage is to be observed for a relatively long interval of the minimum wage distribution. Consequently, the hump shape is very distinct at higher levels of enforcement. However, at low levels of enforcement, comparatively, the upward sloping part of employment response to minimum wages is to be observed for a relatively short interval. This could even be approximately observed as uniform negative effects at very low levels of enforcement, depending on the estimation methodology[1]. This is precisely what is observed in the empirical results. Uniform negative employment effects are observed in low levels of enforcement but a hump-shape emerges at higher levels of enforcement.

The rest of the paper is organized as follows. Section 2 describes the data; Section 3 provides institutional details on minimum wages and enforcement; Section 4 presents the econometric methodology; Section 5 presents the results and their interpretation; Section 6 presents robustness checks and results for specific demographic groups; Section 7 concludes the paper and discusses further research possibilities.

[1]In Stigler's model of perfect enforcement, as long as the minimum wage is below the turnaround threshold, an increase in minimum wage decreases the marginal cost of labor. Hence, employment responses are positive below the threshold. Above the threshold, an increase in minimum wage increases marginal labor cost; consequently, employment responses are negative. The same argument holds in the case of imperfect enforcement in BCK, except now that we are looking at how expected marginal cost of labor changes below and above the threshold and consequently affects employment responses. The threshold itself is a function of enforcement, which is measured by the probability of detection of violation.

2.2 Data Description

The primary data source for this study are six rounds of the National Sample Surveys (NSS) administered in the years 2004, 2004-05, 2005-06, 2007-08, 2009-10, 2011-12. These surveys are conducted from July to June. For example, the 2004-05 survey is conducted from July 2004 to June 2005. The exception is the survey in 2004 which took place from January to June 2004. These are cross section surveys conducted at the household level, inquiring on characteristics of the household, the numerous demographic particulars of all individuals, their employment status and characteristics. Among other things, every member of the household is asked to report up to four "activities" they did in the last seven days, which can include looking for work (unemployed), not looking for work (not in the labor force), or working (employed), and if employed, the industry and occupation of the industry they were employed in. Additionally, the number of days spent in each activity and earnings from the previous week for wage earners are reported for the last week. The key outcomes variables considered in this paper are employment, wages, and days of work in the construction sector [2]. I describe these key variables below.

A defining characteristic of the Indian low-wage labor force is that workers tend to be employed in multiple low paying jobs over the course of the year and

[2]Household members also report labor market activities during the reference period of 365 days preceding the date of the survey (that is, a yearly recall period). They report principal and subsidiary employment in the last one year, but they do not report earnings or number of days of work from this recall.

within a week. For the purpose of this paper, I employ a neighbor criterion to measure employment in the construction industry. Employment in the construction industry is defined as a binary variable taking a value 1 if the worker works in the construction industry and 0 if the worker works in agriculture, the closest ″neighbor″ to the construction industry. Industry B as a “neighbor” to industry A if most workers working in A for their principal work, work in B for their subsidiary work, and vice-versa. Employment, defined this way captures extensive margin, not in the classical sense of working versus not working, but rather working in the construction industry versus working in the neighboring industries. Figures 2.1 and 2.2 present pie-charts of employment in subsidiary industries for wage earners whose primary industry is construction or agriculture, based on a weekly and yearly recall period respectively. It is seen that, those engaged in the construction industry for their primary job, work predominantly in agriculture for their subsidiary job. Similarly, those engaged in agriculture as their primary job, tend to work in agriculture as their secondary job (perhaps plant another crop in the lean season) but a good majority of them are also engaged in construction (this is more obvious from the yearly recall).

The final dataset consists of a homogenous group of workers who share similar social and demographic characteristics and for whom minimum wages are potentially binding. I consider unskilled construction and agriculture workers (classified based on the National Industrial Classification and National Classification of Occupation [3]), and who are educated below middle school, or illiterates.

[3]Semi-skilled and unskilled workers are defined based on the occupational classification re-

There are 37, 339 observations for all years and states altogether. 48% of the overall sample consists of construction workers and the rest are agriculture workers.

2.3 Minimum Wages and the Enforcement Machinery

The Minimum Wages Act 1948 of India legally grants a minimum wage (MW) for workers in many industries and they are defined in Rupees per day at the state level for each covered industry [4]. They are set, implemented and enforced by state (and a few cases, the central) governments [5]. Existence of a large number of minimum wages for different industries/occupation in each state across years makes India's system of minimum wages complicated [6]. Further, it makes enforcement cumbersome, even in theory. State governments enforce the minimum wage law through a cadre of inspectors who randomly inspect construction sites within their jurisdiction. Assuming that a higher number of inspectors im-

ported by the workers in the National Sample Survey. In this paper, occupational categories, 712, 713, 714 and 931, under India's National Occupational Classification, 2004 are classified as unskilled and semi-skilled construction workers. Under NCO 1968 for survey years before 2007-08, occupational classifications 871, 931, 951 to 959 are considered unskilled. For Agriculture: 611 to 620 and 920 under NCO 2004 and 610 to 662, and 670 to 681 are considered unskilled.

[4]Minimum wages are defined only for employments listed under the "employment schedule" of the Minimum Wages Act under the concerned government. Employments other than those listed are not covered under the law.

[5] The concerned government is either the state government or the central government depending on the industry and sector of work. Government owned enterprises and firms in the mining and railway sector belongs to the central sphere; all other firms fall under the state sphere.

[6]Besler and Rani (2011) report that the central government sets 48 minimum wages for different categories including mining, agriculture and oil extraction, or any corporation under its ownership. State governments altogether set minimum wages for 1,123 job categories making a grand total of about 1,171 different minimum wage rates in India.

plies higher enforcement level or in other words higher likelihood of inspection and discovery (as in BCK), I measure enforcement by the number of minimum wage inspectors and this varies across state and time. This may not the most accurate measurement of enforcement because a quantitative measure as this might not reveal aspects of corruption and collusive agreements that could potentially exist between employers and inspectors (Basu, Chau, and Kanbur, 2010). However, assuming the quality and effectiveness of enforcement is uniform through the country and over time, number of inspectors could give a fair sense of enforcement.

Minimum wage and enforcement data are obtained from the "Reports on the Working of the Minimum Wage Law" published by the Labor Bureau, Ministry of Labor & Employment, Government of India. These reports provide state-specific information on minimum wages set in different industries and on the enforcement machinery of the minimum wage legislation for all years[7].

This paper exploits variation in minimum wages across state and time to estimate its effects on labor market outcomes. Figure 2.3 presents spatial variation in minimum wages for construction industry in 2011-12. The lowest minimum wage is in Orissa (Rs. 93/day) and the highest is in Maharashtra (Rs. 229/day). Additionally, to provide a sense of level and variation in minimum wages and its change over time, Table 2.1 provides the mean and standard deviation of min-

[7] The minimum wage data are available in table 3 and the enforcement data are available in annexure II of the "Reports on the Working of the MinimumWage Law" published yearly by the Labor Bureau, Ministry of Labor Employment, Government of India.

imum wages across years. The state-time varying minimum wage data were mapped to the worker level dataset (described in section 2). Workers in the current year were mapped to MW effective as on December 31 of the preceding year[8]. For example, workers surveyed in 2004 (July to December) are mapped to the MW as on December 31, 2003; workers surveyed in 2005 (January to July 2005) are mapped to MW effective as on December 31, 2004. Using MW effective in the year proceeding the year of survey (rather than say after the year of survey), addresses endogeneity concerns because in this case, minimum wages were set before labor market outcomes were realized. Some states like Arunachal Pradesh,Manipur, Mizoram, Tripura, Andaman and Niocobar Islands were extreme outliers in terms of enforcement s for enforcement

Table 2.2 shows the extent of variability across time and states in the enforcement variable. Enforcement data for a survey year (which are parts of full year) is an average of number of inspectors corresponding to the two years constituting the survey. The average (across states) number of inspectors all of India has declined from 187 in 2003-04 to 183 in 2011-12. Further, the number of inspectors at the 25th percentile is at 33 inspectors, at the median is 123, and at 75th percentile is 361, giving a well spread out distribution of enforcement regimes across different states. Number of inspectors at the state level is obviously endogenous to labor market outcomes. An instrumental variable strategy is used to address this and is

[8]In each state, MW for an industry could change multiple times within a year. Tracking the details of each MW change could be challenging because revisions are done decentrally by state governments and such detailed documentation are not available digitally. Sometimes they are available only in a regional language.

presented in section 4 below.

2.4 Econometric Approach

As a starting point, I estimate a non-parametric bivariate model to obtain a descriptive picture of the relationship between employment and log minimum wages (Figure 2.4). The graph presents a non-linear picture with two humps, indicating that a linear Ordinary Least Squares regression model will be far from sufficient. A similar graph for real log daily wages (figure 2.5) and log of days of work (Figure 2.6) also indicate non-linear relationships with log minimum wages.

Taking cues from these preliminary diagnostics, I specify a flexible regression model allowing for these non-linearities as follows:

$$Y_{ist} = f(MW_{s(t-1)}, E_{st}, MW_{s(t-1)} * E_{st}) + \alpha * LGDP + \beta * X_{ist} + D_s + D_t$$

Y_{ist} , the outcome variable represents the individual level outcome for worker i working in state s at time t and could be either (1) Employment taking the value 1 if the worker is employed in the construction industry and 0 if in agriculture (neighbor industry); (2) log daily wage of a worker, conditional on working in the construction industry; or (3) log days of employment in the construction industry in the preceding week, conditional on working in the construction industry.

$f(.)$ is a nonlinear function of minimum wage, $MW_{s(t-1)}$ (the real minimum wage in state s in time $t-1$) and enforcement at state s at time t, E_{st}, measured by the number of inspectors, and the interaction of both. In the above specification, minimum wage appears as dummies representing various levels of minimum wages. Here, I consider four dummy variables representing four quartiles of the minimum wage distribution. The binary variable quartile 1 takes a value 1 if the minimum wage falls in the first quartile of the distribution and 0 otherwise. The binary variable quartile 2 takes a value 1 if the minimum wage falls in the second quartile of the distribution and 0 otherwise. The binary variable quartile 3 takes a value 1 if the minimum wage falls in the third quartile of the distribution and 0 otherwise. The binary variable quartile 4 takes a value 1 if the minimum wage falls in the last quartile of the distribution and 0 otherwise.

$LGDP_{st}$ is log per-worker real construction GDP in state s at time t and controls for aggregate demand conditions. X_{ist} represents individual demographic characteristics such as age, square of age, gender, social group, and sector. Gender is coded as dummy variable and the base category is females. Sector is either rural or urban and the base category in this case is rural. In India, social groups are classified into four major categories – the scheduled caste, scheduled tribes, other backward classes and other castes[9]. Social groups are coded as dummy variables,

[9]The Scheduled Castes (SC) and Scheduled Tribes (STs) are two groups of historically-disadvantaged people recognized in the Constitution of India. Other Backward Class (OBC) is a collective term used by the Government of India to classify castes which are educationally and socially disadvantaged, but not as acutely as SCs and STs. All other castes are grouped as 'Forward caste'. The lists of Forward, Other Backward and Scheduled castes, and Scheduled tribes are compiled by the government of India irrespective of religion.

and the base category is Scheduled Tribes. The model also controls for year fixed effects (D_t) and state fixed effects (D_s).

The dummy variables (of MW) model for all three outcome variables, was estimated using an Ordinary Least Squared (OLS) and Instrumental Variable Two Stage Least Squares (IV-TS) regressions. Additionally, employment variable was also studied using Probit and Instrumental Variable Probit (IV Probit) regressions. The entire sample including construction workers and agriculture workers was used for the employment regression. Wage and days of work regression was based on a sample of workers, conditional on working in the construction industry. Table 2.3 provides the list of endogenous regressors and instruments for the dummy variables model with 4 dummies each taking the value 1 when the log real minimum wages falls in the first quartile, second quartile, third quartile, and fourth quartile of the distribution respectively, and 0 otherwise. Note that this is an exactly identified model with four endogenous regressors and four instruments.

As a first step, instruments are tested for relevance. In a model with multiple endogenous regressors, Angrist and Pichske (2008) provide for the Angrist-Pischke multivariate F-test of excluded instruments, which corresponds to a test based on F-statistic from each first stage regression after netting out the effect of the remaining endogenous regressors. As a rule of thumb, an F-value above 10 is considered significant.

2.4.1 Results and Interpretation

Main Results

Table 2.4 presents the statistics for instrument relevance from the first stage regressions for the dummy variables model based on quartiles of minimum wage distribution. The p-values for the Angrist-Pischke F-test in the employment model and wage/days of work model for each of the five endogenous regressors are reported. All p-values are 0.0, implying each of these regressors are individually identified[10].

Table 2.5 presents the effect of minimum wages on employment at different levels of enforcement using the linear probability model (OLS and IV two-stage method) in panel 1 and probit and IV probit models in panel 2. Ordinary Least Squares (OLS) regression results from columns 1 and 2 (panel 1) indicate a negative relationship between employment and minimum wages at low level of enforcement, say the 25th percentile. Compared to the base category of first quartile (0 to 25th percentile log MW), the likelihood of employment significantly declines by .23 in the second quartile, by .25 in the third quartile and by .18 in the fourth quartile. The Instrumental Variables two-state least squares regression (IV 2SLS)

[10] A linear-quadratic model was also estimated using minimum wage and a minimum wage squared term. This model has three endogenous regressors (MW Inspectors, MW Inspectors* log minimum wage, MW Inspectors * log minimum wage* log minimum wage) and three instruments (Factories inspectors, Factories inspectors * log minimum wage, Factories inspectors * log minimum wage * log minimum wage). The p-value obtained from the AP F-test for each of the three regressors is above .1, implying they are not individually identified by the instruments. Hence, the linear quadratic model was dropped from the main specification.

, which is my preferred specification, confirms these results, although the magnitude of the effect is different, especially in higher quartiles. Column 3 and 4 (panel 1) present the effects at the median level of enforcement, which are positive unlike at lower level of enforcement. The OLS results in column 3 shows that compared to the base category of 1st quartile, the likelihood of employment significantly increases by .28 in the second quartile, by .26 in the third quartile, and by .33 in the fourth quartile. But IV 2SLS results indicate that compared to the base category of 1st quartile, the likelihood of employment significantly increases by .25 in quartile 2, .27 in quartile 3, but drops to -.07 in quartile 4 (although the results are not significant at the fourth quartile). This indicates a hump-shaped relationship between employment and minimum wages. At very high levels of enforcement, say 75th percentile, OLS results (column 5) indicate that compared to quartile 1, the likelihood of employment in quartile 2, quartile 3 and quartile 4 are positive and increasing over the distribution of log minimum wages. But IV 2SLS results (column 6), indicate a clear and significant hump shaped relationship. Compared to the base category of quartile 1, the likelihood of employment in quartile 2 significantly increases by .93 in quartile 2, .92 in quartile 3, and .85 in quartile 4.

These results are robust to alternate specifications. Panel 2 in Table 2.5 presents the results using probit and IV probit regressions. The IV probit regressions, which are my preferred specifications because the predicted probabilities in this case are between between 0 and 1 (unlike the IV 2SLS model), indicate a uniform negative relationship at 25th percentile enforcement, a hump-shaped relationship at the median level of enforcement and higher levels of enforcement.

Table 2.6 presents minimum wage effects on log wages, conditional on working in the construction industry. Wage effects at 25th percentile of enforcement from both OLS and IV 2SLS indicates a negative effect in the second and third quartile and a positive effect in the fourth quartile. The IV 2SLS regression results (my preferred specification), indicates that compared to the base category of quartile 1, log wages in quartile 2 significantly decreased by .45 points in quartile 2, .42 points in quartile 3, and increased by .50 points in quartile 4. At the median level of enforcement, positive and significant effects are observed from OLS and IV regression results. The effects from IV regression are higher in magnitude, compared to OLS. Column 4 indicates that compared to the base category of quartile 1, log wages in quartile 2 are higher by .46 points, in quartile 3 by .39 points and in quartile 4 by 1.15 points. At even higher levels of enforcement (75th percentile), the wage effects are positive but are higher in magnitude compared to lower levels of enforcement. IV 2SLS results in column 6 indicates that compared to the base category of quartile 1, log wages in quartile 2 are higher by 1.77 points, in quartile 3 by 1.56 points and in quartile 4 by 2.09 points[11].

[11] OLS and IV 2SLS regressions were also estimated between between days of work and minimum wages using the same specifications. However, insignificant results were obtained in the IV 2SLS regression throughout the minimum wage distribution.

Interpretation of results

Results in section 5.1 indicates that the relationship between employment and minimum wage and between wages and minimum wages in the construction sector are distinctly different across enforcement levels, clarifying the importance of enforcement in this relationship. At high levels of enforcement (50th percentile and above),the likelihood of employment in the construction industry rises with an increase in minimum wage (quartiles) but declines at the upper tail. But at lower levels of enforcement (say 25th percentile), a rise in minimum wage decreases the likelihood of employment across all quartiles with a mild dent. Wage effects are negative at 25th percentile enforcement and at lower quartiles but are positive at 4th quartile. At higher levels of enforcement, wages effects are uniformly positive although with a mild dent in the third quartile. These results are summarized in a bar graph in figures 2.7 and 2.8 for employment and wages, respectively.

As mentioned earlier, labor market model with imperfect competition and imperfect enforcement as in Basu, Chau and Kanbur (2010) provides a consistent theoretical explanation to these empirical results. BCK's model incorporates imperfect enforcement to Stigler (1946)'s labor market model of imperfect competition.

In BCK's model, imperfect enforcement is modelled as the likelihood λ of inspection and discovery. Under perfect enforcement ($\lambda = 1$), comparative static responses in this model is exactly the same as Stigler's model, which is a hump shaped relationship with the turnaround threshold at the competitive wage equilibrium. The hump shape is predicted in Stigler(1946) and BCK because below the threshold, a perfectly enforced binding minimum wage decreases the marginal cost of labor, which causes employment to increase. However, above the threshold, a perfectly enforced binding minimum wage increases the marginal cost of labor and hence causes employment to decline. With imperfect enforcement, the hump shape between employment and minimum wages are retained but the threshold for sign reversal is lower than the competitive-wage threshold(as in the case of perfect enforcement) and depends uniquely on λ, the enforcement level. With lower enforcement, the threshold at which the expected marginal cost changes from positive to negative with an increase in minimum wage, is lower. The threshold increases with an increase in enforcement. This implies that lower the level of enforcement, the shorter the interval of minimum wage for which employment responses to minimum wages are positive. It also implies that higher the enforcement, longer the interval of minimum wage for which employment responses are positive or more prominent is the hump shape.

This is precisely what we see in the results. The employment response at 25th percentile (low level) enforcement indicates a negative effect, indicating possibly that the upward sloping part of employment response is for a very short interval of minimum wage and that the downward-sloping response is for the longer interval. For higher levels of enforcement (50th and 75th percentile in the Figure 2.7), the upward sloping part of employment is over a larger interval of minimum wage and is more pronounced, creating the hump shape.

Wage responses at higher levels of enforcement (50th and 75th percentile) are positive and increasing through the minimum wage distribution (Figure 2.8). At 25th percentile enforcement, wage effects are negative but very low in magnitude in quartile 2 and 3, but positive and low in magnitude in quartile 4. Firms tend to shirk complying with the law when there is low enforcement, and even reduce wages slightly by a marginal amount. But at higher levels of enforcement wage responses to minimum wage are comparatively more compliant and the magnitude of wage response are higher in the higher tail of the minimum wage distribution.

2.4.2 Robustness and Results for Specific Demographic Groups

Robustness

It is important to check if the results are robust to an alternate definition of the employment variable. In the main results in section 5.1, the employment variable was defined to take the value 1 if the worker worked in the construction industry and 0 if the worker worked in agriculture. In the alternate definition, the 0 category now includes workers in agriculture, retail trade and land transport industries (next closest neighbors to construction after agriculture as in Figure 2.1 and 2.2). Table 2.7 shows the result, at 25^{th},50^{th} and 75^{th} percentile enforcement levels. At 50^{th} percentile enforcement level both IV 2SLS (column 3) and IV probit (column 4) models indicate that the hump shape is retained and is significant. At 25th percentile enforcement, there is a uniform negative effect similar to the main results in table 5 (columns 1 and 2), although with a slight dent, which is again similar to the main results. At 75th percentile enforcement, there is a hump shaped relationship from the IV 2SLS model as seen in column 5, which mimics the IV-2SLS results in table 6. IV Probit results in column 6 indicate an increasing and tapering effect again similar to that obtained in table 6 (panel 2 and column 6). This implies that the results are robust to alternate definitions of the employment variable.

Results for specific demographic groups

Table A1 and table A2 in the Appendix presents employment and wage effects respectively for a sample of workers who belong to the social group called 'scheduled tribes' and 'scheduled castes'. The Scheduled Castes and Scheduled Tribes (STs) are two groups of historically-disadvantaged people recognized in the Constitution of India. Due to the relative disadvantages they face, employers could potentially exert market power on workers belonging to these groups. Results based on this sample mimic the main results for the entire sample in table 5 and table 6. Another group that can potentially face employers' power are workers who reside in rural areas and commute or migrate for a short term to work in urban areas. Assuming, that a large majority of construction activity takes place in urban areas, traveling to work and incomplete information will be a defining factor for workers residing in rural areas. Employment and wage effects estimated using from a sample of rural workers are presented in table A3 and table A4 in the Appendix respectively. Here again, results are similar to those in table 5 and table 6.

2.5 Conclusion

There is growing empirical evidence of imperfect enforcement and high non-compliance of the minimum wage law in both developed and developing country settings. Despite this evidence, studies that estimate the effects of the minimum wage legislation accounting for imperfect enforcement, are missing. The present study addresses this gap by estimating the interactive effects of minimum wage and enforcement among construction industry workers in the Indian context. Regional and time varying minimum wage and enforcement in India provides a unique platform to study these effects.

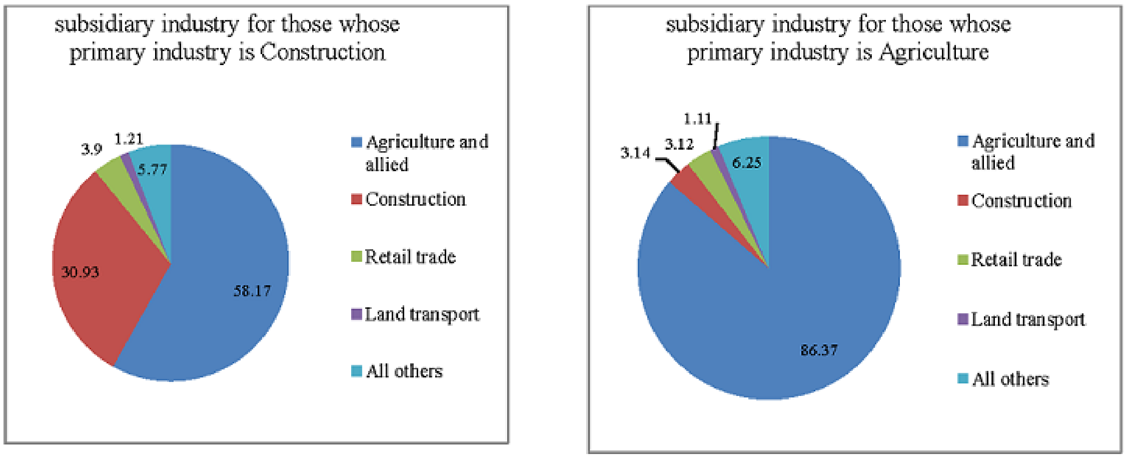
Enforcement in this paper, is measured by the number of inspectors under the minimum wage law and is endogenous because of unobserved heterogeneity affecting enforcement and labor market outcomes at the state level. Further, reverse causality could exist – that is, employment and wage levels can also drive the levels of enforcement. A unique instrument – number of inspectors under the Factories Act, another law implemented and enforced by the states –is employed to address this endogeneity.

The results from this paper strongly indicate that response of employment and wages to minimum wages vary starkly with the levels of enforcement. At low levels of enforcement, employment responses are uniformly negative, and at higher levels, there emerges a hump shaped relationship. These findings underscore the role of enforcement in studying the minimum law and the importance of enforcement as an institution in itself. Further, these results are consistent with models of imperfect competition and imperfect enforcement (Basu, Chau and Kanbur, 2010).

These results raise a number of research and policy questions for further research. While the present paper studies minimum wage effects at different enforcement levels on average levels of employment, wages and days of work for all workers, it brings up an interesting question of whether and how minimum wage effects vary across different enforcements levels for sub-minimum wage workers. This is an important policy question because it strikes the heart of the matter by asking if the minimum wage policy benefits those workers whom it was intended to benefit. Another key issue in the realm of enforcement is whether enforcement by itself and/or in interaction with minimum wage affects the level of non-compliance at all in the Indian context. A few papers have addressed this question in other developing countries (Bhorat et al. (2012) and Ronconi (2010)). Additionally, enforcement could potentially affect the depth of non-compliance and the square of depth of non-compliance; these classes of measures would be similar to the Foster-Greer-Thorbecke generalized measures of poverty. A key issue in these type of research questions, as in the present paper, is to address endogeneity in the allocation of enforcement by the government.

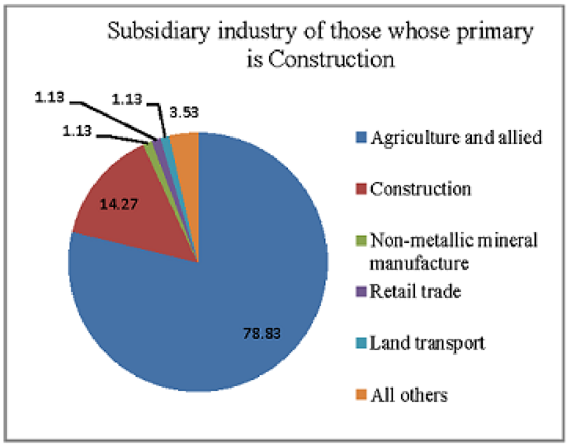
With an understanding of how enforcement affects average and sub minimum wage labor market outcomes as well as generalized measures of non-compliance, it may be worthwhile to theoretically explore the optimal level of enforcement, and empirically test if the levels of enforcement are optimal in the Indian context (or other developing countries depending on the types of availability of data).

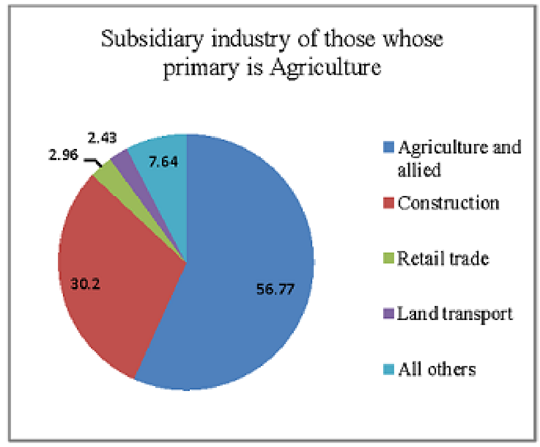
Figure 2.1: Principal and Subsidiary Industry - Weekly Recall



Note: Data from National Sample Survey for the years 2004, 2004-05, 2005-06, 2007-08, 2009-10, and 2011-12. Principal and subsidiary industries based on a weekly recall are determined based on a majority time based criterion. Industry in which the most time was spent, is the principal industry.

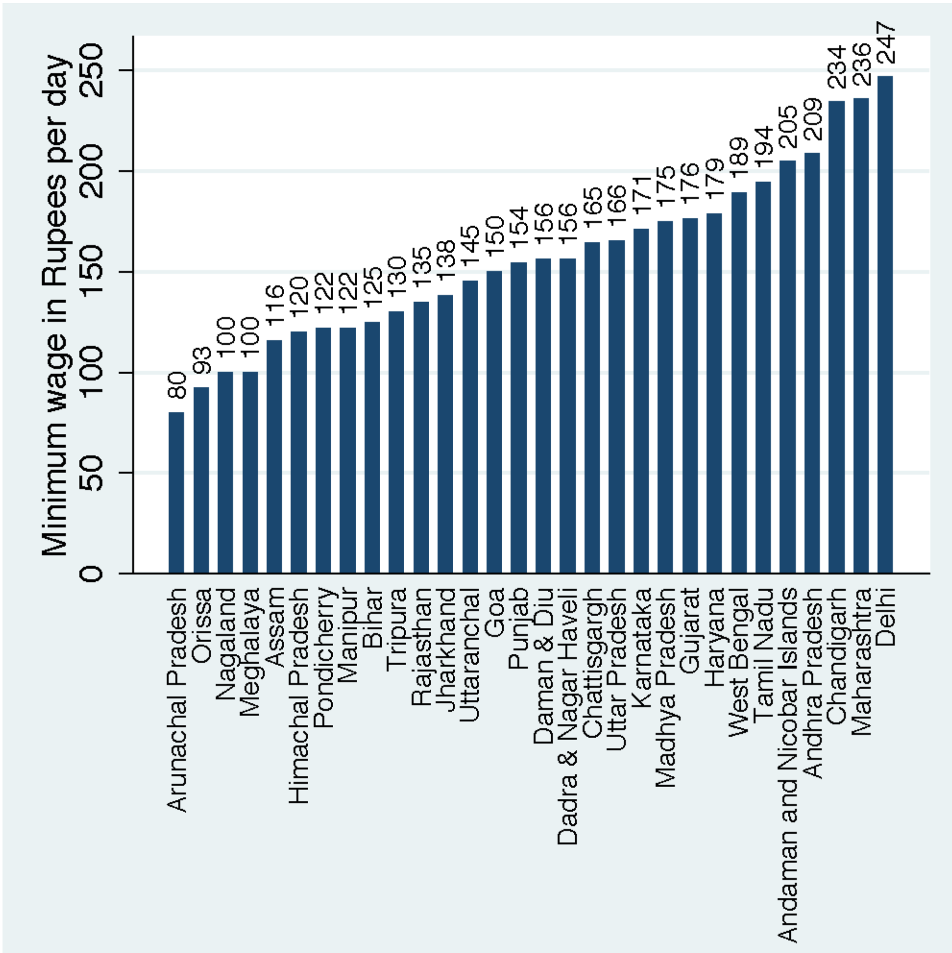
Figure 2.2: Principal and Subsidiary Industry - Yearly Recall





Note: Data from National Sample Survey for the years 2004, 2004-05, 2005-06, 2007-08, 2009-10, and 2011-12. Principal and subsidiary industries based on a yearly recall are determined based on a majority time based criterion. Industry in which the most time was spent, is the principal industry.

Figure 2.3: State Specific Minimum Wages in 2011



Source: Reports on the Working of the Minimum Wage Law, 2011

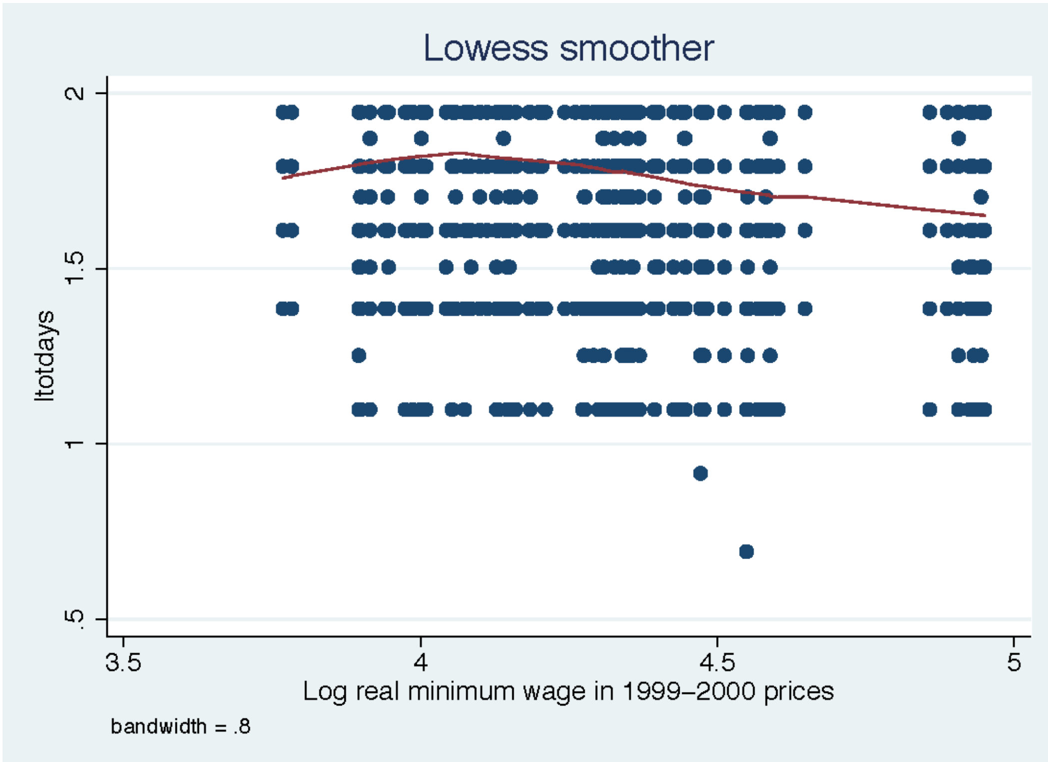
Figure 2.4: Lowess Smoothing Estimate of Minimum Wage on Employment

Note:Blue dots are scatter plots; red lines are estimated relationships

Figure 2.5: Lowess Smoothing Estimate of Minimum Wage on Wages

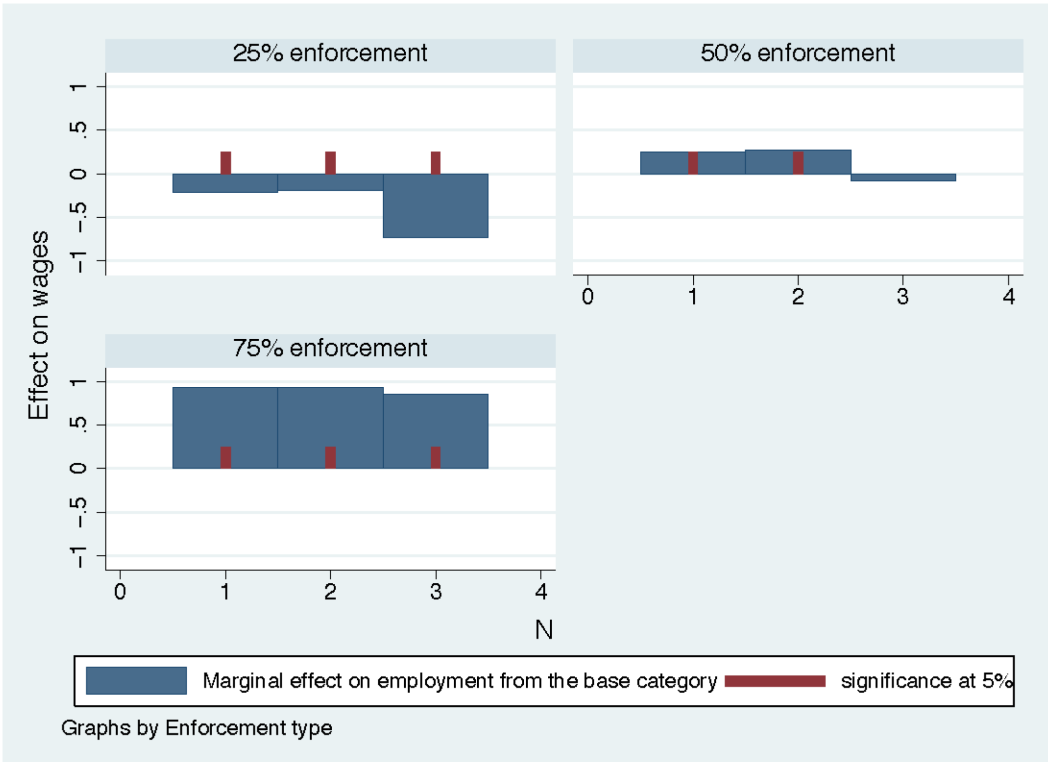
Note: Blue dots are scatter plots; red lines are estimated relationships

Figure 2.6: Lowess Smoothing Estimate of Minimum Wage on Days Worked



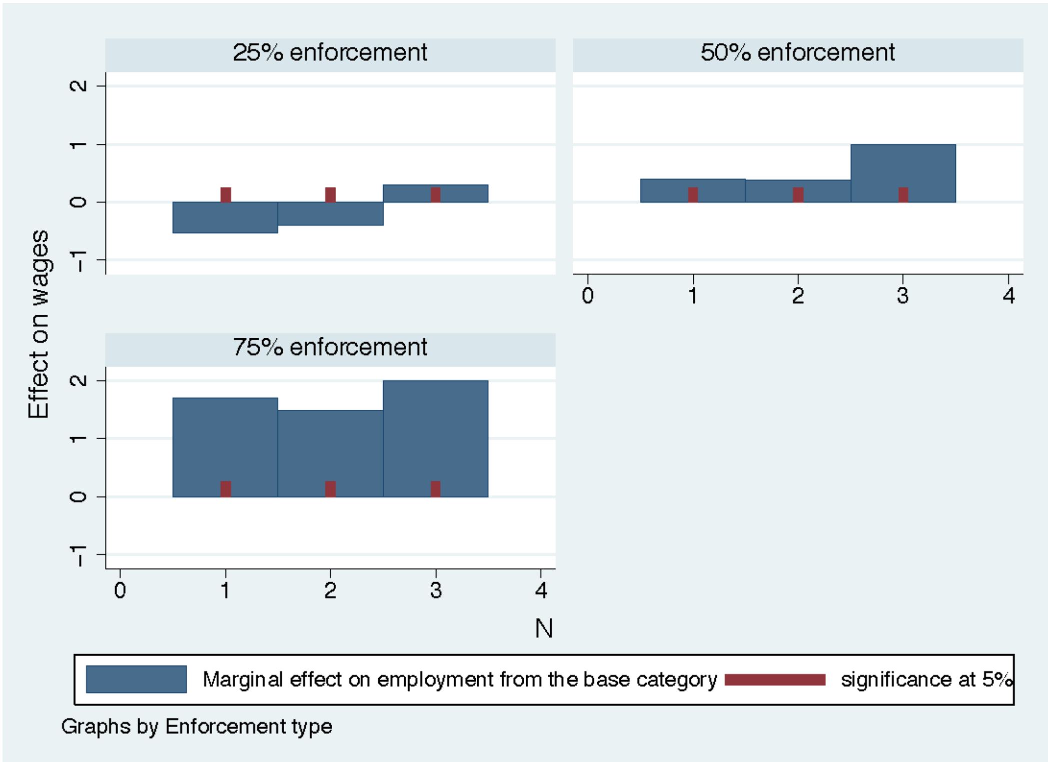
Note: Blue dots are scatter plots; red lines are estimated relationships. Log days worked in the last week on the Y-axis.

Figure 2.7: Employment Effects at Different Levels of Enforcement, IV-2SLS Estimates



Note:Red spike indicates that the estimate is significant at 5% level

Figure 2.8: Wage Effects at Different Levels of Enforcement, IV-2SLS Estimates



Note: Red spike indicates that the estimate is significant at 5% level

Table 2.1: The Minimum Wage in the Construction Industry in India

Year	Mean	Stadard Deviation
2003	81.07	26.11
2004	85.41	24.02
2005	86.51	23.06
2006	94.86	32.23
2007	100.59	29.75
2008	117.38	39.3
2009	122.02	27.78
2010	149.32	38.4
2011	156.26	43.18

Source: Reports on the Working of the Minimum Wage Law, various years.

Table 2.2: Minimum Wage Inspectors

Year	Mean	Standard Deviation
2003-04	187.01	221.50
2004-05	189.25	212.60
2005-06	193.06	209.58
2007-08	198.80	207.66
2009-10	174.84	211.38
2011-12	183	214.13

Source: Reports on the Working of the Minimum Wage Law, various years

Table 2.3: Instrumental Variables Strategy

Model	Endogenous regressors	Instruments
Dummy variables model- A case of 4 dummies representing each quartile.	MW inspectors, MW inspectors*quartile 2, MW inspectors*quartile 3, MW inspectors*quartile 4.	Factories inspectors, Factories inspectors*quartile 2, Factories inspectors*quartile 3, Factories inspectors*quartile 4.

Table 2.4: Tests for Instrument Relevance

Endogenous regressors	P-value for employment regression	P-value for wage/days regression
MW Inspectors	0.0	0.0
MW Inspectors*quartile 1	0.00	0.00
MW Inspectors*quartile 2	0.00	0.00
MW Inspectors*quartile 3	0.00	0.00
MW Inspectors*quartile 4	0.00	0.00

Table 2.5: Employment Effects at Different Levels of Enforcement

	LINEAR PROBABILITY MODEL					
Enforcement	25th percentile		50th percentile		75th percentile	
	(1)	(2)	(3)	(4)	(5)	(6)
Log minimum wage	OLS	IV 2SLS	OLS	IV 2SLS	OLS	IV 2SLS
Quartile 1 (base category)	-	-	-	-	-	-
Quartile 2	-0.23***	-0.21***	0.28***	0.25***	1.02***	0.93***
	(0.03)	(0.06)	(0.03)	(0.06)	(0.07)	(0.21)
Quartile 3	-0.27***	-0.18**	0.26***	0.27***	1.02***	0.92***
	(0.03)	(0.07)	(0.03)	(0.06)	(0.07)	(0.22)
Quartile 4	-0.18***	-0.72***	0.33***	-0.07	1.07***	0.85***
	(0.03)	(0.10)	(0.03)	(0.10)	(0.07)	(0.23)

	PROBIT AND IV PROBIT REGRESSIONS					
Enforcement	25th percentile		50th percentile		75th percentile	
Log minimum wage	Probit	IV Probit	Probit	IV probit	Probit	IV Probit
Quartile 1 (base category)	-	-	-	-	-	-
Quartile 2	-0.09	-0.28*	0.32***	0.35***	0.51***	0.65***
	(0.07)	(0.16)	(0.03)	(0.05)	(0.03)	(0.09)
Quartile 3	-0.22***	-0.29	0.24***	0.32***	0.50***	0.60***
	(0.06)	(0.18)	(0.03)	(0.05)	(0.04)	(0.08)
Quartile 4	0.01	-0.40**	0.42***	0.23**	0.60***	0.61***
	(0.08)	(0.17)	(0.04)	(0.11)	(0.03)	(0.06)

Note: *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%; Robust standard errors in parentheses for all models; bootstrap standard errors are reported for IV probit regressions; controls in all regressions include (1) at the individual level: age, age-squared, social group, and sector (Rural/urban); (2) at the state level: per worker construction sector state net domestic product, time dummies and state dummies. Quartile *i* is a dummy for belonging to the i_{th} quartile of minimum wages and the base category is quartile 1. Effects in quartile 'i' is the simply difference of predicted log wages at quartile *i* from quartile 1. For the probit and IV probit models, effects were calculated by differencing the probit index function at quartile *i* from quartile 0.

Table 2.6: Wage Effects at Different Levels of Enforcement

Enforcement	25th percentile		50th percentile		75th percentile	
	(1)	(2)	(3)	(4)	(5)	(6)
Log minimum wage	OLS	IV	OLS	OLS	IV	OLS
Quartile 1 (base category)	-	-	-	-	-	-
Quartile 2	-0.02	-0.45***	0.18***	0.46***	0.48***	1.77***
	(0.04)	(0.08)	(0.04)	(0.09)	(0.09)	(0.31)
Quartile 3	-0.04	-0.42***	0.19***	0.39***	0.54***	1.56***
	(0.04)	(0.10)	(0.04)	(0.08)	(0.09)	(0.32)
Quartile 4	0.13***	0.50***	0.34***	1.15***	0.64***	2.09***
	(0.04)	(0.11)	(0.04)	(0.13)	(0.09)	(0.33)

Note: *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%; Robust standard errors in parentheses for all models; bootstrap standard errors are reported for IV probit regressions; controls in all regressions include (1) at the individual level: age, age-squared, social group, and sector (Rural/urban); (2) at the state level: per worker construction sector state net domestic product, time dummies and state dummies. Quartile *i* is a dummy for belonging to the i_{th} quartile of minimum wages and the base category is quartile 1. Effects in quartile 'i' is the simply difference of predicted log wages at quartile *i* from quartile 1. For the probit and IV probit models, effects were calculated by differencing the probit index function at quartile *i* from quartile 0.

Table 2.7: Effects on Employment - "neighbor" Industry Includes Retail Trade and Land Transport

Enforcement	25th percentile		50th percentile		75th percentile	
	(1)	(2)	(3)	(4)	(5)	(6)
Log minimum wage	IV 2SLS	IVProbit	IV 2SLS	IVProbit	IV 2SLS	IVProbit
Quartile 1 (base category)	-	-	-	-	-	-
Quartile 2	-0.22***	-0.24**	0.40***	0.26***	1.29***	0.43***
	(0.08)	(0.10)	(0.08)	(0.03)	(0.28)	(0.06)
Quartile 3	-0.15	-0.16	0.43***	0.30***	1.28***	0.40***
	(0.09)	(0.12)	(0.07)	(0.03)	(0.29)	(0.06)
Quartile 4	-0.34***	-0.30**	0.32**	0.21***	1.27***	0.42***
	(0.11)	(0.13)	(0.12)	(0.08)	(0.30)	(0.05)

Note: *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%; Robust standard errors in parentheses for all models; bootstrap standard errors are reported for IV probit regressions; controls in all regressions include (1) at the individual level: age, age-squared, social group, and sector (Rural/urban); (2) at the state level: per worker construction sector state net domestic product, time dummies and state dummies. Quartile i is a dummy for belonging to the i_{th} quartile of minimum wages and the base category is quartile 1. Effects in quartile i is the simply difference of predicted wages at quartile i from quartile 1. For the probit and IV probit models, effects were calculated by differencing the probit index function at quartile i from quartile 0.

CHAPTER 3

CONTRACT WORK AND ENDOGENOUS FIRM PRODUCTIVITY IN THE INDIAN MANUFACTURING SECTOR

3.1 Introduction

Recent years have seen a surge in firms hiring contract workers by means of temporary fixed-term contracts mediated by licensed third-party staffing agencies (Autor, 2008). Despite the growing importance of such work arrangements in developing and industrialized countries, there is limited evidence on its ramifications on an important aspect of firm performance, namely productivity. Contract work arrangements provide the much needed labor market flexibility to firms because, firing costs prescribed by employment protection legislations that are applicable to directly hired regular workers, are absent for contract workers (Houseman, 2001; Abraham and Taylor, 1996; Chan 2013; Barrientos 2008). Workers hired on temporary contracts could possess high motivation and exert high effort, potentially positively contributing to firm productivity (Engellandt and Riphahn, 2005; Ichino and Riphahn, 2005; Hirsch and Mueller 2010). However, if firms repeatedly engage with workers in short term contracts, there could be little scope for the accumulation of firm specific human-capital, which in turn can stifle firm productivity growth (Jovanovic, 1979).

On balance, are there productivity impacts in employing contract workers? Should these effects exists, are the contemporaneous effects different from lagged effects? In exploring these questions, I provide the first set of casual effects of contract work usage on firm productivity among large manufacturing firms in India, where contract work is gaining importance evident from the increase in its share of worker mandays from 15% to 33% between 1998-99 and 2010-11. The relationship between contract work and factory productivity is particularly important in developing countries and emerging economies, where the share of contract workers is high and policy makers are increasingly targeting high manufacturing sector output growth as an important policy objective.

The institutional contours of contract work assumes various shapes across the world. In most developing countries, contract work is overwhelming popular and comprises over 50% of the workforce, and intermediaries in these setting called contractors or brokers. For instance, contractors channeled the hiring of over 50% of the knitwear factories in Bangladesh (Chan 2013), 35% of the worker mandays in Indian manufacturing (Ramaswmany 2013), and 50% of horticulture farm employment in South Africa (Barrientos, 2008)[1]. In comparison, Temporary Agency Work (TAW) in high income countries currently assumes a much smaller role in their overall labor force. TAW accounted only 1.8 % of the workforce in the United States, 2% in Germany, and 3% in the United Kingdom (Hirsch and Mueller, 2010;

[1]Other examples include Chile (fruit industry) and Jordan (garment industry) where a large number of workers are employed through labor contractors by the means of unwritten contracts (Barrientos and Kritzinger (2004).

CIETT 2012)[2]

Stringent employment protection regulations for regular workers increase the likelihood of firm's usage of contract workers (Houseman 2001; Pierre and Scarpetta, 2013). In India, the Industrial Disputes Act 1947 (IDA) requires firms to provide severance pay and issue notice three months in advance for firing regular workers, and obtain government permission for mass layoffs due to exit, closure, or other reasons. These restrictions are not applicable to contract workers. The strong role of the IDA on the burgeoning use of contract labor has been robustly demonstrated in some recent studies (Sen 2010; Ramaswamy 2013; Chaurey 2015; Sapkal 2015).

While these studies greatly enable our understanding of factors contributing to contract worker usage, comparatively little effort has been put into rigorously examining how firm performance is affected as a result, especially in developing countries and emerging economies. Using unpaid overtime work and absenteeism as indicators, Engellandt and Riphahn (2005) employ the Swiss Labor Force Survey to show that workers on temporary contracts provide more effort than permanent employees. Hirsch and Mueller (2010), exploiting a large firm level panel data set in Germany (IAB Establishment Panel) and using a system Generalized Method of Moments estimator, show a robust hump-shaped effect

[2] Temporary employment is relatively better enforced in industrialized countries. For example, Germany set sectoral minimum wages for temps in 2003, and this is complied with by almost all agencies.

of the extent of temporary agency work on firm productivity. That is, temporary workers positively affect productivity until a certain point owing to benefits from screening and flexility, but has a negative effect beyond that critical share of temporary worker employment because of temporary workers' low firm-specific human capital and spill-over effects on user plants permanent employees. Notably, existing studies deals with one-period models (Hirsch and Mueller 2010; Bryson 2013) overlooking inter-temporal effects, and largely focusses on industrialized countries where the proportion of contract workers is small. Cross-section data are commonly used (Arvanitis 2005; Kleinknecht et al.2006; Bryson 2007) without satisfactorily addressing endogeneity issues (Beckman and Kuhn 2009), a crucial component in consistent productivity and production function estimations [3] This paper is the first to present productivity effects of contract work in any emerging economy, and is the first in any setting to tease out contemporaneous effects from lagged effects.

Central to my analysis is a firm's model, which differentiates two kinds of labor - regular and contract workers. While regular workers are directly hired by

[3]Beckman and Kuhn (2009) report an inverted U-shaped relationship in Germany using an OLS and firm fixed effects model, but when firms temp share is instrumented with a group specific mean of temp shares (groups according to plant size, sectors and the like) they find an implausibly large effect in the linear-quadratic specification (e.g. a maximum productivity effect of roughly 400% in their IV fixed effects regressions) and no positive effect in the dummy specification, casting doubts on their IV approach. Other studies see no significant effect or observe mixed effects. Arvanitis (2005) does not find significant effects of temp workers on average labour productivity in Switzerland, Kleinknecht et al. (2006) does not find any relationship between temp work and firm sales growth rate in Netherlands; Bryson (2007) shows that TAW presence has a significantly positive effect on sales per worker in the UK, but no impact on a subjective measure of workplace productivity and the value added per employee.

the user firms, contract workers are hired and paid through contractors. A representative firm produces output, by choosing inputs while solving a dynamic profit maximization problem, with capital, labor, and productivity as state variables, and material input as a free variable. The productivity growth equation of this optimization problem explicitly captures the relationship between productivity and contract work. To elaborate, I model current productivity as a function of lagged productivity, and the share of contract worker man-days as a proportion of total man-days in the current and last period. This equation explicitly captures the contemporaneous and lagged effects of contract work on productivity. It portrays endogenous productivity evolution, where productivity grows intrinsically based on firm's choices, in an improvement and extension from earlier studies that model productivity growth as an exogenous Markov process, where current productivity depends only on lagged productivity.

I jointly empirically estimate a production function and a productivity evolution equation in a semi-structural framework proposed by Olley and Pakes 1996 (henceforth OP) and extended by Levinsohn and Petrin (2003) (henceforth LP), Ackerberg, Caves and Fraser (2007) (henceforth ACF), and Doraszelski and Jaumandreu (2013) (henceforth DR). These class of estimators directly address the estimation bias in production function estimation arising from unobserved productivity being correlated with its input usage (Marschak and Andrews 1944), by employing a free-input of the underlying dynamic optimization problem as a proxy variable for productivity. Since free inputs, by definition move freely with current productivity shocks, unobserved productivity can be backed-out from observing the free inputs using formal mathematical inversion and controlled for in the production function.

Following Doraszleksi and Jaumandreu(2013), the study relaxes the assumption of exogenous productivity growth based on an exogenous Markov process and explicitly allows productivity to grow endogenously as a controlled process. This way of modeling is consistent with reality in that productivity growth is not alien to the firm, but indeed that a firm's input choices and organizational structure are integral to it. A similar approach was taken by Kasahara and Rodriguez 2008 (KR) and DR, who endogenize the productivity evolution process based on imported inputs and R&D expenditure respectively. To avoid the collinearity problem in estimating a partial linear model (elaborated in ACF), I assign a functional form to the productivity term. Since the free (proxy) input is determined from a single period profit maximization problem in a competitive market, an appropriate demand function can be derived from the first order condition of this optimization problem. This parametric input demand function is then inverted to yield a parametric form for productivity, which avoids collinearity and aids identification.

A vector of moment conditions forms the core part of the identification strategy. Exogenous variation in contract share and its lag in the productivity evolution equation are captured using the following two sets of instruments. First, I use lags of state-time variation in rainfall deviations from normal, which are shown to be temporary household income shocks, which in turn translate to temporary product demand shocks at the firm level. Temporary demand shocks in turn influence the hiring of contract workers (Chaurey 2015), particularly when faced with stringent employment protection regulations, which forms the second set of instruments. I use an index developed by Besley and Burgess (2004) (BB) and modified by Gupta, Hasan and Kumar (2009) (GHK), which classifies Indian states as "pro-worker", "pro-employer" and "neutral", based on their amendments over time between 1958 and 1992 to the Industrial Disputes Act 1947 and the resultant variation in job security of regular workers. Based on this classification, firms in pro-worker states face stricter employment protection for their regular workers compared to other states, because of which they are more likely to hire contract workers. Input lags are used as instruments for inputs in the production function.

The Annual Survey of Industries (ASI), a panel data set of manufacturing firms spanning 13 years from 1998-99 and 2010-11, is employed for estimations. The ASI is a survey of formal sector firms containing well-reported data on important firm level characteristics such as capital, material usage, and revenue from sales, and employment mandays for contract workers and regular workers separately. My analysis focusses on large firms, above the size of 100. Large firms are interesting to study because they, unlike small firms, are subject to the Industrial Disputes Act. Evidently, since the late 1990s, large firms (as opposed to small firms) have particularly increasingly relied on contract workers supplied by staffing companies (graph below). For analysis, I consider six broad industry categories namely, (i) Textiles, (ii) Food, (iii) Motor Vehicle and other transport equipment, (iv) Basic metals, and (v) Rubber, Wood & paper (vi) Chemicals. This broad coverage of industries allows me to examine the link between contract labor and productivity in a variety of settings that differ greatly in the importance of contract work and capital intensity of production.

Generalized method of moments estimates indicate that average contemporaneous productivity effect of contract work are positive in most industries, consistent with prior empirical evidence that contract workers are highly motivated, provide more effort, and contribute positively to productivity. In contrast, average productivity effect after one period (lagged effect) is negative in most industries. These adverse dynamics are consistent with the notion that if firms engage with workers in repeated short term contracts, there is little scope for the accumulation of firm specific human capital, which could potentially prevent productivity growth (Jovanovic, 1979). Further, most industries witness potentially undesirable dynamic effects in employing excessive contract workers; that is, productivity effects are particularly highly negative if contract workers constitute a very high proportion of the firm's workforce.

These observed productivity losses do not imply that firms are irrational or that they are unaware of the productivity consequences of their actions. That productivity effects are particularly worse at very high levels of contract share is in fact consistent with the firm behavior that firms do not go all the way in hiring only contract workers, but maintain a core set of regular workers. Further, although firms maximize a future stream of discounted profits, they perhaps place a higher weight on current profits rather than future profits, and to that extent find future productivity losses acceptable.

The remainder of the article is organized as follows. Section 2 elaborates the background details, pathways, and sets the stage for analysis. Section 3 presents a model of contract labor employment detailing its identification, estimation and implementation. Section 4 describes the data sources, and provides basic descriptive statistics. Section 5 presents the production function estimates and the contemporaneous and lagged effects of contract work on productivity. Section 6 concludes.

3.2 Background and Pathways

The Indian Ministry of Labour & Employment, Government of India defines contract workers as all persons who are not employed directly by an employer (firm), but through a third party contractor on fixed term temporary contracts. These workers do not have direct work contracts with the firm and do not appear in its payroll records, but have formal or informal contracts with licensed contractors who pay them[4]. The Contract Labour Act 1970, applicable to any workplace where there are twenty or more workmen are employed as contract workers, primarily mandates the registration of establishments employing contract workers and licensing of contractors among other things[5], but does not protect or regular contracted jobs or strictly enforce other aspects of their work[6]. On the contrary, regular workers in reasonably large registered formal firms are governed by a number of legislations (Minimum Wages Act 1948, The Payment of Wages Act 1936, Industrial Regulations Act 1956, The Provident Fund Act 1952), including the Industrial Disputes Act which protects the employment of regular workers. According to the IDA's section V-B, no worker may be laid-off or retrenched in large firms (of size 100 and above) without the prior permission of the government, and application must be filed with the government at least ninety days before the proposed closure. Contract workers are not considered workmen under the IDA and are thus exempt from the application of clauses under the IDA.

On the account of this obvious dichotomy in job security regulations between regular and contract workers, flexibility remains the top reason for hiring con-

[4]The channelling of wages through third party intermediaries is also the case for temp workers employed through temporary agencies in countries such as Germany and the US.

[5]It also mandates the availability of a first aid box, canteens and rest rooms for contract workers, most of which are hardly adhered to, by firms

[6]In Germany too, temp workers are not covered by any major regulation. A reform in 2003 freed agencies from all regulations concerning temporary workers thus far existed as a part of the Temporary Employment Agencies Act. However, by replacing all existing regulations (such as maximum period of assignment, a prohibition of fixed-term contracts, a ban on re-employment as well as a synchronisation ban, and from 2002 a principle of equal treatment between temps and perms in the user firms), agencies among other things had to sign a collective sectoral minimum wage for temps (Hirsch and Mueller 2010).

tract workers (National Commission for Enterprises in the Unorganized Sector (NCEUS), 2009)[7]. Empirical evidence supports the positive association between strict employment protection and high contract employment in a variety of settings highlighting the role of labor market flexibility in hiring contract workers (Shire et al. 2009, Nunziata and Staffolani 2007, Houseman 2001). [8] Studies focusing on India use the BB's employment protection index and its subsequent modifications by Gupta et al. 2009 (GHK) and Ahsan and Pages (2009) based on criticisms offered by Bhattacharjea (2006). [9]. Chaurey 2015 demonstrates that firms located in "pro-worker" states (where firing laws are stricter) facing transitory demand shocks (proxied by district level rainfall shocks) hired higher share of contract workers compared to firms in other states reaffirming that labor market flexibility is an important factor for hiring contract workers in India. So, rainfall shocks (demand shocks) and employment protection index provide useful exogenous variation for contract labor use at the firm level.

[7]Since parent firms do not list contract worker in their payroll, disputes, accidents and their associated time costs are not the firm's responsibility. This non-commitment also make hiring contract workers attractive.

[8]In Germany, plant's self reported data indicate that temporary requirements such as seasonal needs and peaks in demand (73%) and temps's fast availability (71%) are the most important reasons for their use of TAW (Hirsch and Mueller 2010). This was followed by Uncertainty about economic prospects (28%), Screen job candidates for permanent jobs (19%), Save on recruitment and separation costs (19%), Required qualification hard to find on the regular labour market (13%), and others (8%).

[9]Some of these studies find that pro-worker states tend to have lower output, employment, investment, and productivity in formal manufacturing (Ahsan and Pages 2009, Besley and Burgess 2004). Bhattacharjea 2006 particularly questions BB's results on output and productivity losses for pro-worker states which in BB's results disappear with adding state specific time trends. Other studies find that pro-worker states have lower demand elasticities and respond less to trade reforms (Hasan et al. 2007), and lower sensitivity of industrial employment to local demand shocks (Adhvaryu et al. 2013). Other scholars question whether amendments made to the IDA have increased or decreased flexibility in firing (Bhattacharjea 2006) or whether these regulations have even been enforced (Nagaraj 2002).

Besides flexibility, there could be other reasons for hiring contract workers. Firms may hire contract workers to screen workers before offering them permanent jobs, and such jobs may also be viewed by workers as a stepping stone to future permanent employment [10]. Firms may seek specialized services not readily available on the market or within their regular workforce, and it may be cost-effective for firms to employ contract workers for these special tasks.

If firms screen workers, or if contract workers foresee a transition to permanent jobs in the future, workers may exert high level of effort in a hope to attain permanent status (Engellandt and Riphahn, 2005). Specialized contract workers also are expected to contribute positively to productivity. While the ASI data do not provide data on skill levels of workers, note that such workers are usually paid higher wages compared to other non-specialized contract workers as well as regular workers. High relative wages for contract workers (compared to regular workers), can then indicate special skills. Figure A1 (appendix) reveals that wage ratios between contract and regular workers has a huge spread; however, wage ratios in most firms falls below 1, indicating that contract workers are not specialized but perform regular jobs.

Contract workers could possess lower human capital compared to regular

[10] A moderately growing empirical literature tries to understand if contract jobs indeed lead to future permanent employment. The evidence here is mixed and depends on the context. The answer is affirmative in Britain (Booth et al. 2002) and among migrants in Denmark (Jahn and Rosholm 2013), but negative in the United States (Autor and Houseman 2001). Owing to the non-availability of long panel datasets required for such studies, there is no evidence on the stepping stone hypothesis in developing countries such as India.

workers, and the human capital related productivity effects could exacerbate over time. Since contract workers are employed only for a fixed term, both workers and firms have little incentive to invest in the firm-specific human capital of workers. To the extent that firm specific human capital is valuable, we could expect that the usage of contract workers could stifle productivity growth. Related productivity costs could be particularly worse for firms which rely heavily on contract workers. However, suppose that the same group of contract workers return to a firm repeatedly for different assignments. This phenomenon is prevalent in the Motor Vehicle industry (Gopalakrishnan and Mirer, 2014) and Textile industry (Kalhan, 2008) in India. In these settings, where there is a longer duration of contact and a stronger relationship between firms and contract workers, there are opportunities and incentives for firm specific learning, which can increase productivity. My analysis below differentiates effects across industries, enabling us to distinguish these underlying mechanisms in different settings.

3.3 A Model of Contract Labor Employment

3.3.1 Firm's Dynamic Optimization Model

The representative firm follows a Cobb-Douglas production technology whose logarithmic form is as follows:

$$y_{it} = \alpha_0 + \alpha_t t + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + \omega_{it} + \epsilon_{it} \tag{3.1}$$

where log real gross revenue of firm (y_{it}) is a function of log real gross value of capital (k_{it}), log number of worker mandays (l_{it}), and log real value of intermediate material input (m_{it}). Labor includes both regular workers directly hired by the firm and contract workers hired through third party contractors. α_0 is the constant term and α_t is the time trend.

ω_{it} represents the unobserved total factor productivity and ϵ_{it} is the independent and identically distributed (i.i.d) error term. Unlike OP-LP, ω does not evolve as an exogenous Markov process but endogenously as a function of i.i.d innovation in productivity (ξ_{it}), lagged share of contract to total worker mandays (cs_{it-1}) and the current contract share, cs_{it}. This formulation of law of motion for productivity allows complementarities between usage of contract labor (lagged and current) and past productivity in determining current productivity, a representation closer to reality compared to exogenously evolving productivity. The firm anticipates the effect of contract labor on productivity in period t when making the decision about it in $t-1$.

Capital accumulates deterministically based on the rate of depreciation (ζ), last year's capital (k_{t-1}) and investment (q_{t-1}). Labor evolves based on κ, rate of separation of regular workers hired in the last period, regular workers hired in the last period (hr_{it-1}), and contract workers hired in an intermediate period $t-b(0 < t < 1)$ (hr_{it-b}). κ is typically small due to large associated firing costs with regular workers. Note that the separation rate for contract workers is 100% by definition because they are only hired for a period. Further, among regular labor, contract labor, and raw material, regular work is most inflexible due to recruitment and high firing costs. Contract work is more flexible than regular work, but not as much as material usage because hiring contract workers occurs through third party contractors which normally takes some lead time. Material usage is the most flexible and fluid and responds most readily to productivity shocks. While recruitment of regular labor takes place in $t-1$ before the realization of productivity shock ξ_{it}, contract laborers are hired when the productivity shocks are partially realized in time $t-b$. Collectively, labor is a dynamic variable because the choices of regular and contract workers each are individually dynamic in nature. That is, both are hired before period t. Further, contract work is a dynamic variable by the virtue of its effect on future productivity. Material usage is completely determined in period t. The timing decisions of these inputs are crucial in obtaining moment conditions aiding identification, as explained in section 3.4.

The firm maximizes the present value of expected current and future profits, $\pi_{it} = P_t Y_{it} - C_{it}$ where P_t is the price of it's output and C_t, the total cost of inputs at time t. Firm's dynamic profit maximization problem is stated as follows:

$$\begin{aligned} \underset{i_{it}, hr_{it}, hc_{it}, M_{it}}{\text{maximize}} \quad & E_0 \sum_t \delta^t \pi_{it} \\ \text{subject to} \quad & K_{it} = (1-\zeta)K_{it-1} + q_{it-1}, \\ & L_{it} = (1-\kappa)(1-cr_{t-1})L_{it-1} + hr_{it-1} + hc_{it-b}, \\ & \omega_{it} = g(\omega_{it-1}, cr_{it}, cr_{it-1}) + \xi_{it}. \end{aligned} \tag{3.2}$$

E_0 represents the expected value at time period 0 and δ is the depreciation rate. In this dynamic optimization problem K_{it}, L_{it}, and ω_{it} are state variables and M_{it} is a free variable. The Bellman equation for input choices of an incumbent firm can be written as the following[11]:

$$V_t(\omega_t, K_t, L_t) = \max_{i_t, hr_t, hc_t} (\pi_t(\omega_t, K_t, L_t) + \delta E[V_{t+1}(\omega_{t+1}, K_{t+1}, L_{t+1})]) \tag{3.3}$$

where V_t represents the value function of the firm.

[11]This Bellman equation, similar to those of LP, ACF, and DR, does not account for sample selection by modelling a firm's exit decision because the Industrial Disputes Act makes it costly for a firm to exit the industry immediately after receiving an adverse shock to productivity. So in a country like India, firm entry and exit are not smooth functions of productivity shocks.

3.3.2 Estimation Strategy

The joint estimation of Cobb-Douglas production function and the productivity evolution equation is achieved through a structural approach proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). These class of estimators account for unobserved productivity using proxy variables that move freely with productivity. Free variables, by the virtue of being completely determined in the current time period are entirely based on productivity shocks. Should there exist a monotonous relationship between productivity and demand for the proxy input, the latter function can be inverted to express the former in terms of the proxy and other state variables [12].

Material usage is an excellent proxy because it is a freely variable input and their data are readily reported by firms. Suppose the material demand function is expressed as the following based on the solution to the dynamic optimization problem.

$$M_{it} = M_{it}(K_{it}, L_{it}, \omega_{it}, P_{it}^{m}) \tag{3.4}$$

where P_{it}^{m} denotes to input price in time period t. Assuming monotonicity holds, the above equation can be inverted to obtain an expression for productivity,

$$\omega_{it} = h_{it}(K_{it}, L_{it}, M_{it}, P_{it}^{m}) \tag{3.5}$$

[12] See Ackerberg et al. 2006 for a complete review of this methodology.

Intuitively, equation 3.5 implies that conditional on a firm's level of capital, labor, and input price, it's choice of materials reveals unobserved productivity, ω_{it}.

To proceed with estimation, I first substitute equation 3.5 in the productivity evolution equation, which is in turn substituted in the production function (equation 3.1). The series of substitutions yield the following estimable structural equation which jointly estimates both the production function and productivity growth equation:

$$y_{it} = \alpha_0 + \alpha_t t + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + g_t(h_{it-1}, cr_{it}, cr_{it-1}) + \xi_{it} + \epsilon_{it}. \tag{3.6}$$

3.3.3 Identification

Identification is achieved by a set of moment conditions arising from timings restrictions of inputs. These are characterized as follows:

$$E[A(Z_{it}).(e_{it} + \xi_{it})] = 0 \tag{3.7}$$

where $A(Z_{it})$ are is an array of functions of exogenous variables specified below.Since all inputs are be definition orthogonal to the i.i.d error term e_{it}, those that are orthogonal to ξ_t, the exogenous productivity shock, can serve as instruments. The state equations of K_{it} reveals that investment and hiring decisions happen in $t-1$; consequently, capital is orthogonal to ξ and can serve as an instrument. Although regular labor is determined in $t-1$, contract labor is determined only in $t-b$ after the partial realization of the productivity shock. However, L_{it-1} can serve as an instrument. Material input at t is determined after the realization of the current productivity shock, but lagged material input (M_{it-1}) is uncorrelated with the current innovation in productivity serving as an additional moment condition [13].

To obtain exogenous variation in the use of contract work, following Chaurey(2014)[14], I use spatial-time varying deviations to normal rainfall (D_{st}) (at state (s) and time (t)), spatial variation in the index of labor regulations developed by GHK (GHK_{st}) and their interaction as instruments. While high rainfall translates to higher yield and to higher agricultural production (Jayachandran (2006), Kaur (2012) and ACS), Chaurey (2014) additionally demonstrated that rainfall shocks in India are in fact demand shocks due to their positive effects on household monthly per capita expenditure, industrial wages, and industrial labor.

Equation 5mmeq:structuraleq represents a semi-parametric model that is partially linear. In these models, a fundamental criterion for identification is that

[13]During implementation, the unknown function g_t is expanded non-parametrically using a second degree polynomial. Higher order expansion terms in g are identified using additional non-linear functions of instruments as described in section 3.4.

[14]While Chaurey uses district level rainfall shocks, I use state level rainfall shocks owing unavailability of district level identifiers in my data

there should be no functional relationship between the variables in the parametric and non-parametric part (Robinson (1988) and (Newey et al., 1999)). If h is non-parametric, variables in the production function can be perfectly predicted by the arguments of h, rendering the model unidentified. This "collinearity problem" was identified as an important issue with estimation in the models of OP-LP, by ACF. However, assigning a credible function form for h can tackle this issue. To see how, start with the premise that h is non-parametric. Then the capital variable (k_t) which is in turn a function of k_{t-1} and $q_{t-1}(k_{t-1}, L_{t-1}, \omega_{t-1}, Pm_{t-1})$ (from the capital evolution equation), can be directly predicted from $(k_{t-1}, L_{t-1}, Pm_{t-1}, M_{t-1}, cr_t, cr_{t-1})$, the arguments in h and g. This is because, by construction, ω is a function of all arguments of h. Assigning a credible functional form for h can avoid this collinearity problem. The central question about identification then boils down to whether (k_{it-1}, i_{t-1}) are predictable from the value of h (as opposed to its arguments), cr_t, and cr_{t-1}. The answer is negative because, apart from h, prices and other state variables are required for this perfect prediction. Hence, with a credible functional form for h, the model is identified.

An expression for material demand function derived from the lagrangian of cost minimization at period t is as follows.

$$m_{it} = \frac{1}{1-\beta_m}((lnP_m - lnP) - \alpha_k k_{it} - \alpha_l l_{it} - \omega_{it} - ln\alpha_0 - ln\alpha_m + \alpha_t t) \tag{3.8}$$

Mathematically inverting it to solve for ω, I obtain the following.

$$\omega_{it} = h_{it}(K_{it}, L_{it}, M_{it}, P^m_{it}) = -ln\alpha_0 - ln\alpha_m + (1-\alpha_m)m_{it} - \alpha_k k_{it} - \alpha_l l_{it} + (lnP_m - lnP) - \alpha_t t \quad (3.9)$$

3.3.4 Implementation

The structural equation 3.6 is estimated in a Generalized Method of Moments (GMM) framework described below. First, define the residuals of equation (6) as a function of the parameters θ as below.

$$\nu_{it}(\theta) = y_{it} - (\alpha_0 + \alpha_t t + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + g_t(h_{it-1}, cr_{it}, cr_{it-1})) \quad (3.10)$$

The GMM problem is given by:

$$\min_{\theta}\left[\frac{1}{N}\sum_{i} A(Z_i)\nu_i(\theta)\right]^{\mathrm{T}} W_N \left[\frac{1}{N}\sum_{i} A(Z_i)\nu_i(\theta)\right] \quad (3.11)$$

where A(.) is a LxT_j matrix of functions of the exogenous variables, Z, and $\nu()$ is a T_jx1 vector of parameters θ; L is the number of instruments, T_j the number of observations of firm j, and N the number of firms. I use the two-stage GMM estimator of Hansen (1982) (as in DR). In the first stage, a consistent estimate $\hat{\theta}$

of θ is obtained based on weights $W_N = \frac{1}{N}\sum_i A(Z_i)A(Z_i)^{\mathrm{T}}$ [15]. In the second stage, robust efficient weights are constructed based on $\hat{\theta}$ (Hoxby and Paserman, 1998) to estimate the optimal θ.

Unknown functions like g are expanded using a series approximation of degree two. There are 14 parameters in total, including the constant term, time trend, coefficients of capital, labor, material, 9 coefficients in the series expansion of g. Instruments include the constant term, time trend, k_{it}, linear and squared terms of each factor comprising function h_{it} (namely, k_{it-1}, l_{it-1}, P^m_{it-1}, and m_{it-1}), cr_{it-1} and cr_{it-2}. Two years lagged rainfall deviations ($D_{s(t-1)}$ and $D_{s(t-1)}$) and labor regulation index (2 dummy instrumental variables since there are three categories, ″pro-worker″, ″pro-employer″ and ″neutral″), provide four additional instruments. This gives a total of 19 instruments. Thus, we have an over-identified model.

3.4 Data

The data used in the study are from the Annual Survey of Industries (ASI), administered by the ministry of statistics and programme implementation, Government of India. The ASI is the most well-reported and accurate nationally representative data-set of formal sector manufacturing firms in India, because it is a statutory sur-

[15]This is also the first step in the NL2SLS estimator of Ameniya (1974).

vey based on the returns filed by registered manufacturing firms [16] under rules 3 and 4 of the Collection of Statistics Act (Central Rules), 1959. The ASI data is comprised of a census sector and a survey sector. The census sector is a census of all large firms with a size above 100 and actively operating. Firms not in the census sector are randomly sampled using a systematic circular sampling technique within each state x Industry x Sector x 4-digit NIC-2008 stratum, and comprise the survey sector[17].

A panel of firms for 13 years between 1998-99 to 2010-11 are utilized in this study. Reference period for ASI is the accounting year of the industrial unit ending on any day during the fiscal year. For instance, data for the year 2010-11 correspond to all activities between 1st April 2011 and 31st March 2012. Uniquely, the dataset contains information on the number of contract and regular workers and the corresponding mandays, their wages and benefits separately for each firm. The survey also differentiates mandays spent in manufacturing work from non-manufacturing work. The former involves core factory jobs directly relevant to production and the latter involves peripheral work such as security, catering, or cleaning services. This distinction is important since only activities related to core

[16] All manufacturing firms employing 10 workers or more (without using electricity) or employing 20 workers or more (with or without using electricity), are required to register under The Factories Act, 1949, the central piece of legislation regulating manufacturing firms in India.

[17] Apart from the large firms, the census sector also comprises of: 1) All industrial units belonging to the six less industrially developed states/ UT's viz. Manipur, Meghalaya, Nagaland, Sikkim, Tripura and Andaman & Nicobar Islands; (2) All factories filing Joint Returns. (3) After excluding the above units, as defined above, all units belonging to the strata (State x District x Sector x 4 digit NIC - 2008) having less than or equal to 4 units are also considered under the Census sector.

manufacturing are directly relevant to the estimation of production function and total factor productivity.

Total revenue is simply the nominal rupee value of production[18]. To deflate revenue, I use the Whole Sale Price Index for the major product of the firm identified according to its 2-digit National Industrial Classification (NIC) code. Material at time t is the rupee value of all materials used in production in the accounting year. Material prices are constructed as a time and industry varying price index, using the top 5 most widely used material inputs used in each sub-industry comprising the five broad industries considered. This is either a 5 digit level or 3 digit industry level variation depending on the availability of data. Relevant material price indices are obtained from the web site of the ministry of commerce and industry, and mapped to the ASI data [19]. The capital variable is the gross capital value at the beginning of the time period t. It is the sum of value of land, buildings, plant&machinery, transport equipment, computer equipment including software, and pollution control equipment. The whole sale price index (WPI) for "machine and machinery tools" is used as a deflator to calculate the real value of capital. State level actual and normal rainfall data are both available from the web site of the Indian Meteorological department (`http://www.imd.gov.in/`).

I use the state level employment protection regulation index constructed ac-

[18]This figure only comprises revenue form sales, and not from other activities of the firm, such as rent received on buildings or interest received

[19]`http://www.eaindustry.nic.in/home.asp`

cording to the amendments to the Industrial Disputes Act 1947 by GHK. GHK's classification is as follows: "pro-worker states" — West Bengal, Maharashtra, Orissa, "pro-employer states" — Rajasthan, Karnataka, Kerala, Tamil Nadu, Andhra Pradesh and "neutral states" — Punjab, Haryana, Himachal Pradesh, Uttarakhand, Uttar Pradesh, Bihar, Assam, Chhattisgarh, Jharkhand, Madhya Pradesh, Goa, Gujarat and Kerala. The original index was developed by Besley and Burgess (2004), but it was subject to criticism (Bhattacharjea 2006). Further modification were made to the BB index by Ahsan and Pages (2009) and Bhattacharjea (2006). GHK uses a simple majority rule based on all these previous indices, to assign codes to states and created a composite index.

Analyses are conducted separately for different industries or groups of industries identified at the two-digit broad classification level as per the National Industrial Classification of India (NIC). Since NIC definitions changed twice over the study period (2004 and 2008), three NIC classification definitions (NIC-1998, NIC 2004, and NIC 2008) were mapped across the 13 study years. I picked two industries below the median contract mandays ratio, two around the median, and finally two below the median. This choice of industries also ensure a good spread of capital intensity of production measured by capital-labor ratio. The list of industries includes: i)Textiles (spinning, weaving and finishing), (ii)Food products and beverages, (iii)Motor Vehicle and other transport equipment, (iv)Basic metals, and (v)Rubber, Wood & paper (vi) Chemicals and Chemical products. I only retain large firms (census sector firms) [20] with positive amounts of contract man-days for analysis. Finally, since I investigate dynamic effects which are based on two-period lags, I retain only firms with three or more consecutive years of data.

Figure 3.1 shows that the share of contract manufacturing man-days among total manufacturing mandays more than doubled from 15% in 1998-99 to 33% in 2010-11. Note that the share of contract workers and the growth in the share of contract workers are both higher among large firms than small firms. There is significant change in the usage of contract workers between successive years. Figure 3.2 shows that only 23% of the observations have the same contract labor share in successive years. Industry specific description of key variables are presented in Table 3.1. In the analysis sample, ″Food products & beverages″ and ″Rubber, wood and paper″ are the largest and smallest industries respectively (columns 1 and 2). Average firm size, in the analysis sample is highest in ″Motor vehicle & other transport″ and lowest by ″Food products & beverages″ (column 3)[21]. All industries saw reasonably good revenue growth in the study period, with highest growth obtained by ″Motor vehicle & other transport″ and lowest by ″Food products & beverages″ (column 4). Average contract man-days ratio in the sample was highest in the Food industry (61.12% each) and lowest in the textile industry (41.85%) (column 5). ″Chemicals & products″ is the most capital intensive industry (capital-output ratio is 2.08) and the food is the least (ratio is 0.42) (column

[20] Appendix table A1 provides the share of large factory-year observations in each industry

[21] Compare this to the weighted average firm size in both census and survey sectors together in the original dataset which is 73 for Basic Metals, 55 for Chemicals, 35 for Rubber, Wood & paper, 28 for Food, 85 for ″Textiles, and 95 Motor Vehicles

6). Table 3.2 reports average real capital stock in the beginning the finacial year (column 3), total real raw material usage (column 4), worker mandays (column 5), and real revenue (column 6) in the analysis sample.

3.5 Results

3.5.1 Production Function Estimates

Production function estimates from the Ordinary Least Squares regression are presented in Table 3.3. Material, capital and labor coefficients are statistically significant, and economically reasonable and meaningful. The returns to scale, as given by $\alpha_k + \alpha_l + \alpha_m$ are close to a constant.

Table 3.4 presents the generalized method of moments production function estimates from the endogenous productivity growth model. Here too, the coefficients of inputs (columns 1-3) are statistically significant and economically meaningful. Due to the presence of over-identifying restrictions, the validity of the moment conditions can be tested using the Hansen's J-test [22]. The chi-square statistic and the corresponding p-values are reported in columns 4 and 5. In conducting

[22] The J-statistic is the value of the GMM objective function for the optimal estimator, scaled by N, the total number of observations. This statistic has a limiting χ^2 distribution with L-P degrees of freedom, where L is the number of instruments and P the number of parameters to be estimated

estimations, current capital proved more likely to be a valid instrument in capital-intensive rather than in labor intensive industries. For the sake of uniformity, I present the estimation results only using lagged capital, but without using current capital as instrument for all industries. For most industries, the p-value for this test is above 0.05 indicating that moment conditions cannot be rejected at 5% level of significance. The coefficients in the function $g(\omega_{it-1}, csit, cs_{it-1})$, contributing to firm's total factor productivity, are tested jointly for significance. Columns 6 and 7 report the chi-square statistic and p-values for this test respectively. In most industries, coefficients constituting ω are jointly significant, offering credibly to the estimates of productivity and elasticity derived from them.

Lagged rainfall deviations (last two periods) and the labor regulation indices (two dummy variables) are important instruments. To more explicitly validate them, I compute the difference in the value of the objective function for the structural model to its value when the subset of moments involving either lagged rainfall or the labor regulation are excluded. The exogeneity assumption of either lagged rainfall deviations or labor regulation index cannot be rejected in any industry [23]

[23] The rows and columns corresponding to the excluded moments are deleted from the weighting matrix of the optimal estimator, so as to employ the same weighting matrix for both specifications.

3.5.2 Relating Contract work and Productivity

I capture the relationship between contract work and productivity in a variety of ways. First, I simply look at revenue weighted mean differences in productivity levels for firms using above-median and below-median share of contract labor. That is, $\overline{g_{cr_t>=cr_{@.5}}} - \overline{g_{cr_t<cr_{@.5}}}$. Similarly I report mean differences in productivity levels above and below the median lagged contract share, $cr1_{@.5}$ or $\overline{g_{cr_{t-1}>=cr1_{@.5}}} - \overline{g_{cr_{t-1}<cr1_{@.5}}}$. The t-statistic of the difference is obtained as the following:

$$t = \frac{\bar{g_1} - \bar{g_0}}{\sqrt{(s_1^2/n_1) + (s_0^2/n_0)}} \tag{3.12}$$

where g_0, g_1, s_0 and s_1 are the two means and their standard errors respectively. Revenue share of firms are employed as weights in obtaining these means.

Second, I derive a series of elasticity measures from the g function, including elasticity of output (productivity) with respect to current contract labor, lagged contract labor, and past productivity. I then study the mean elasticities in each case, and the relationship between elasticities and contract share. Contemporary elasticity is given by $\frac{\partial g}{\partial cs_t}$. Lagged elasticity is the sum of direct effect of lagged contract labor and its effect through persistence of productivity from the last period. That is, $\frac{\partial g}{\partial cs_{t-1}} = \frac{\partial g}{\partial cs_{t-1}} + \frac{\partial g_{t-1}}{\partial g_{t-1}} * \frac{\partial g_{t-1}}{\partial cs_{t-1}}$. Since the elasticities themselves depend on past period productivity, contract labor in the current and past period, I am able to derive an estimate of elasticity for each firm and consequently a distribution of elasticities. Further, the relationship between these elasticities and contract labor is interesting in understanding the non-linearities in the effects of contract labor on productivity. I study this relationship descriptively by plotting elasticity values against lagged contract share for each industry. In each industry, these graphs holds current contract share and lagged productivity constantly at their median values [24]. Persistence of productivity is the part of productivity carried over from the past period to the current period, and is defined as $\frac{\partial g}{\partial \omega_{t-1}}$. I report mean differences in the persistence of productivity between firms with above-median share of contract workers and below median share of contract workers.

3.5.3 Contemporaneous Effects

Table 3.5 presents the mean difference between firms whose contract share is above-median and below-median, and the corresponding t-value of the difference. Over-all, and in most industries, this difference is positive indicating productivity gains accruing from contract labor in the current period. Table 3.6 presents the distribution of contemporaneous elasticities by industry. Here, the mean as well as second and third quartile values are positive, reaffirming that contract labor largely have beneficial effects in the current period consistent with Table 3.5.

[24]Similar graphs on the relationship between contemporaneous elasticity and contract labor is available upon request from the author.

These positive effects could be interpreted as either specialized skills or high motivation levels among contract workers in a hope to attain permanent status. However, specialized workers only form a small portion of the entire contract labor workforce in India. The proportion of firms where contract workers receive higher wages compared to regular workers, which indicates specialization, range from 13% in the Food industry, 19% in Textiles, 5% in Chemicals, 17% in Basic Metals, 8% in the Motor Vehicles, and 10% in rubber, wood and paper. Possibly then, the motivation effect is the predominant channel through which these positive contemporaneous effects can be interpreted. Negative contemporaneous productivity differences between firms using high versus low contract workers in some industries, and negative contemporaneous elasticities observed in specific firms in all industries could simply mean that contract workers possess low general and firm specific human capital in those specific cases.

3.5.4 Lagged Effects

Table 3.7 reports mean differences between above- and below-median lagged contract share. Overall and in specific industries, these differences are negative and statistically significant in most cases. Negative differences in this case is consistent with low levels of firm specific human capital accumulation in these settings. Lagged elasticities reported in Table 3.8 are negative in most parts of the distribution reaffirming the importance of firm specific human capital channel. Dynamic positive elasticities in the upper tails of the distribution in most industries and particularly in textiles and motor vehicles, corroborate with industry level evidence that contract workers repeatedly come back to work in the same firm.

Corroborating these results are the cumulative distribution plots of normalized firm productivity with below-median (maroon) and above-median (blue) lagged contract share in Figure 3.3. The maroon line for the most part lies below the blue line, indicating that it stochastically dominates blue line. A formal Kolmogorov–Smirnov test was used to test the equality of these two cumulative distributions. Table 3.9 provides the test results. The test rejects the null hypothesis that below-median lagged contract share firms contains *smaller* productivity values than above-median lagged contract share, but does not reject the null hypothesis that below-median contract share firms contains *higher* productivity values than above-median contract share. This reaffirms the graphics in Figure 3.3.

Figure 3.4 presents the relationship between contract work and lagged productivity elasticities across different industries (maroon line). The black reference line indicates the actual proportion of contract share in the industry. Quadrant 4 (representing negative elasticities) is shaded bluish-gray for visual aid. In two industry graphs in Figure 3.4 (basic metals and chemical industries), the relationship between lagged elasticities and contract share falls entirely on the fourth quadrant indicating negative elasticities at all levels of contract share. But in these industries, the elasticity itself has an inverted U-shaped relationship with contract work, indicating an overall downward shaping concave relationship between lagged contract work and productivity. In rubber, wood, and paper, lagged elasticity starts with a positive value at low levels of contract work and declines reaching zero at a contract share a little over 50%. This indicates that modest usage of contract workers could be productivity enhancing, but very high usage of contract workers may not. In textiles, elasticities are negative at low values of contract share and increase with an increase in contract share to become positive at about 45% contract share. In Motor Vehicles, elasticities show a declining relationship with contract share but remain positive through most of the distribution. The heterodox results in Textiles and Motor Vehicles can be explained by the fact that, in these industries, reports points to how contract workers come back to work in the same factories on different projects there by having the opportunities to build firm specific human capital.

Finally, Table 3.10 shows that the average persistence in productivity is significantly higher for firms with below-median lagged contract share compared to firms with above-median contract share in most industries separately, and in the overall sample, indicating that firms that rely excessively on contract workers may not see their productivity persist over time.

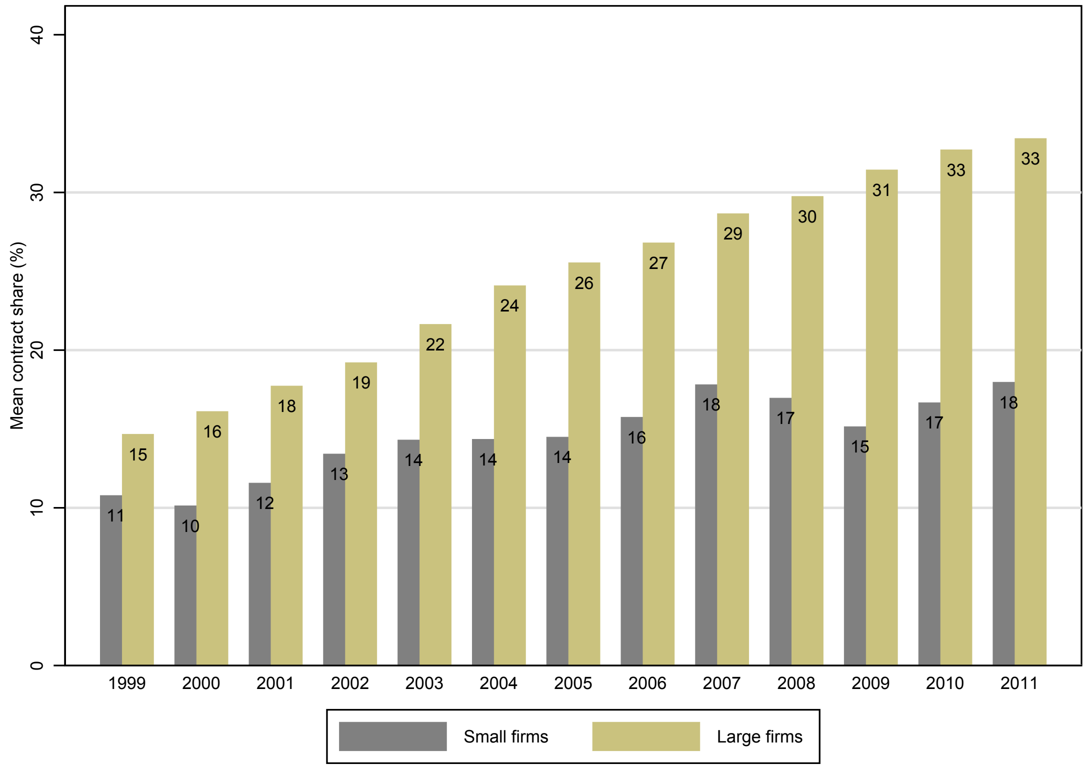
3.6 Conclusion and Policy Implications

Contract work or temporary agency work is an important and growing labor market institution. Such work arrangements constitute 1-2% of the workforce in Germany to about 50% in Bangladesh and South Africa. Although a large number of studies recognize the role of strict regular employment protection laws in rise of contract work across the globe, till date, few studies analyse how this institution affects firm performance and productivity. This paper fills this gap by employing a semi-structural model to estimate a production function and an endogenous productivity growth equation, separately across six broad manufacturing industry groups in India. The productivity evolution equation delineates contemporaneous and lagged relationships between productivity and contract labor intrinsically, and is jointly estimated with the production function in a single step. This is unlike most prior studies that assume an exogenous Markov process for productivity evolution to obtain productivity estimates in the first step, and then regress estimated productivity on characteristics of interest in the second step.

Results indicate that, on average, contemporaneous productivity effects of contract work are positive on average, consistent with prior empirical evidence on high motivation levels of temporarily hired workers (Engellandt and Riphahn, 2005). In contrast, average lagged productivity effect is negative. These adverse dynamics is consistent with the theoretical evidence that contractual work arrangements that typically last only for a fixed term, potentially hinder the accumulation of firm specific human capital (Jovanovic, 1979), consequently affecting productivity. Further, most industries witness potential undesirable dynamic effects in employing excessive contract workers; that is, productivity effects are particularly highly negative if contract workers constitute a large part of the firm's workforce.

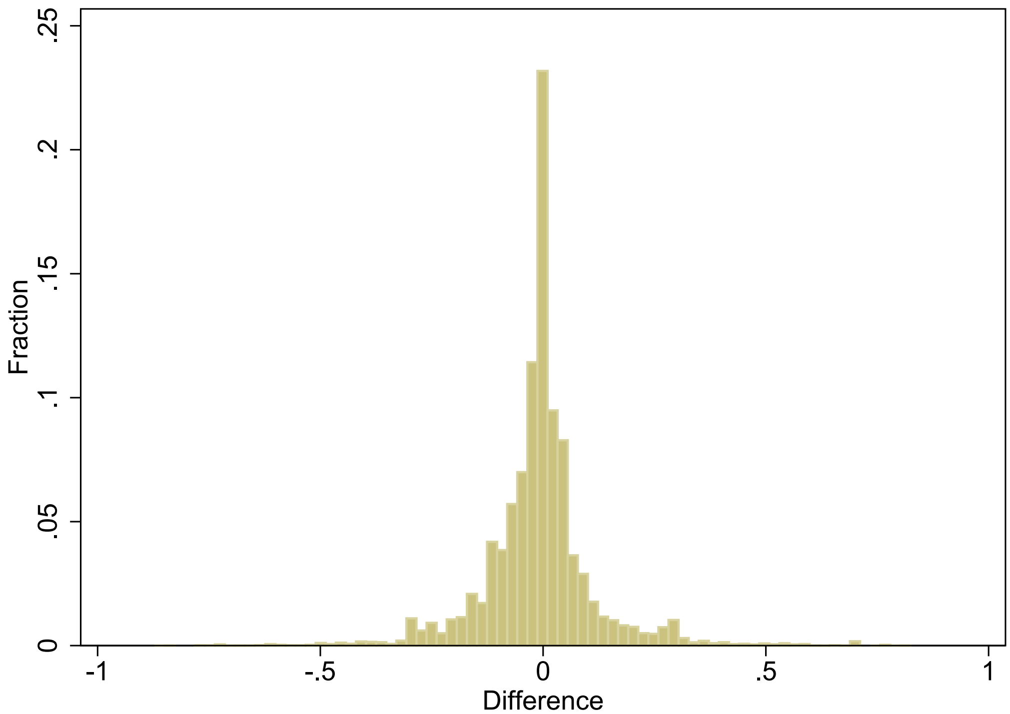
These adverse productivity effects indicate that employment protection laws, in protecting a section of the work force (regular workers), are also creating a separate pool of workers (contract workers) who are unable to invest in and contribute greatly to firms they work in, simply because they do not stay long enough and/or build useful and sustainable firm specific human capital. What options do policy makers have in improving productivity in these settings? If productivity losses are channeled through temporary nature of jobs, will setting a minimum contract length improve productivity? Alternately, can policies improve human capital by mandating job training by firms or staffing companies? On the other extreme, should we altogether prohibit contract workers from doing core manufacturing jobs and restrict them to jobs peripheral to the establishment, such as cleaning and catering? While these specific questions remain unanswered and is left to future research, this paper contends that adverse productivity consequences of contract work should be an important consideration in future policy and regulatory discourses on contract workers.

Figure 3.1: Proportion of Contract Mandays in Total Mandays



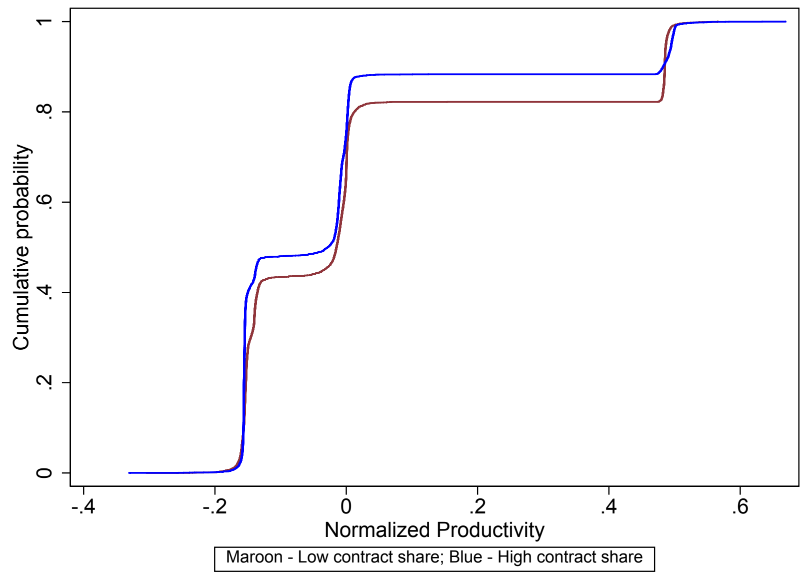
Source: The Annual survey of Industries, India

Figure 3.2: Difference in Current and Lagged Contract Share in Successive years



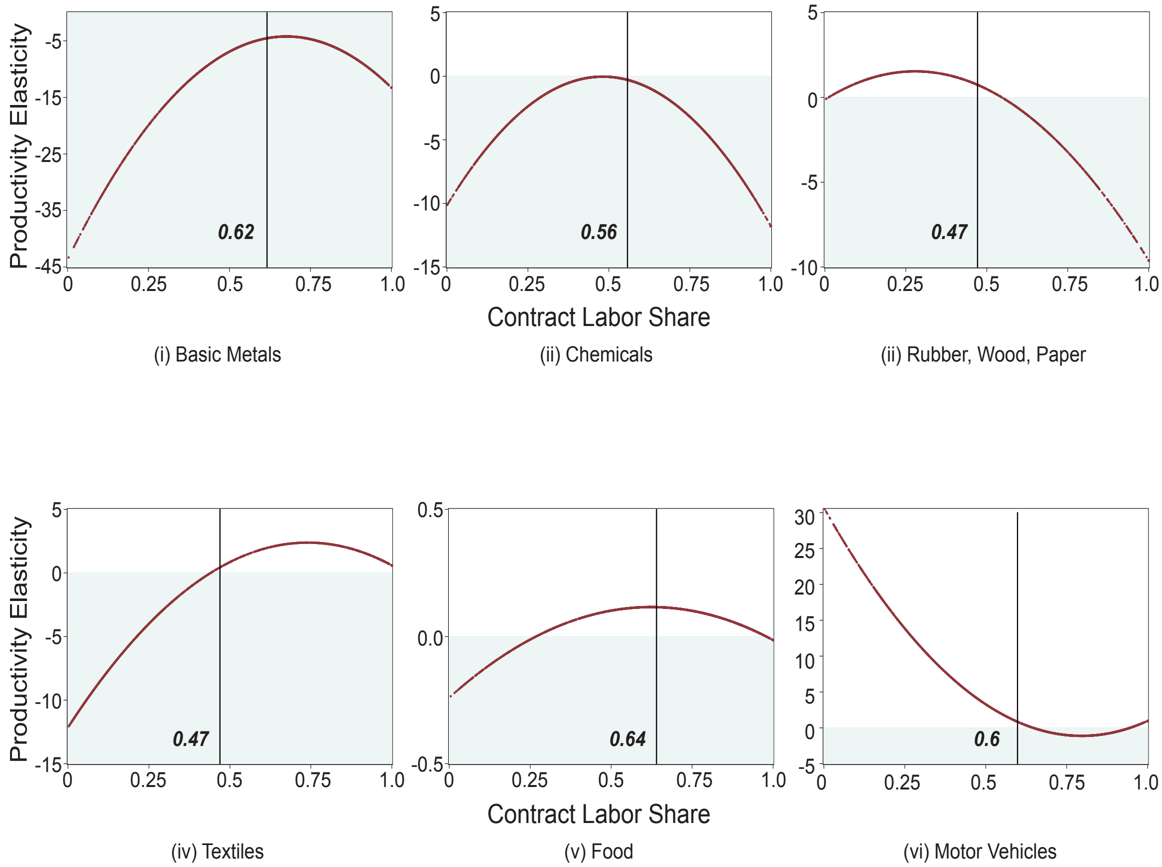
Source: The Annual survey of Industries. Note: Reported are simple difference between current (cs_t) and lagged contract shares (cs_{t-1}) for each observation in the dataset.

Figure 3.3: Cumulative Distribution Plots of Productivity



Note: Normalized productivity levels obtained from the endogenous model. Low contract share refers to firms with below-median levels of lagged contract share (maroon line), and High contract share refers to firms with above-median levels of contract share (blue line).

Figure 3.4: Productivity Elasticities with respect to Lagged Contract Share



Note: Reported are lagged elasticity which is the sum of direct effect of lagged contract labor and its effect through persistence of productivity from the last period. That is, $\frac{\partial g}{\partial cs_{t-1}} = \frac{\partial g}{\partial cs_{t-1}} + \frac{\partial g_{t-1}}{\partial g_{t-1}} * \frac{\partial g_{t-1}}{\partial cs_{t-1}}$. Current contract share and lagged productivity are maintained at median value.

Table 3.1: Sample Size and Industry Characteristics

Industry	(1) Obs	(2) Firms	(3) Firm-Size	(4) Growth	(5) %contract	(6) K-L
Textiles	1,306	298	576	3.56%	41.85%	0.54
Food products & beverages	2,796	584	288	2.67%	61.12%	0.42
Basic Metals	1,989	395	564	5.35%	59.95%	1.15
Chemicals & products	2,592	648	466	4.64%	55.74%	2.08
Rubber,wood, & paper	537	135	551	5.33%	45.47%	0.76
Motor vehicle & other transport	1,750	374	596	10.65%	57.31%	0.67

Source: The Annual Survey of Industries, India. Analysis sample, which comprises large firms (census sector), and those reporting positive contract labor, and at least three successive years of data for all variables. %contract is the average share of contract worker mandays at the firm level. Growth represents average revenue growth in the study period. K-L ratio is the average capital to output ratio.

Table 3.2: Descriptive Statistics by Industry

Industry	(1) Obs.	(2) No. Firms	(3) Capital	(4) Inputs	(5) Revenue	(6) Mandays
Textiles	1,306	298	1.07	0.75	1.18	199.01
Food products & beverages	2,796	584	0.39	1.09	1.79	94.30
Basic Metals	1,989	395	2.21	2.53	4.47	192.28
Chemicals & products	2,592	648	3.36	2.29	4.30	161.03
Rubber,wood, paper	537	135	1.45	0.98	1.79	190.80
Motor vehicle & other transport	1,750	374	1.21	2.56	3.67	180.89

Note: Capital is real value of gross capital stock in the beginning of the year, Input represent real value of raw material usage in the current year, Revenue is the real total revenue from sales in the current year, Worker mandays is total manufacturing mandays in thousands (regular and contract together) in the current year. All values are in billion Indian Rupees. Source: The Annual Survey of Industries, India. Analysis sample, which comprises of large firms (census sector), and those reporting positive contract labor, and at least three successive years of data for all variables.

Table 3.3: Production Function Estimates - OLS

	(1) Material	(2) Capital	(3) labor	(4) R-sq
Textiles	0.455***	0.188***	0.263***	0.891
	(0.026)	(0.027)	(0.030)	
Food products & beverages	0.583***	0.254***	0.183***	0.857
	(0.015)	(0.026)	(0.023)	
Basic Metals	0.663***	0.165***	0.181***	0.950
	(0.020)	(0.013)	(0.017)	
Chemicals & products	0.601***	0.190***	0.223***	0.918
	(0.019)	(0.027)	(0.021)	
Motor vehicle & Other transport	0.682***	0.162***	0.189***	0.954
	(0.022)	(0.016)	(0.024)	
Rubber,wood&paper	0.568***	0.166***	0.318***	0.947
	(0.046)	(0.024)	(0.04)	

Note: Standard errors clustered at the firm level are in parenthesis; Constant term and a time trend are included in these regressions, but their coefficients are not reported here. All estimates are significant at 1 percent Level of Significance

Table 3.4: Production Function Estimates - Endogenous Productivity Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GMM estimates			J-test		Significance of Omega	
	Material	Capital	Labor	χ^2	p-value	χ^2	p-value
Textiles	0.682	0.119	0.274	4.478	0.346	28197.67	0.00
	(0.050)	(0.037)	(0.056)	(4)		(9)	
Food & beverages	0.775	0.129	0.084	14.83	0.00	28.10	0.00
	(0.019)	(0.019)	(0.026)	(4)		(9)	
Basic metals	0.645	0.177	0.164	18.64	0.00	3075.23	0.00
	(0.054)	(0.059)	(0.118)	(4)		(9)	
Chemicals & Products	0.645	0.186	0.208	15.3	0.00	13317.84	0.00
	(0.059)	(0.034)	(0.066)	(4)		(9)	
Motor Vehicle & Others	0.740	0.114	0.126	4.74	0.31	19.66	0.02
	(0.031)	(0.030)	(0.037)	(4)		(9)	
Rubber,wood&paper	0.593	0.178	0.310	2.55	0.63	11.78	0.22
	(0.062)	(0.053)	(0.054)	(4)		(9)	

Note: Robust standard errors clustered at the firm level are in parenthesis under production function estimates; Degrees of Freedom are in parenthesis under chi-square statistics. Constant term and a time trend are included in these regressions but not reported. All estimates are significant at 1% level of significance.

Table 3.5: Differences in Productivity Levels - Contemporary

	(1) Mean Productivity Difference	(2) T-statistic
Textiles	.37	13.36
Food products & beverages	-.04	-5.59
Chemicals & Products	.29	8.02
Basic metals	0.33	7.04
Motor Vehicle & Other Transport	.002	0.07
Rubber,wood&paper	-.16	-8.68
All industries	.22	14.24

Note: Column (1) reports mean differences in productivity between above and below median contract share. Column (2) reports associated t-statistics. Firm revenue share are used as weights. For differences across all industries, the difference in averages are reported after accounting for industry fixed effects.

Table 3.6: Distribution of Contemporaneous Elasticity($\frac{\partial g}{\partial cs_t}$)

	(1)	(2)	(3)	(4)
	Q1	Q2	Q3	Mean
Textiles	-.27	1.28	2.81	1.23
Food products & beverages	-.93	-.19	.75	-0.03
Chemicals & Products	-.61	1.68	4.67	2.28
Basic metals	-.34	4.90	9.02	3.82
Motor Vehicle & Other Transport	-3.89	-.89	3.12	0.79
Rubber,wood, & paper	-3.86	-1.44	.65	-1.51
All industries	-1.47	1.07	4.90	1.86

Q1, Q2, and Q3 represent 25th, 50th, and 75th percentile values of the contemporary elasticity distribution respectively.

Table 3.7: Differences in Productivity Levels - Lagged

	(1) Mean Productivity Difference	(2) T-statistic
Textiles	.31	11.23
Food products & beverages	-.05	-6.94
Chemicals & Products	-.13	-3.51
Basic metals	.001	0.04
Motor Vehicle & Other Transport	-0.06	-1.93
Rubber,wood&paper	-.14	-7.33
All industries	-.05	-3.23

Note: Column (1) reports mean differences in productivity between above- and below- median contract share. Column (2) reports associated t-statistics. Firm revenue share are used as weights. For differences across all industries, the difference in averages are reported after accounting for industry fixed effects.

Table 3.8: Distribution of Lagged Elasticity ($\frac{\partial g}{\partial cs_{t-1}}$)

	(1) Q1	(2) Q2	(3) Q3	(4) Mean
Textiles	-2.90	-1.35	.58	-1.26
Food products & beverages	-.72	-.11	.40	-0.17
Chemicals & Products	-7.28	-1.72	1.15	-3.62
Basic metals	-7.20	-4.21	.036	-2.78
Motor Vehicle & Other Transport	-2.63	.83	3.32	-0.75
Rubber,wood, & paper	-.87	.98	2.62	0.80
All industries	-5.11	-.96	1.47	-2.05

Note: Q1, Q2, and Q3 represent 25th, 50th, and 75th percentile values of the contemporary elasticity distribution respectively.

Table 3.9: Two-sample Kolmogorov-Smirnov Test for Equality of Distribution Functions

Null hypothesis	D	P-value
Low contract share contains *smaller* productivity values than high contract share	0.052	0.00
Low contract share contains *larger* productivity values than high contract share	-0.18	0.000
Equality of distributions of low and high contract share	0.18	0.000

D represents the largest difference between the distribution functions. Low-contract share represents below-median contract share, and high-contract share represents above-median contract share.

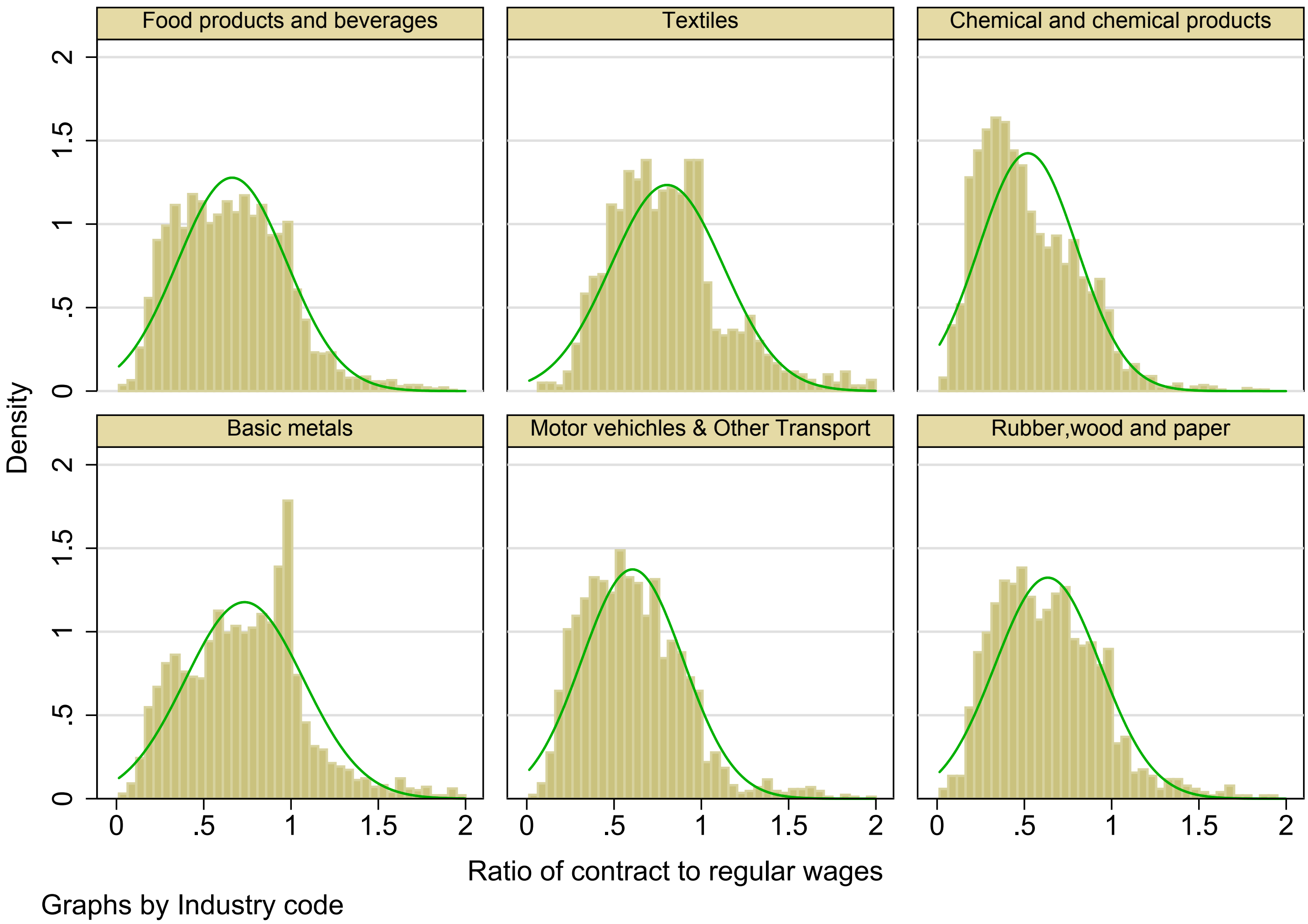
Table 3.10: Persistence in Productivity ($\frac{\partial g}{\partial \omega_{t-1}}$)

	(1) Difference	(2) T-statistic of Difference
Textiles	-0.21	-45.34
Food products & beverages	0.08	48.47
Chemicals & Products	-0.30	-22.84
Basic metals	0.24	11.84
Motor Vehicle & Other Transport	-0.06	-3.99
Rubber,wood, & paper	-0.09	-13.67
All industries	-0.04	-5.45

Note: Column (1) reports mean differences in the persistence of productivity between above and below median contract share. Column (2) reports associated t-statistics. Firms revenue share are used as weights. For differences across all industries, the difference in averages are reported after accounting for industry fixed effects.

APPENDIX TO CHAPTER 3

Figure A1: Ratio of Contract Wages to Regular Wages: by Industry in 2011



Source: The Annual survey of Industries

Table A1: Share of Large Firms in Original Dataset

Industry	Share of large factory-year observations
Chemicals & Products	41.06%
Basic Metals	40.29%
Rubber,wood, & paper	25.86%
Food products & beverages	21.42%
Textiles	53.28%
Motor Vehicle & Other Transport	48.72 %

Source: Annual Survey of Industries.

CHAPTER 4

POLITICAL CLIENTELISM AND POLITICAL ACTIVISM: EVIDENCE FROM AN INDIAN PUBLIC WORKS PROGRAM

Nancy H. Chau[1] Yanyan Liu[2] Vidhya Soundararajan

4.1 Introduction

Political parties are known to strategically redirect public resources through decentralized programs to secure and expand their party base. In a large and long-standing literature, such activities have been referred to as tactical redistribution, and/or political clientelism (Downs, 1957; Wright, 1974; Wyatt, 2013; Dixit and Londegran 1996). What determines the identity of the so-called swing voters? To date, research has focussed on voter characteristics such as the strength of their ideological attachments (Lindbeck and Weibull 1987), political affiliation (Cox and McCubbins 1986), and the tendency for reciprocal behavior (Finan and Schechter 2011), for example. A number of recent studies investigate the role of voter information (Grossman and Helpman 1996, Wantchekon 2003), by uncovering cases

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where politicians alter their vote buying patterns to target voters who attended education programs about the practice of vote buying (Vincente 2014), and voters who received information about the qualification of candidates (Banerjee et al, 2011).

Voters in these earlier studies exclusively play the passive role of recipients of political transfers and information. In this paper, we highlight two voter identities: (i) swing voters who change political allegiance by provided with transfers and/or information, and (ii) political activists who can additionally respond to preferential transfers by changing the manner in which they participate in political campaigns. Importantly, an individual voter can embody none, one, or both of these identities. Given the opportunity, do politicians opt to influence voters by offering preferential transfers directly to swing voters, or indirectly to political activists who carry information to voters? We study this question in the context of a decentralized public works program, the Mahatma Gandhi Rural Employment Guarantee Scheme in the southern Indian state of Andhra Pradesh.

The MNREGS is a decentralized labor and social-security based public works program which legally assures rural households up to 100 days of employment per year. The program transferred an unprecedented levels of funds – USD 793 million in Andhra Pradesh alone and USD 7.2 billion in India. It was a flagship program of the United Progressive Alliance (UPA) that held power in the India's central government for two consecutive five-year term periods spanning 2004 to 2009 and 2009 to 2014. The UPA was a coalition of center-left political parties that held power both at the center and in the state of Andhra Pradesh in our study period [3]. Andhra Pradesh offers an interesting case to study because of its inherent political dichotomy. On the one hand, the state endeavors to stay transparent and efficient in implementing the MNREGS and initiated several measures to ensure accountability through real-time availability of data, and improved channels for public vigilance and civil society participation (Aiyar and Samji, 2009; Subbarao et al.2013). On the other hand, the state's cash-for-vote electoral politics stunningly stands out from the rest of the country. Andhra Pradesh leads the Indian states in term of the total money seized during elections, a phenomena particularly acute in local elections (Centre for Media Studies, 2014). More than half the voters in Andhra Pradesh are distributed cash on eve of elections, and the state endures highest per-voter cash transfer in India. In this context, we examine the presence of clientelistic targeting under the seemingly transparent MNREGS program, by studying the effects of household affiliation to particular political party or coalition, on their receipt of MNREGS work and payment.

In classic probability voting models, political parties target transfers to marginal - or "swing" – voters, i.e., those closest to the centre of the political spec-

[3]UPA members in 2004 state elections in Andhra Pradesh included the Indian National Congress (INC), Telangana Rashtriya Samiti (TRS), Communist Party of India (CPI), CPI (Marxist), and Majlis-e-Ittehadul Muslimeen (MIM). The non-UPA parties are the Telugu Desam Party (TDP) and the Barathiya Janata Party (BJP) comprised the UPA-rival group. We use the UPA coalition definition from footnote 11 in Sheahan et al. (2014).

trum, since a one dollar transfer to this group leads to a greater increase in political support than a transfer to groups with more extreme ideological attachments (Lindbek and Weibull, 1987, Dixit and Londregan, 1996, 1998, Stokes, 2005). In these settings, voter-cum-activists whose ideological attachments are presumably most intense will not be recipients of clientelistic transfers as they are effectively the least willing individuals to switch political alliance by assumption. In a simple model of political clientelism where we maintain this assumption, we furthermore argue that individuals with the most intense ideological attachments are also most likely to be themselves active in political campaigns. These activists produce a public good that can change the information voters have about incumbent and rival politicians. By spelling out these distinctive voter identities, this model allows politicians to simultaneously buy support from swing voters with relatively mild political attachments, as well as from voter-cum-activists who spearhead political campaigns, so long as the transfers engender support from *other swing voters* if not the activists themselves.

There is a strong empirical literature examining clientelism at the aggregate level such as state, district, district sub-division (mandal or block), village, and election constituencies [4]. For MNREGS particularly, Sheahan et al. (2014) use

[4]Case 2000 observed that communes that voted for the Democratic party received a higher level of assistance in a later period. Schady (2002) finds that Peruvian social Fund expenditures were higher in poor provinces, as well as provinces in which the marginal political impact of expenditures was likely to be greatest. Khemani (2004) finds that fiscal transfers to states serve the electoral interests of the ruling party in India; Asher and Novosad (2015) conclude that firms in constituencies aligned with state level coalitions in India, see a 1% rise in employment over a period of 7 years and stock prices yield 10-15% positive cumulative abnormal returns in the month

mandal level fund allocation data in Andhra Pradesh, India, and find no evidence of clientelism in the initial years of MNREGS program implementation before the state election, but find mild patronage effects (statistically significant but economically small) in the years following the state election. Himanshu et al. (2015) use a sample of 328 villages in 75 multi-village Panchayats in Rajasthan, and find evidence of rationing of MNREGS jobs in favour of the village where the village president resides. Gupta and Mukhopadhyay (2016) use longitudinal data from two waves of block council elections (in 2005 and 2010) and MNREGS fund allocation to all blocks for the financial years 2009–10, 2011–12 and 2012–13 in Rajasthan, and find that greater amount of funds were allocated to blocks where INC had lower seat share. Household level studies studying clientelism under decentralized welfare programs are rich in the Indian context, and they provide compelling evidence that elected local politicians offer preferential treatment in allocating benefits of decentralized programs to core supporters (Besley, Pande, Rao, 2005; Markussen, 2011; Das, 2014) [5]. For MNREGS particularly, Das (2014) uses a household survey in West Bengal, and employs a Heckman selection correction

following the election in the firm's headquarter constituency. Dahlberg and Johansson (2002) find that grants were allocated to constituencies with large numbers of swing voters in Sweden. Fried (2011) finds little evidence that political criteria explain the difference between the number of poor families that live in a municipality and the number of families that receive support

[5]Besley, Pande and Rao (2005) (BPR) show that politician households are more likely to own a Below Poverty Line card in the southern Indian states Kerala, Tamil Nadu, Karnataka, and Andhra Pradesh in 2002. Markussen (2011) uses the same datatset as BPR and employs a 2-Stage Least Square estimator to show that households affiliated to the president's party are more likely to hold a Below Poverty Line card. He explicitly addresses the endogeneity of household party affiliation by instrumenting affiliation with a binary variable for households sharing the same occupation, educational background and village of residence with the President. However, these estimates face the issue of weak instruments, as demonstrated by the low F-statistics (4.24) of their instrument relevance test.

model to address self-selection in job seeking under the MNREGS to demonstrate the households affiliated with the local ruling political party and politically active were favored with more MNREGS jobs.

We build upon this empirical literature by examining clientelism in a setting (MNREGS in Andhra Pradesh) that has not been explored before. We also explicitly differentiate our analysis based on the actual political party of the local leader (like Das 2014), a distinction that crucially differentiates the leader's capacity to engage in clientelism, especially if certain limbs of program implementation are top-down, like ours (more below). We study clientelism at the household level because we argue that household level studies may offer alternate perspectives compared to the aggregate level studies even within the same context. Since local village bodies form the lowest body of governance and often the point of contact for potential beneficiary households, the factors and motives influencing them to favor one household over the other under clientelistic programs, if at all, may vastly differ from those influencing a bureaucrat to allocate program funds across different states, districts or other higher-level governing bodies.

Our main contribution to the empirical literature is in tackling the issue of reverse causality in examining the effects of political affiliation on clientelistic benefits, by exploiting the timing of our survey which uniquely captures household political affiliation before they received MNREGS benefits. Das (2014) rightly acknowledges the reverse causality issue in studying clientelism through MNREGS in West Bengal under the left-front (alliance of left-wing parties) government, but does not address it because of their cautious claim that households tend to be historic supporters of parties and may not necessarily change parties once they receive MNREGS. However, as Bardhan et al. (2009) argue, the left-front in Bengal has been continuously renewing its support base by offering clientelistic favors. In other words, although supporters appear unswerving, the underlying clientelistic relationship responsible for their support is too crucial to be missed [6].

Our sample consists of 1,077 households in UPA-sarpanch villages and 315 households in non-UPA sarpanch villages in Andhra Pradesh in the year 2006. Surveyed households reported their MNREGS job-card number if they possessed one, which enabled us to merge annual administrative data on MNREGS workdays and payments for the years 2006 and 2007 [7] into our data set. The survey also records a plethora of socio-demographic and economic particulars, political participation indicators, and awareness indicators, which we employ as control variables. The timing of events play a crucial role in our paper. The MNREGS was implemented in a staggered non-random fashion through the entire country in three stages. It came force in the 200 most backward districts in February 2006 (phase - I), extended to an additional 130 districts in April 2007 (phase-II), and

[6] Bardhan et al. 2012; Bhattacharya 2009, Majumdar 2009, and Dasgupta 2009 provide detailed narratives.

[7] Administrative data is available for download from the MNREGS web site at http://www.nrega.ap.gov.in/Nregs/

all remaining rural districts in April 2008 (phase-III). Our survey in August 2006 captures political affiliation of households around or before the commencement of the MNREGS program in phase-I and phase-II villages respectively. Using a rich set of explanatory variables that control for unobserved heterogeneity at the household level, effectively then, we are able to causally estimate the effects of political affiliation in 2006 on MNREGS work and payments received cumulative in 2006 and 2007. In our study period, while UPA member parties enjoyed great clout because the same coalition also held power at the federal government level, non-UPA representatives were relatively less resourceful. While concerns for re-election remain important for both UPA and non-UPA sarpanches, the former's clout affords them the financial mileage to engage in clientelism. We started by studying the presence of clientelism in UPA-sarpanch villages.

We find robust evidence for political support-buying in a village economy. In villages governed by a UPA-sarpanch, compared to households affiliated to the UPA-coalition (supporters), unaffiliated households and those affiliated to UPA-rival parties (non-supporters) obtained significantly higher days of work and payment cumulatively in 2006 and 2007. Furthermore, in UPA-sarpanch villages, political active rival party households are specifically targeted. These results starkly contrast all other studies on India which show that leaders patronize loyalist households by offering them more benefits, compared to swing groups or rival party supporters.

In exploring the mechanisms that drive these results, we furthermore report results of estimations that ascertain the role of the overall degree of political activism in a village on support-buying. Interestingly, we find that both UPA rival and unaffiliated households in villages with high level of political activism overall – proxied by the fraction of politically active households in among those included in our survey – tend to receive higher days of work and payment. Other voters in these villages tend to receive significantly less work and payment. The overall level of political activism in our context thus operates in ways analogous to the voter information intervention programs in Banerjee et al. (2011) and Vincente (2013), where informed voters are found to become targets of vote-buying. We interpret these as suggestive evidence that politicians target preferential transfers to both types of voter identities singled out in this paper.

The causal interpretation of the effects of political affiliation on receiving MNREGS benefits rests on the assumption that household political affiliation is exogenous. However, there may be confounding factors that are correlated with both political affiliation and demand for and receipt of MNREGS benefits that could affect the causal interpretation of this relationship. We address this concern by including a rich set of control variables including poverty status, land ownership, occupation, gender, and education of the household head, political involvement, awareness levels, and village level fixed effects, all of which influence households seeking and obtaining work. Some reverse causality concerns could still exist. Political affiliation reported in the survey could itself be a result of MNREGS benefits received after the program started in February 2006, for phase-I villages. However, note that affiliation was measured in August, not long after the program came into force in February, and when the program was still in its infancy with minimal household participation. We show that our results remain qualitatively robust, if we repeat our analysis for households who did not receive MNREGS benefits between program commencement and our survey month.

The next section introduces the MNREGS in India and Andhra Pradesh (section 2). Subsequent sections explain the theoretical model (section 3), describe the data and present the methodology (section 4), and present the results (section 5). We conclude in section 7.

4.2 The Mahatma Gandhi Rural Employment Guarantee Scheme

Unlike other social welfare policies, MNREGS obtained constitutional recognition and came into force as a law in September 2005. In 2012-13, the program generated 2.3 billion person-days of employment for 49.9 million households nationwide, from a budget of USD million 47.93. Adults in rural households can demand up to 100 days of employment to be shared among its members. Infrastructure works like water conservation and water harvesting; drought proofing including afforestation; irrigation works; restoration of traditional water bodies; land development; flood control; rural connectivity, and other works notified by the government, are some important works permissible under the radar of the scheme. Further, the act sets a minimum limit to the wages to be paid on a time-rate basis or on a piece-rate basis, without gender discrimination. Certain transparency and accountability measures are supposed to be in place, through mechanisms like "squaring of accounts", conducting social audits to ensure accountability through public vigilance and participation of civil society, and finally the maintenance of records by the implementing agencies and ensuring their availability for evaluation and scrutiny.

Figure 4.1 represents various stakeholders and within state work flows under the MNREGS as per the federal guidelines. Households request and obtain a job-card, which forms the basis of identification, and is a legal document where number of days worked are recorded in order to claim wages. Job-card holders can seek jobs to the Gram Panchayat (GP), the village level body or block office, stating the duration for which work is sought. Work requests from households are consolidated into a shelf of projects by the village gram panchayat, headed by the sarpanch, and presented to the officers at the block level (district sub-division). The block panchayat and programme officer scrutinizes and consolidates GP's plans and appeals for funds from the district headquarters. The district panchayat and programme officer in turn ensure administrative and technical approvals for this shelf of projects and release funds accordingly. The state apex body, State

Employment Guarantee Council (SEGC) nominates the list of proposed works to the central government. Note that, the work generated under the scheme is initiated by household requests after which it goes through various local bodies for approval, before coming to a full circle back at the village level. In short, the entire scheme is supposed to work bottom-up.

In the villages of Andhra Pradesh, apart from the sarpanch (village leader), a state-appointed 'field assistant' (FA) (not elected) administers the scheme. Although as per the books, the FA is only required to measure works and maintain registers, his/her actual role seems to more powerful than that (Chamorro et al. 2010). Nevertheless, gram panchayat's stake in MNREGS implementation remains largely crucial because the sarpanch is concerned about support, vote-bank and re-election. With the clout they enjoy, UPA affiliated sarpanches could forge alliance with or control the state appointed FAs, who are already likely to be supporters of the UPA (Maiorano 2014). In this case, FAs and sarpanches are natural partners in action and plausibly work to achieve the same objectives (expanding UPA's support bank). In contrast, non-UPA sarpanches may seem weaker and not have the access to resources to engage in clientelism. Since these sarpanches are not natural allies with FAs, outcomes here are fuzzy and are a result of power play between the two.

Andhra Pradesh's MNREGS endeavors to stay efficient and transparent in the middle and lower echelons of the state government. Several initiatives, along with continued support from the top-level state administration resulted in great success in generating jobs and obtaining people's trust. The state of Andhra Pradesh, unlike most others, initiated and institutionalized transparency and efficiency measures for improved functioning of the scheme. These measures along with AP' political commitment is often cited as an important reason for its successful track of job creation (Maiorano 2014). For example, social audits were mandated through the Strategy and Performance Innovation Unit, instituted under the state's department of Rural Development (RD) for better transparency. Efficient and honest officials were deliberately inducted into the RD department to ensure commitment and success of the MNREGS. Further, detailed records of each MNREGS participant were made publicly available over the Internet (Johnson 2009), making it the only state to have implemented an advanced information system for tracking participation data.

Despite these transparency and efficiency measures, and the political commitment, AP MNREGS lacks bottom up planning (Maiorano 2014; Chamorro et al. 2010). The set of works is decided not entirely based on demand, but after political priorities and technical feasibilities receive their due considerations. For example, Scheduled Caste/Scheduled Tribe's [8] private land development was a priority of the state government, owing presumably to the former's poor economic status

[8]The Scheduled Castes (SCs) and Scheduled Tribes (STs) are official designations given to various groups of historically disadvantaged people in India. The terms are recognized in the Constitution of India and the various groups are designated in one or other of the categories.

and to retain their contribution to the wide support base for congress party [9]. That most villages cease offering employment in the agricultural peak season at the behest of a powerful farmer lobby supported by the state government, is another illustration of top-down planning [10]. Lastly, a Member of the Legislative Assembly (MLA)'s [11] affiliation to the Indian National Congress is a strong correlate of employment generation under MNREGS in that constituency, perhaps because of the presence of honest and competent officials in those constituencies (Maiorano 2014) [12].

Figure 4.2 details the within-state implementation details specific to Andhra Pradesh. Besides the sarpanch, a prominent figure in AP villages managing the MNREGS implementation is a field assistant who is chosen by the Block Development Officer (BDO) from a list of candidates that includes the GP's shortlist (up to three members) and any other "eligible candidates" directly applying to the BDO (Government of Andhra Pradesh, 2006). While the books suggest that role of a field assistant is limited to assisting the panchayat secretary [13] in maintaining

[9] Maiorano (2014) notes that over a quarter of work occurring in SC/ST's private lands "were not required or not meeting owner's needs."

[10] Figure 1 in Maiorano (2014) shows a notable dip in employment between July and December in many states

[11] The Legislative Assembly is the lower house of the state legislature in a bicameral system, whose members are representatives of people chosen through direct state-level elections.

[12] "In 2011–12 the average number of person-days generated per household was 67.07 in Congress MLA's constituencies as against 54.95 in non-Congress ones. Among the top ten performers, seven are Congress constituencies, which include those of the present chief minister and two cabinet ministers. Conversely, among the worst ten constituencies, only two belong to the Congress." (Maiorano 2014)

[13] "The Panchayat Secretary at the village level, is a staff working in the Gram Panchayat office in administrative tasks like recording decisions, keeping minutes, preparing budget estimates and

records such as work muster rolls, materials procurement-consumption register, and measuring work done by households (Government of Andhra Pradesh, 2006), field assistants play a more powerful role in implementation than that anticipated in design (Chamorro et al. 2010). Maiorano (2014) notes that FAs provide job-cards and jobs, and decide on the list of projects, all of which are duties of the gram panchayat (of which sarpanch is a member) as per the operational guidelines.

Despite the presence of these two stakeholders, village sarpanches have an important stake in the implementation of MNREGS – to demonstrate performance and/or to appease their constituents – arising from their need to renew their positions of power. They can control or ally with FAs depending on their power position within the village and beyond, to influence project planning, job allocation, and payments. That the GPs also short list candidates in choosing FAs, indicate their leverage on FAs. Since FAs are state appointed, we can safely assume their allegiance to UPA-sarpanches (even though their political explicit affiliations are unavailable).

In what follows, we theoretically model the problem that a UPA sarpanch – the ruling party politician – face in an attempt to bolster political support through

reports, and does other sundry jobs like preparing notices, explaining circulars, organizing Gram Sabha meetings etc." source: http://www.yourarticlelibrary.com/politics/the-three-tier-system-of-panchayati-raj-in-india/4827/

the tactical distribution of MNREGS benefits. Our objective is to extend canonical models of political support to account for voter level characteristics that may alter the pattern of political clientelism.

4.3 A Simple Model of Political Clientelism

There are two political parties, respectively the ruling party o and the rival party r. We consider an electorate of size normalized to unity. Each member j of the electorate affiliated with a political party has a preference function $u_p(y_j, k_j, a)$. u_p is taken to depend on j's individual political preference type p, income y_j, the utility derived from his stated political affiliation $\theta_a, a = o, r$, and the intensity of his political preference $k > 0$.

$$u_p(y_j, k_j, a) = y_j + k_j \theta_a^p.$$

We assume that members of the electorate are potentially heterogeneous in all three dimensions p, y, and k. Their individual decision problem involves the choice of party affiliation a conditional on p, y and k. To fix ideas, we assume that there are two groups of individuals in the electorate with heterogeneous political preference p. A fraction q_o of the electorate is pro-ruling party ($p = o$), while $1 - q_o$ is the pro-rival ($p = r$) party share. Accordingly, let $\theta_a^p = \{\theta^+, \theta^-\}$, with $\theta^+ > 0 > \theta^-$, be a preference parameter that reflects the utility associated with political affiliation $a = o, r$. For a fraction q_o of the electorate, $\theta_o^o = \theta^+$ and $\theta_r^o = \theta^-$. For the remaining $1 - q_o$ share of pro-rival party voters, $\theta_r^r = \theta^+$ and $\theta_o^r = \theta^-$.

Next, the intensity of political preferences, $k \in [0, \infty)$ is also heterogeneous among voters. k can take on one of N values $\{k_1, ..., k_N\}$. k reflects the propensity for political activism of the individual, for example, participation in political campaigns and meetings as well as through monetary contributions. The cumulative probability distribution of political activism k among all voters is given by $\phi_i = Prob(k \leq k_i) \in [0, 1]$, with $\phi_N = 1$.

For a voter who chooses to remain unaffiliated with any of the two political parties, his utility is

$$u(y_j, u) = y_j + \theta_u$$

where $\theta_u \in \mathbb{R}$ and naturally, the level of political activism does not impact the utility of an unaffiliated individual.

Finally to capture heterogeneity in income, we assume that y_j is i.i.d. and uniform for all k and θ_a in the range $[y^-, y^+]$.

Voter Affiliation without Political Clientelism

In the absence of political clientelism, let N_i denotes the fraction of voters with chosen political affiliation $i = o, r, u$. Also let k_o denote the threshold level of political activism such that a pro-ruling party voter is just indifferent between being a ruling party supporter and remaining unaffiliated, and let k_r denote the threshold level of political activism such that a pro-rival party voter is just indifferent between being a rival party supporter and remaining unaffiliated.Note that in the absence of political clientelism, pro-rival party voters will not choose to affiliate with the ruling party by definition, and likewise pro-ruling party voters will not choose to affiliate with the rival party.

$$k_o = \min\{k|y_j + k\theta^+ > y_j + \theta_u\}, \quad k_r = \min\{k|y_j + k\theta^+ > y_j + \theta_u\}.$$

It follows that the fraction of voters who choose to be ruling party supporters, rival party supporters, and those who remain unaffiliated are:

$$N_o = q_o(1 - \phi(k_o))$$
$$N_r = (1 - q_o)(1 - \phi(k_r))$$
$$N_u = q_o\phi(k_o) + (1 - q_o)\phi(k_r)$$

Thus, pro-ruling party supporters exhibit relatively high levels of political activism $k > k_o$, and have political preferences that favor the ruling party $\theta_o = \theta^+$. By contrast, pro-rival party supporters also exhibit sufficiently high levels of political activism $k > k_r$, but they favor the rival party $\theta_r = \theta^+$. Finally, unaffiliated voters is a heterogeneous group encompassing both pro-ruling party and pro-rival party preferences. However, they are the least political engaged voters and hence optimally opt to stay out of formal political affiliation.

Political Clientelism in a Heterogeneous Voter Pool

Political clientelism in our setting refers to targeted transfers by the ruling party leaders directed at select individuals in the voter pool. In our setting, an individual voter can be identified by his income level y_j, the intensity of his political preference k, [14] and his political affiliation $a = o, r$, or lack thereof. To bolster political support,[15] the ruling party may target support to the rival party affiliates N_r, and/or to unaffiliated voters N_u. Within each group, the ruling party may further target support based on an individual's intensity of political preference k, as well as his income level y_j. Our objective here is to determine the conditions under which selection occur along the dimensions of y_j and k_j, conditional on the original political affiliation of the individual, r or u.

[14] In our empirical examination, k can be gauged by the level of political activity that a voter is seen to engage in.

[15] We only look at political support buying in this model. The basic model can be extended to allow for randomness in voter preferences from one period to the next, which will then justify targeted transfers by the politician to ruling party supporters as well. As we will show in our empirical examination, the evidence strongly suggests that political support buying is the dominant feature in the context of the MNREGS program.

To do so, we allow for targeted transfers to impact both the income y_j, and the political preference θ_a of the voter. Specifically, for a targeted transfer b, the income of the voter increases from y_j to y_j+b, while the preference for switching affiliation to align with the ruling party changes from θ_i^p to $\theta_i^p+g(b,k,y,\mathbf{B})$. These two changes are distinctive for two reasons. Since b is an unconditional transfer in the sense that the politician cannot require a switch in political affiliation subsequent to the transfer, the income change from y_j to y_j+b is independent of which political party the voter decides to affiliate with.

By contrast, the political preference parameter is strictly party affiliation-specific. $g(b;y,k,\mathbf{B})$ gauges the change in the utility from affiliating with the ruling party conditional on the size of the transfer b, the income of the individual y, and the intensity of political preference k. For example, if there is diminishing marginal utility of income asociated with g, we let $g_y \leq 0$ and thus a higher income voters require a larger transfer in order to elicit a change in political alliance conditional on k. The effect of k on g is of interest as well. If $g_k \leq 0$, a more politically active individual would likewise require a larger transfer in order to a elicit a change in political alliance.

We let $\mathbf{B} = \sum_i {}_i\phi_i\bar{b}_i$ to reflect the effectiveness of targeted transfers by the ruling political in influencing the overall message conveyed by voters who are active in political campaigns. $\bar{b}_i$ is the average level of transfers to voters with political activism k_i across all voter income levels. ϕ_i as discussed refers to the share of voters with political activism k_i. Finally, $i \in [0,1]$ is a weight that indicates the effectiveness of transfers to influence the behaviors of voters with political activism k_i. Whenever $g_{\mathbf{B}} \geq 0$, an individual voter's gains from switching political alliance to support the ruling party rises with ruling party transfers to political activists.

Consider to begin with targeted transfers to unaffiliated voters with political preference p. Such a voter will switch political affiliation to support the ruling part if and only if

$$y + b + k\theta_o^p + g(b, k, y, \mathbf{B}) > y + b + \theta_u, p = o, r$$

or,

$$k\theta_o^p + g(b, k, y, \mathbf{B}) > \theta_u$$

Thus, for given b, poorer individuals with low y are more likely to change affiliation if and only if $g_y \leq 0$. Furthermore, more politically active individuals are less likely to change affiliation if and only if $g_k \leq 0$. Meanwhile, transfers are made to politically active individuals in the village if and only if $g_{\mathbf{B}} \geq 0$.

Turning now to party-based targeted transfers to rival voters, a rival party support switches to the ruling part if and only if

$$y + b + k\theta^{-} + g(b, k, y, \mathbf{B}) > y + b + k\theta^{+}$$

or equivalently,

$$u(y + b, k, o) - u(y + b, k, r) = k(\theta^{-} - \theta^{+}) + g(b, k, y, \mathbf{B}) > 0.$$

In a way analogous to unaffiliated voters, given b, poorer individuals with low y, and individuals with relatively mild political preference are more likely to change affiliation. Nonetheless, the ruling party may still prefer to target funding to influence high politically active individuals. This occurs when $g_{\mathbf{B}} \geq 0$, and as such doing so will facilitate alliance switching from other voters with relatively lower k and y.

The key message of the above is that the ruling party can increase its support base by directly targeting transfers to swing voter, or by indirectly targeting transfers to influence the messages of the politically active individuals. The former requires transferring funds to the relatively politically inactive individuals, while the latter requires the transfer of funds to the most politically active individuals. We turn to the empirical salience of these possibilities in the data in the context of the MNREGS program in what follows.

4.4 Data Description

We use a dataset of 1077 households from UPA-sarpanch villages collected from a primary field survey in Andhra Pradesh. The survey was conducted in the months of August and September in 2006. Our core dataset spans four districts namely Kadappa, Nalgonda, Warangal and Nellore (first three belongs to phase-I, last one belongs to phase-II) of which the latter two currently belong to the state of Telengana [16].

Our main set of variables are days worked and payments received under the MNREGS scheme, and political affiliation and activism levels of households. The survey collected job-card numbers for all participating households, enabling us to merge into our survey, publicly available annual administrative data (available online at http://nrega.ap.gov.in/), exhaustive in their coverage of participating households and information on workdays and payments [17]. Our surveys also collected data on households' affiliation to a particular political party if any, which we code into alliances namely, UPA, UPA-rival, and unaffiliated (the last category

[16]Telangana was carved out of the north-western part of erstwhile Andhra Pradesh in 2013. Kadappa and Nellore are still a part of Andhra Pradesh.

[17]The administrative data in AP are verified routinely through independent social audits in the gram panchayats across the state (see http://www.socialaudit.ap.gov.in). We also conducted verification exercises in select villages in 2014 which suggest that the administrative data is reliable. Household interviews on wages earned and work done by job-card holders match entries in post-office or bank books wherever these were available. Likewise individual recall data on the type of work done and number of days are also consistent with administrative data, as are the list of assets created since inception. Details of this verification exercise are available upon request.

implies not affiliated to any party or affiliated to a few fringe parties) based on the coalition formation in the previous state election in 2004 [18][19]. Political affiliation of village sarpanches are not directly available because elections to the Gram Panchayat do not run on party labels. However, we were able to deduce sarpanch's party affiliation from households' response to the three following questions in our survey: (1) Did you vote for the winner in the last GP election? (2) If so, is that vote for party affiliation reasons? (3) Which party are you affiliated to?". There are mixed responses on sarpanch's affiliation across households, reflecting that many villagers are unaware of this aspect about their sarpanch. Considering this heterogeneity in repoting, we assigned sarpach's party affiliation in a village to be the one that more than 50% of the sampled households reported in the village. In villages without this majority, we left sarpanch's affiliation blank. Households stating affiliation to a particular party were also questioned the intensity of participation in political activities, which we coded as "Politically Active" (campaigning, attending meetings, giving speeches and writing pamphlets, attending rallies and offering donations), and "Politically Inactive". The involvement level of all unaffiliated households were set to "inactive".

Table 4.1 provides the distribution of households in our sample based on a

[18]The same questions were asked to females and males in the household, but in this study we use data reported by males because unlike males, women participate less in politics, are politically less influential, and make fewer household economic decisions than men.

[19]There could be a concern that since party affiliation is self-declared, it may not reflect actual voting behavior but a desire to show gratitude to the gram panchayat leaders. However, this is not a concern because the survey was conducted in the interviewees' house by enumerators, and panchayat leaders are not expected to see the information in the survey.

variety of characteristics. Highest representation is by backward caste (43.73%), followed by Scheduled Caste (29.9%), Higher Caste (18.66%), and Scheduled Tribe (7.71%). 56.92% household-heads are not formally literate (they may have received informal education), a little over a quarter received secondary education or below, and only about 17.92% receive high school education. The most popular occupation is casual work in agriculture and other sectors (39.65%), followed by salaried work in agriculture and other sectors (31.85%), own business or self-employed - agriculture/other sectors (14.39%). Nonworking adults, who are typically pensioners/rentiers, dependents, students and those focusing on households chores, form 9.47% of the sample. 3.16% own common property resources and manage livestock, 1.49% are engaged in other occupations.

Almost two-thirds households belong to the category ”Poorest of the Poor and Poor”, about 34 households represent the ”Not so poor/Not poor” category. Nearly 63% households are UPA-affiliated, while the rest are affiliated to UPA-rival parties (16.25%) and unaffiliated (20.43%). 60% of the household heads indicate low awareness levels (indicated by their regular and frequent attendance of village meetings), and 40% have high awareness levels (indicated by their non-attendance or rare attendance in village meetings). About 29% households participate in political activities (campaigning, attending meetings, giving speeches, writing pamphlets, attending rallies, giving donations - cash and kind and others), and 71% are inactive.

Table 4.2 descriptively shows that most households do not participate in politics (64% among UPA and 61% among UPA-rival households). Naturally, and according to our assignment, all unaffiliated households are politically active. 36% UPA households and 39% UPA-rival households are politically active. Among UPA-rival households, the trend is reverse; 15% households are actively involved and 24% households are semi-involved.

Table 4.3 describes cumulative MNREGS benefits in 2006 and 2007. In UPA sarpanch villages, unaffiliated households obtained the highest proportion of job-cards (56.8%), followed by UPA households (53.8%) and UPA-rival households (50.8%). A similar trend was obserbed for Days worked and payments received, which was highest among the unaffiliated households (21.93 days and Rs. 1671), followed by UPA households (19.72 and 1621.81), and UPA-rival households (17.42 and 1455.24). However these are merely descriptive statistics, and with the lack of control variables and an appropriate empirical framework, do not yield causal estimates of the effects of political affiliation on MNREGS payment and days. We resort to udnerstanding these relationships in the section below.

4.5 Empirical Methodology

In this section, we empirically examine if households obtain higher or lower MNREGS benefits if they have allegiance with a particular political coalition. Consider the latent variable model below.

$$y_{vi} = \gamma_0 + \gamma_1 PARTY_{vi} + \gamma_2 ACTIVISM_{vi} + \gamma_3 PARTY_{vi} * ACTIVISM_{vi} + \gamma_4 Xvi + \gamma_5 D_v + \epsilon_{vi} \quad (4.1)$$

y_{vi} is a latent variable determined by the above process, which in turn yields the following observables for household i at village v : (1) log(days+1), logarithm of days worked in MNREGS by household i, and (2) log(amount earned+1), logarithm of amount earned through MNREGS by household i, cumulative over 2006 and 2007 [20]. In this latent variable model, the threshold above which work is performed is zero (for both days worked and payment), and this movtivates a Tobit framework in empirical analysis. ϵ_{vi} is an orthogonal error term.

$PARTY_{vi}$ is a vector indicating household political affiliation: UPA (base category), UPA-Rival, and unaffiliated. $ACTIVISM_{vi}$ is a vector indicating household's political activism: politically inactive (base category) and politically active. The parameters of interest are γ_1, γ_2, and γ_3 which suggest what groups (defined

[20] log(x+1) is an effective method to deal with zero values in x.

by the combination of party affiliation and political activism) were considered swing voters in this context. X_i refers to the following socio-demographic and economic indicators in 2006: Social group, poverty status, household head's age, household size, primary occupation and education of the household head, log per capita expenditure, log land ownership, and attendance of village meetings. We also control for revenue-village fixed effects and cluster standard errors at that level.

In equation 2, endogeneity concerns for the identification of the effects of political affiliation, arises from two sources. First, there could be self-selection in job-card seeking as well as job seeking which is a concern if seeking is correlated with political affiliation. However, as we show, job-card issuance in Andhra Pradesh is straightforward, need-based, and not mired by clientelism (Table 4.9, explained in section 4.6.3). Anecdotal evidence in Andhra Pradesh also strongly suggests that households seeking a job-card almost always obtain one. To the extent that job-card seeking also reflects job-seeking, we can assume job-card ownership implies job-seeking.

Second, party affiliation could potentially be endogenous. We worry about two aspects of this. First, we care about the correlation of party affiliation with unobserved factors that also influences MNREGS benefits. This concern is diluted by our rich set of control variables, described above that could effectively control for household level unobserved heterogeneity. Our poverty measure, in particular, having been developed from a combination of quantitative and participatory qualitative methods, is unique and precisely captures household's status. Village level fixed effects further, are crucial for identification because they capture supply side unobservables including the availability of MNREGS jobs and funds at the village level, factors that affect MNREGS demand such as rainfall, ratio of landlords versus landless, nonfarm opportunities, and other factors that may correlate with party affiliation of villagers. Second, we want to rule out reverse causality concerns wherein party affiliation itself is a result of benefits received under MNREGS. To illustrate how we tackle this concern, a time-line of events is presented in Figure 4.3. For phase-1 villages where the program started in February 2006, we measure political affiliation in the survey months of August to October, just after the commencement of MNREGS but not long after. In phase-2 villages, we capture political affiliation of households in 2006, before the program started in April 2007. Thus identification in phase-2 villages are cleaner, but there is a lapse of six months after which the program started and before which we measure political affiliation in phase 1 villages where households in our sample may have receied MNREGS benefits. We conduct an additional robustness check by repeating the analysis by removing households who received jobs in these six months.

To explore the mechanisms, we include the share of politically active households, which represents the political information available at the village level, and its interaction with household political affiliation in a new specification.

$$y_{vi} = \gamma_0 + \gamma_1 PARTY_{vi} + \gamma_2 ACTIVISM_{vi} + \gamma_3 PARTY_{vi} * ACTIVISM_{vi} + \gamma_4 SHAREACTIVE_v + \gamma_5 PARTY_{vi} * SHAREACTIVE_v + \gamma_6 Xvi + \gamma_7 D_v + \epsilon_{vi} \quad (4.2)$$

where, $SHAREACTIVE_v$ denotes the share of politically active households at the village level.

4.6 Results

4.6.1 Main Results

Tobit regression results of MNREGS days and payment on political affiliation, political activism and other household characteristics are presented in tables 4.4 and 4.5 respectively. Columns 1, 2 and 3 in each table presents the results without the political variables, with the political variables, and with the political variables including the interaction terms, respectively.

Results from all the three columns indicate that targeting by UPA-sarpanches are based on household needs to a large extent. Households whose heads are casual workers, the most vulnerable of categories, obtain more MNREGS work and payment compared to all other households. Heads who are not literates and who did not receive any informal education received more jobs and payment compared to those with higher education. Sarpanches offer more jobs to those who rarely attend village meetings rather than those who frequently attend, implying effective targeting where sarpanches identify the poor and whose opportunity cost of attendance is high. Older household heads obtain more jobs, but the influence of age decreases as age increases. This is consistent with the labor intensive nature of MNREGS work which perpahs older people struggle with. An increase in land holdings is associated with higher MNREGS work and payment, but the effects decline with high land-holdings. These results are intuitive because small and marginal farmers with little land may have other income sources (such as casual work or migration income) which may limit their incentives to pursue the MNREGS. On the other hand, large land holders who also tend to be richer may not find the MNREGS attractive because they may have other work even in the agricultural lean season (such as feeding animals, developing land, and maintaining machineries). Consequently, it is reasonable that full-time farmers with moderate land size were more likely beneficiaries of MNREGS.

However, having controlled for these variables, targeting is not necessarily need based in some cases. Compared to higher caste, lower caste households belonging to the Scheduled Castes (SC) and Other Backward Castes (OBC) receive higher jobs as expected since lower caste households are in general poorer with less access to basic needs[21]. However, Scheduled Tribe (ST) households receive less work than higher caste households, contrary to expectations. This is perhaps because ST households live in hamlets/habitations where infrastructure is poorer and implementing MNREGS projects are harder compared to central areas of a village. Even though we control for village level fixed effects, we do not control for habitation/main-village effects (due to unavailability of those indicators) which could account for habitation level unobserved characteristics such as those affecting project implemention and access. The negative correlation between MNREGS and household size is probably contrary to intuition, but this could be ascribed to other unobserved confounding factors correlated to household size that affects the choice of work.

Columns 2 and 3 in Tables 4.4 and 4.5 indicate that, after controlling for all the need-based variables, political variables still significantly influence MNREGS work and payment. The specifications in column 3 in both tables form our preferred specification. Column 3 in Table 4.4 indicates that compared to UPA-affiliates, unaffiliated households get 0.65 log days more work and UPA-rival households get log 0.46 days more work (1.91 days and 1.58 days respectively). In

[21] In India, there is strong evidence of caste differentials in favor of higher caste in consumption, income, education, occupations, and development indices (e.g. see Deshpande (2001), Hasan and Mehta (2006), Mehrotra (2006), Mohanty (2006), Srinivasan and Mohanty (2004), and Sundaram (2006)).

column 3 of Table 4.5, we observe that Unaffiliated households received log 1.25 rupees more and UPA-rival households receive log 0.767 rupees more than UPA households (Rs 3.49 and Rs. 2.15). These results support clientelisitc support-buying among UPA-sarpanches who offer MNREGS benefits to non-party members to expand their support base.

In addition to political affiliation, activism or involvement also plays a significant role. UPA sarpanches offer politically active rival party households more work and payment compared to inactive households. To recall, politically active households are engaged in party work such as campaigning, attending meetings, giving speeches, writing pamphlets, and attending rallies. Politically inactive households do not participate in any of these activities.

To trace the mechanisms that drive these results, we introduce three additional variables, namely the fraction of political active households at the village level, and its interaction with the binary variable for unaffiliated households, and the binary variable for UPA-rival households. The results presented in Table 4.6 shows that both the interaction terms are positive and highly significant, indicating that UPA-rival and unaffiliated households receive significantly more work and payment if they reside in villages with a high level of political activism overall. Other households in these villages tend to receive significantly less work and payment. UPA-sarpanches appear to target transfers to political activists in rival parties, as well as individual households depending on the scale of the influence of political activists in the village. We interpret these as suggestive evidence consistent with the two types of voter identities examined in our model.

4.6.2 Discussion

Our results show that need-based variables that influence households to demand more jobs such as occupation and education of the household head, poverty level, log per capita consumption, landholdings, household head's age, are all significant with expected signs. In other words, while clientelism is significant, the program also functions by the book with jobs allocated as per the household needs. Similar results were observed by Das (2014), who finds significant correlation between MNREGS work and socio-economic indicators such as household land ownership, Below Poverty Line card ownership, and religion, as well the head's occupation and age [22]. Sheahan et al.(2014) show that the variation in the funding allocation at the sub-district level are explained far more by the needs rather than by the election variables, even though both set of variables are significant. For a program that emphasizes rights-based legal obligation of households in obtaining work and operating at a massive scale, the significant correlation between need based variables and MNREGS work with the right sign should be significantly

[22] Das (2014) - Table 5, last column, page 208.

applauded. Our robust results on clientelism do not implicate the performance of the MNREGS, but is instead consistent with the larger problems facing decentralization which has been observed in other government programs among various other political parties in several countries.

Our results differ from other studies in the Indian context that find local leaders patronizing loyalist households by offering them more benefits compared to swing groups or rival party supporters. Two aspects of our study could explain this difference [23]. First, unlike previous studies, we address the issue of reverse causality using the unique timing of our survey. Second, the power position of the congress led United Progressive Alliance both in the center and in Andhra Pradesh was different from that of the Left front government in West Bengal where Das (2013) and Bardhan et al. (2009) are based on, which may lead to different strategies pursued by these different parties. Remarkably, the commonly cited Cox and Mccubins (1986)'s model that support empirical evidence on a risk-averse leader's preference for their own affiliates, also explicitly note in a separate section that a risk-neutral or risk-loving candidate already feeling secure about their loyalists, would tend to focus on expanding their party base by targeting others.

[23] Prior literature on India as noted in the introduction finds that party loyalists and members are given preference in welfare programs (Das, 2013; Bardhan et al. 2009; Besley, Pande and Rao, 2005; Markussen, 2011)

Additionally, our findings that village leaders in Andhra Pradesh target rivals and the unaffiliated households, are different from Sheahan et al. 2015's in the same state that finds no partisan-influenced spending before the 2009 election and that the political leaning of a mandal played only a small part in fund distribution after the 2009 election. This contrast strengthens the initial motivation for our work, that within-village household-level resource allocation could be different from aggregate level resource allocation.

4.6.3 Additional Results and Robustness

Columns 1 and 2 in Table 4.7 present the regression of MNREGS days and payment on household characteristics in non-UPA sarpanch villages. Notably, the political variables are not significant here. That clientelism is absent in non-UPA sarpanch villages reinforces our claim that non-UPA sarpanches lack the resources for engaging in clientelism and/or are not able to ally or dominate field assistants who likely belong to UPA to achieve common political objectives [24]. Further, as Gupta and Mukhopadhyay (2016) point out, since the program was originally conceived by the INC-led UPA government in 2006, there may be "leakage of goodwill" for non-UPA parties to engage in vote/support buying using the MN-

[24]We conducted similar analysis exclusively for UPA-rival sarpanches (comprising only BJP or TDP party sarpanches), and find no support for clientelism. These results are not presented in this paper, but are available upon request.

REGS.

Table 4.8 presents the results from a probit regression of job-card ownership on household characteristics for days worked (column 1) and payment (column 2). There is no evidence of clientelism in job-card seeking, as explained before. This alleviates the concern about household self-selection on job-card and job seeking, and the latter particularly to the extent that the two are correlated.

The lapse of six months between the commencement of the program (February 2006) and our survey (August-October 2006) for phase-I villages does not rule out the possibility that receiving MNREGS benefits in these six months affect the measured political affiliation in our survey. This situation could cause reverse causality issues in equation 1 where β_1 and β_2 measures the effects of political participation on MNREGS benefits. However, we show that our results remain qualitatively robust if we estimate our empirical model excluding households that received MNREGS work between March and their interview month (columns 1 and 2 of Table 4.9 for days worked and payment received respectively). This reaffirms our casual claim of the effect of political affiliation on MNREGS benefits.

Table 4.10 shows the tobit regression results when we redefine the political activism as categories. In this new definition, only extremely active activities were placed in the politically active group (who are involved with campaigning, attending meetings, giving speeches and writing pamphlets, and are more likely to shape public opinion), and the households engaged in less extreme activities (attending rallies) and no activity households were placed in the less active group. The results from this regression are mostly qualitatively similar to before, where active rival households, and unaffiliated and rival households in villages where there are a large proportion of politically active households obtained more benefits. This provides robustness to the theory on two types of voter identities examined in our model.

4.7 Conclusion

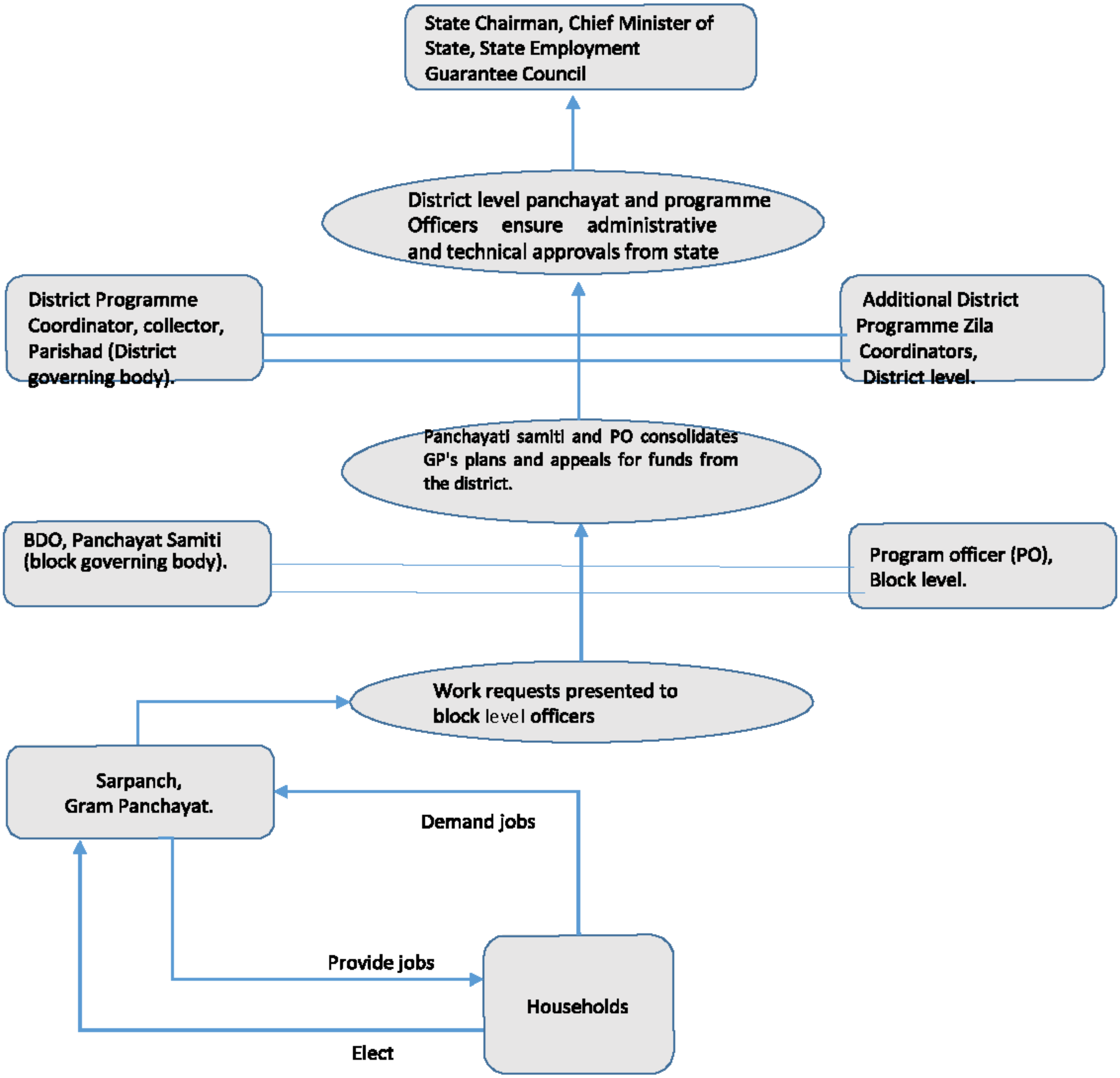
This paper begins by exploring a model of political clientelism based on observable voter attributes including political affiliation and political activism. We show here that the ruling party can increase its support base by directly targeting transfers to swing voters, or by indirectly targeting transfers to influence the messages of the politically active individuals. The former requires transferring funds to the relatively politically inactive individuals, while the latter requires the transfer of funds to the most politically active individuals.

We take these model predictions to the data, and examine the clientelistic practices of local village leaders under the Mahatma Gandhi Rural Employment Guarantee Program (MNREGS) in India, a public works program operating at a very high budget. Particularly, we ask if and how the political affiliation of households affects how much MNREGS benefits they receive. Our results provide robust evidence for clientelism in UPA-sarpanch villages, where the sarpanch is able to strategically allocate resources to opposition members/affiliates and unaffiliated households, compared to his/her own affiliates, in order to elicit support responses from them. We furthermore uncover evidence that, within the rivals, UPA sarpanches target active households more than inactive as well as rival party and unaffiliated voters who reside in locations with greater popular involvement in political activism. We argue that this evidence sheds new light on vote buying both as a means to mobilize support form swing voters, as well as to influence the behavior of political activists themselves. Clientelism is absent in villages under a non-UPA sarpanch, consistent with their low financial ability and clout, as well as due to potential "leakage of goodwill" for them if they employ MNREGS to buy support.

The MNREGS was introduced by the UPA government in 2005. UPA's central election manifesto in 2009 stressed the "outstanding success" of the MNREGS. UPA's campaign highlighted their record of introducing the MNREGS and other social and welfare measures, which resonated well with the disadvantaged groups. This strategy worked very well, and UPA was reelected to form the government at the center and in states such as Andhra Pradesh. Commentators and academicians view that the MNREGS played a major role in the coalition's reelection (Ramani, 2009). We may then want to reconcile our results on clientelism with UPA's reelection in Andhra Pradesh's assembly elections in 2009, with an important caveat that electors may consider different factors while deciding to vote for or support gram panchayat leaders vis-a-vis state legislative assembly members. From the election results and popular perceptions about UPA's victory, even though the magnitude of the clientelism is not exorbidantly high, possibly the tactical redistribution strategy evident from our results also worked in UPA's favor [25].

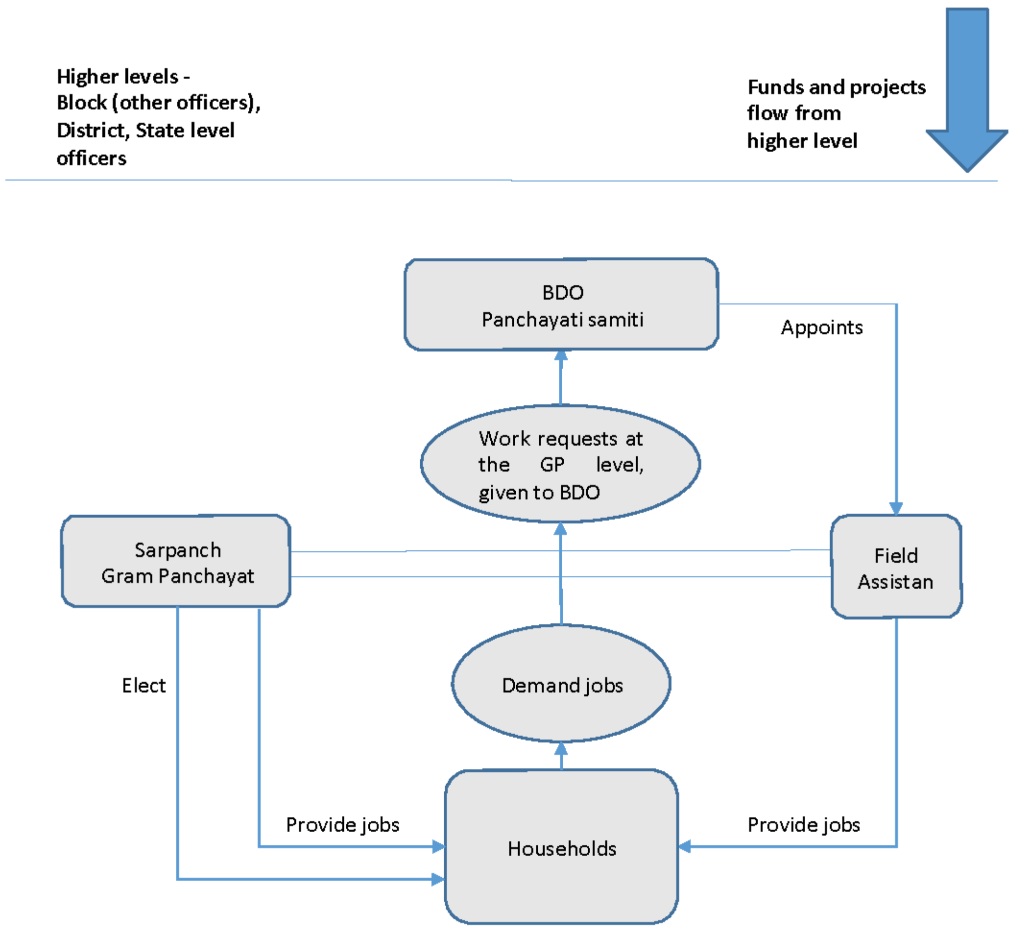
[25] Note that the parties constitution UPA also changed between 2004 and 2009. INC's vote share remained more or less constant in the 2004(37.56%) and 2009(36.56%) elections, but any movements into and out of UPA are not obvious from these numbers.

Figure 4.1: Hierarchy and Workflow in the MNREGS, All-India



Note: BDO- Block Development Officer

Figure 4.2: Hierarchy and Workflow in the MNREGS, Andhra Pradesh



Source: Maiorano(2014)

Figure 4.3: Timeline of Events

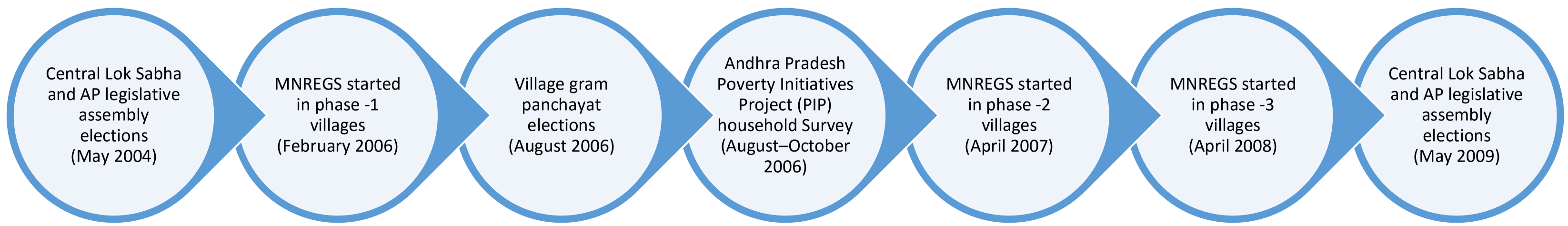


Table 4.1: Descriptive Statistics in UPA-Sarpanch Villages

Social group	
Scheduled Caste	29.90 %
Scheduled Tribe	7.71 %
Backward Caste	43.73 %
Other Caste	18.66 %
Education of the household head	
Not literate or received informal education	56.92%
Secondary education and below	25.16%
High schoolers and graduates	17.92%
Primary occupation of the household head	
Casual work (Agriculture/others)	39.65 %
Salaried work (Agriculture/others)	31.85%
Own business or self-employed (Agriculture/others)	14.39%
Nonworking adults	9.47%
Common property resources, Livestock management	3.16 %
Other	1.49%
Poverty status	
Not so poor/not poor	33.80 %
Poorest of the poor/poor	66.20 %
Attendance of village meetings (awareness)	
Almost or mostly (high awareness)	40.76%
Never or rarely (low awareness)	59.24%
Political alliance affiliation	
United Progressive Alliance (UPA)	63.32%
UPA-rival	16.25%
Unaffiliated	20.43%
Political involvement	
Politically Active	29.06%
Politically Inactive	70.94%
Sample size	1076

Note: Politically Active refers to involvement in party activities such as attending rallies, campaigning, attending meetings, giving speeches and writing pamphlets; Politically Inactive means that the household does not participate in political activities. The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to ”Politically Inactive”. Nonworking adults are pensioners/rentiers, dependents, students and those focusing on households chores.

Table 4.2: Political Involvement Across Political Affiliation in UPA-Sarpanch Villages

Household affiliation	UPA	Unaffiliated	UPA-rival
Political involvement			
Politically Active	243 (36%)	0 (0%)	69 (39%)
Politically Inactive	439 (64%)	219 (100%)	106 (61%)
Sample size	682	219	175

Note: Politically Active refers to involvement in party activities such as attending rallies, campaigning, attending meetings, giving speeches and writing pamphlets; Politically Inactive means that the household does not participate in political activities The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to ”Politically Inactive”.

Table 4.3: MNREGS Benefits Across Political Affiliation in UPA-Sarpanch Villages

Household affiliation	UPA households	Unaffiliated households	UPA-Rival households
%Job-card owned	53.8%	56.8%	50.8%
Days worked	19.72	21.93	17.42
Payment (Rs.) received	1621.81	1671.00	1455.24
Sample size	682	219	175

Note: % Job card owned represents the proportion of households that obtained a job card either in 2006 or 2007. Days worked and amount earned are summarized for job-card holders only. The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival

Table 4.4: Tobit Regression of MNREGS Days on Political Affiliation in UPA-Sarpanch villages

VARIABLES	(1)	(2)	(3)
Household Political Affiliation (base: UPA)			
1.Unaffiliated		0.685***	0.650***
		(0.0167)	(0.0172)
2.UPA-rival		0.613***	0.460***
		(0.0149)	(0.0523)
Politically Active (base:Politically Inactive)		0.124***	0.0265
		(0.0175)	(0.0301)
UPA-Rival X Politically Active			0.380***
			(0.0718)
Social groups (base: Higher Caste)			
Scheduled Caste	1.304***	1.312***	1.324***
	(0.0243)	(0.0249)	(0.0248)
Scheduled Tribe	-0.586***	-0.578***	-0.558***
	(0.0226)	(0.0231)	(0.0230)
Other Backward Caste	0.976***	0.934***	0.948***
	(0.0232)	(0.0234)	(0.0233)
Education of HH head(base:Not-literate/Informal Edu)			
1. Secondary and Below	0.00712	-0.0381**	-0.0410**
	(0.0154)	(0.0163)	(0.0166)
2.Higher Secondary and Graduate	-1.048***	-1.092***	-1.097***
	(0.0212)	(0.0216)	(0.0220)
Occupation of HH head(base:Casual work-Ag/others)			
1.Salaried workers - Ag/others	-0.839***	-0.815***	-0.809***
	(0.0305)	(0.0299)	(0.0299)
2.Own business or Self-employed	-1.074***	-1.089***	-1.091***
	(0.0308)	(0.0313)	(0.0318)
3.Nonworking adults	-0.758***	-0.711***	-0.703***
	(0.0317)	(0.0311)	(0.0312)
4.Common property resources, Livestock management	-0.680***	-0.642***	-0.638***
	(0.0327)	(0.0340)	(0.0340)
5. Others	-1.857***	-1.857***	-1.861***
	(0.0211)	(0.0239)	(0.0256)
Poorest of poor/poor(base: not so poor/not poor)	0.769***	0.717***	0.711***

Continued on next page

Table 4.4 – *Continued from previous page*

VARIABLES	(1)	(2)	(3)
	(0.0135)	(0.0147)	(0.0148)
Log Per Capita Consumption	-0.823***	-0.863***	-0.866***
	(0.00129)	(0.00133)	(0.00134)
Rarely attend village meetings(base:Frequently attend)	0.207***	0.187***	0.178***
	(0.00784)	(0.00908)	(0.00901)
Household Size	-0.0314***	-0.0354***	-0.0337***
	(0.00225)	(0.00226)	(0.00223)
Household Head's Age	0.124***	0.121***	0.121***
	(0.000274)	(0.000279)	(0.000280)
Household Head's Age Squared	-0.00163***	-0.00160***	-0.00161***
	(5.35e-06)	(5.37e-06)	(5.40e-06)
Log Land Holdings	0.426***	0.475***	0.474***
	(0.0351)	(0.0347)	(0.0348)
Log Land Holdings Squared	-0.184***	-0.223***	-0.223***
	(0.0152)	(0.0150)	(0.0150)
Constant	-13.00***	-12.98***	-12.87***
	(0.0113)	(0.0117)	(0.0118)
Sigma	2.856***	2.846***	2.846***
	(0.00536)	(0.00524)	(0.00519)
Log Likelihood	-1366.4179	-1363.8474	-1363.6995
Pseudo R2	0.1511	0.1527	0.1528
Number of clusters	163	163	163
Observations	1,076	1,076	1,076

Note: Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include village fixed effects. Politically Active refers to involvement in party activities such as attending rallies, campaigning, attending meetings, giving speeches and writing pamphlets; Politically Inactive means that the household does not participate in political activities. The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to "Politically Inactive". Nonworking adults are pensioners/rentiers, dependents, students and those focusing on households chores.

Table 4.5: Tobit Regression of MNREGS Payment on Political Affiliation in UPA-Sarpanch Villages

VARIABLES	(1)	(2)	(3)
Household Political Affiliation (base: UPA)			
Unaffiliated		1.366***	1.250***
		(0.0366)	(0.0378)
UPA-Rival		1.275***	0.767***
		(0.0326)	(0.116)
Politically Active(base:Politically Inactive)		0.426***	0.104
		(0.0383)	(0.0662)
UPA-Rival X Politically Active			1.252***
			(0.158)
Social groups (base: Higher Caste)			
Scheduled Caste	2.867***	2.881***	2.924***
	(0.0535)	(0.0547)	(0.0545)
Scheduled Tribe	-1.218***	-1.215***	-1.148***
	(0.0484)	(0.0496)	(0.0494)
Other Backward Caste	2.263***	2.184***	2.231***
	(0.0512)	(0.0516)	(0.0514)
Education of HH head(base:Not-literate/Informal Edu)			
1.Secondary and Below	-0.0845**	-0.185***	-0.194***
	(0.0338)	(0.0359)	(0.0367)
2.Higher Secondary and Graduate	-2.375***	-2.472***	-2.488***
	(0.0475)	(0.0484)	(0.0492)
Occupation of HH head(base:Casual work-Ag/others)			
1.Salaried workers - Ag/others	-1.882***	-1.850***	-1.828***
	(0.0661)	(0.0649)	(0.0650)
2.Own business or Self-employed	-2.461***	-2.495***	-2.499***
	(0.0667)	(0.0679)	(0.0689)
3.Nonworking adults	-1.759***	-1.668***	-1.640***
	(0.0680)	(0.0667)	(0.0668)
4.Common property resources, Livestock management	-1.612***	-1.549***	-1.536***
	(0.0699)	(0.0725)	(0.0726)
5.Others	-4.133***	-4.191***	-4.202***
	(0.0443)	(0.0506)	(0.0546)
Poorest of poor/poor(base: not so poor/not poor)	1.675***	1.586***	1.565***

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Table 4.5 – *Continued from previous page*

VARIABLES	(1)	(2)	(3)
	(0.0299)	(0.0325)	(0.0327)
Log Per Capita Consumption	-1.581***	-1.658***	-1.667***
	(0.00281)	(0.00290)	(0.00293)
Rarely attend village meetings(base:Frequently attend)	0.390***	0.389***	0.360***
	(0.0174)	(0.0200)	(0.0198)
Household Size	-0.0520***	-0.0579***	-0.0524***
	(0.00489)	(0.00495)	(0.00486)
Household Head's Age	0.255***	0.248***	0.250***
	(0.000602)	(0.000613)	(0.000615)
Household Head's Age Squared	-0.00340***	-0.00333***	-0.00336***
	(1.18e-05)	(1.19e-05)	(1.19e-05)
Log Land Holdings	0.831***	0.937***	0.931***
	(0.0765)	(0.0755)	(0.0758)
Log Land Holdings Squared	-0.323***	-0.401***	-0.403***
	(0.0336)	(0.0331)	(0.0331)
Constant	-29.93***	-29.93***	-29.55***
	(0.0247)	(0.0257)	(0.0258)
Sigma	6.238***	6.220***	6.219***
	(0.0120)	(0.0118)	(0.0117)
Log Likelihood	-1710.9943	-1708.7023	-1708.364
Pseudo R2	0.1224	0.1236	0.1237
Number of clusters	163	163	163
Observations	1,076	1,076	1,076

Note: Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include village fixed effects. Politically Active refers to involvement in party activities such as attending rallies, campaigning, attending meetings, giving speeches and writing pamphlets; Politically Inactive means that the household does not participate in political activities. The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to "Politically Inactive". Nonworking adults are pensioners/rentiers, dependents, students and those focusing on households chores.

Table 4.6: Tobit Regression of MNREGS Benefits on Political Affiliation and Proportion of Politically Active Housheolds

	Days	Payment
Household Political Affiliation (base: UPA)		
Unaffiliated	-0.0944**	-0.461***
	(0.0408)	(0.0901)
UPA-Rival	0.320***	0.597***
	(0.0837)	(0.186)
Politically Active (base:Politically Inactive)	0.153***	0.366***
	(0.0311)	(0.0686)
UPA-Rival X Politically Active	0.232**	1.051***
	(0.110)	(0.244)
Proportion Politically Active in Village	-2.335***	-5.073***
	(0.0330)	(0.0723)
UnaffiliatedXProportion Politically Active in Village	4.165***	9.585***
	(0.190)	(0.418)
UPA-RivalXProportion Politically Active in Village	0.725***	0.846
	(0.241)	(0.537)
Social groups (base: Higher Caste)		
Scheduled Caste	1.312***	2.901***
	(0.0249)	(0.0548)
Scheduled Tribe	-0.616***	-1.289***
	(0.0229)	(0.0493)
Other Backward Caste	0.945***	2.226***
	(0.0236)	(0.0518)
Education of HH head(base:Not-literate/Informal Edu)		
1. Secondary and Below	-0.0360**	-0.187***
	(0.0163)	(0.0360)
2. Higher Secondary and Graduate	-1.126***	-2.553***
	(0.0222)	(0.0497)
Occupation of HH head(base:Casual work-Ag/others)		
1.Salaried workers - Ag/others	-0.798***	-1.801***
	(0.0299)	(0.0648)
2.Own business or Self-employed	-1.074***	-2.454***
	(0.0321)	(0.0697)

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Table 4.6 – *Continued from previous page*

	Days	Payment
3.Nonworking adults	-0.696***	-1.624***
	(0.0313)	(0.0671)
4.Common property resources, Livestock management	-0.598***	-1.457***
	(0.0345)	(0.0736)
5. Others	-1.846***	-4.171***
	(0.0253)	(0.0540)
Poorest of poor/poor(base: not so poor/not poor)	0.738***	1.636***
	(0.0151)	(0.0336)
Log Per Capita Consumption	-0.884***	-1.712***
	(0.00130)	(0.00284)
Rarely attend village meetings(base:Frequently attend)	0.193***	0.398***
	(0.00932)	(0.0205)
Household Size	-0.0391***	-0.0652***
	(0.00217)	(0.00476)
Household Head's Age	0.120***	0.246***
	(0.000278)	(0.000611)
Household Head's Age Squared	-0.0016***	-0.0033***
	(5.43e-06)	(1.20e-05)
Log Land Holdings	0.466***	0.918***
	(0.0352)	(0.0763)
Log Land Holdings Squared	-0.216***	-0.384***
	(0.0151)	(0.0331)
Constant	-12.12***	-28.47***
	(0.0114)	(0.0250)
Sigma	2.842***	6.210***
	(0.00512)	(0.0115)
Log pseudolikelihood	-1362.5528	-1707.0949
Pseudo R2	0.1535	0.1244
Number of clusters	163	163
Observations	1076	1076

Note: Robust standard errors clustered at the village level in parentheses.*** p<0.01,** p<0.05,* p<0.1. All regressions include village fixed effects. Politically Active refers to intense party activities such as attening rallies, campaigning, attending meetings, giving speeches and writing pamphlets; Politically Inactive means that the household does not participate in political activities. The

Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to ”Politically Inactive”. Nonworking adults are pensioners/rentiers, dependents, students and those focusing on households chores.

Table 4.7: Tobit Regression of MNREGS Benefits on Political Affiliation in non-UPA-Sarpanch Villages

VARIABLES	Days (1)	Payment (2)
Household Political Affiliation (base: UPA)		
Unaffiliated	0.435	0.978
	(0.866)	(1.859)
UPA-Rival	-0.0240	0.0848
	(0.577)	(1.290)
Politically Active (base:Politically Inactive)	0.236	0.592
	(0.943)	(1.958)
UPA-Rival X Politically Active	-1.836	-4.006
	(1.165)	(2.455)
Proportion Politically Active in Village	1.907	4.134
	(1.638)	(3.553)
Unaffiliated X Proportion Politically Active in Village	-0.451	0.165
	(3.671)	(7.893)
UPA-Rival X Proportion Politically Active in Village	2.044	4.351
	(2.086)	(4.604)
Social groups (base: Higher Caste)		
Scheduled Caste	2.336**	5.449**
	(0.985)	(2.107)
Scheduled Tribe	0.302	0.984
	(1.070)	(2.330)
Other Backward Caste	1.390	3.378*
	(0.890)	(1.914)
Education of HH head(base:Not-literate/Informal Edu)		
1. Secondary and Below	-0.199	-0.445
	(0.412)	(0.884)
2. Higher Secondary and Graduate	-1.855**	-4.159**
	(0.888)	(1.862)
Occupation of HH head(base:Casual work-Ag/others)		
1.Salaried workers - Ag/others	-1.027*	-2.148*
	(0.559)	(1.162)
2.Own business or Self-employed	-1.174	-2.111

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Table 4.7 – *Continued from previous page*

VARIABLES	Days (1)	Payment (2)
	(0.874)	(1.843)
3.Nonworking adults	-0.752	-1.405
	(0.973)	(2.135)
4.Common property resources, Livestock management	-1.178	-2.393
	(1.418)	(3.068)
5. Others	-1.513	-3.161
	(1.293)	(2.678)
Poorest of poor/poor(base: not so poor/not poor)	0.742	1.518
	(0.695)	(1.474)
Log Per Capita Consumption	-0.488	-0.935
	(0.303)	(0.640)
Rarely attend village meetings(base:Frequently attend)	-0.268	-0.534
	(0.244)	(0.506)
Household Size	0.0796	0.167
	(0.148)	(0.319)
Household Head's Age	0.153	0.273
	(0.120)	(0.254)
Household Head's Age Squared	-0.00188	-0.00355
	(0.00123)	(0.00263)
Log Land Holdings	0.949	1.913
	(0.681)	(1.493)
Log Land Holdings Squared	-0.268	-0.527
	(0.327)	(0.724)
Constant	-0.392	-0.639
	(0.260)	(0.543)
Sigma	2.238***	4.852***
	(0.147)	(0.304)
Log pseudolikelihood	-420.98048	-526.06474
Pseudo R2	0.1331	0.1122
Number of clusters	52	52
Observations	315	315

Note: Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include village fixed effects. Politically Active refers to involvement in party activities such as attending rallies, campaigning, attending meetings, giving speeches and writing pamphlets; Politically Inactive means that the household does not participate in political activities. The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to ”Politically Inactive”. Nonworking adults are pensioners/rentiers, dependents, students and those focusing on households chores.

Table 4.8: Probit Regression of Job-Card Ownership on Political Affiliation

	UPA-sarpanch village	non-UPA sarpanch village
Household Political Affiliation (base: UPA)		
Unaffiliated	0.121	0.162
	(0.176)	(0.298)
UPA-Aival	-0.0568	-0.187
	(0.165)	(0.331)
Politically Active (base:Politically Inactive)	0.0962	0.0639
	(0.165)	(0.420)
UPA-Active x Politically Active	0.371	-0.232
	(0.347)	(0.474)
Social groups (base: Higher Caste)		
Scheduled Caste	0.658***	1.515***
	(0.209)	(0.461)
Scheduled Tribe	0.0357	0.318
	(0.287)	(0.530)
Other Backward Caste	0.511***	0.845**
	(0.186)	(0.392)
Education of HH head(base:Not-literate/Informal Edu)		
1. Secondary and below	0.0946	0.193
	(0.142)	(0.247)
2. Higher Secondary and Graduate	-0.360**	-0.810**
	(0.184)	(0.374)
Occupation of HH head(base:Casual work-Ag/others)		
1.Salaried workers - Ag/others	-0.125	-0.425
	(0.140)	(0.276)
2.Own business or Self-employed	-0.361**	-0.684
	(0.168)	(0.423)
3.Nonworking adults	-0.0885	-0.00540
	(0.222)	(0.550)
4.Common property resources, Livestock management	0.0342	0.191
	(0.352)	(0.580)
5. Others	-0.924**	0.759

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Table 4.8 – *Continued from previous page*

	UPA-sarpanch village	non-UPA sarpanch village
	(0.460)	(0.733)
Poorest of poor/poor(base: not so poor/not poor)	0.322***	0.315
	(0.121)	(0.311)
Log Per Capita Consumption	-0.304*	-0.147
	(0.159)	(0.309)
Rarely attend village meetings(base:Frequently attend)	0.191	0.0693
	(0.121)	(0.225)
Household Size	-0.00172	0.0191
	(0.0351)	(0.0754)
Household Head's Age	0.0724**	0.134*
	(0.0308)	(0.0687)
Household Head's Age Squared	-0.0008***	-0.00151**
	(0.000312)	(0.000723)
Log Land Holdings	0.0256	0.369
	(0.161)	(0.346)
Log Land Holdings Squared	-0.0277	-0.0183
	(0.0651)	(0.121)
Constant	0.0607	-2.335
	(1.615)	(2.894)
Log pseudolikelihood	-554.91086	-150.18336
Pseudo R2	0.2525	0.3079
Number of clusters	163	52
Observations	1076	315

Note: Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include village fixed effects. Politically Active refers to intense party activities such as attending rallies, campaigning, attending meetings, giving speeches and writing pamphlets; Politically Inactive means that the household does not participate in political activities. The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to "Politically Inactive". Nonworking adults are pensioners/rentiers, dependents, students and those focusing on households chores.

Table 4.9: MNREGS Benefits on Political Affiliation, excluding Households with jobs during February 2006-interview Month

	Days	Payment
Household Political Affiliation (base: UPA)		
1. Unaffiliated	-0.00174	-0.148
	(0.0501)	(0.115)
2.UPA-rival	0.421***	0.944***
	(0.103)	(0.234)
Politically Active	0.361***	0.837***
	(0.0377)	(0.0862)
UPA-Rival X Politically Active	0.620***	1.793***
	(0.137)	(0.312)
Proportion Politically Active in Village	-2.782***	-6.651***
	(0.0411)	(0.0927)
Unaffiliated X Proportion Politically Active in Village	4.716***	10.80***
	(0.227)	(0.517)
UPA-Rival X Proportion Politically Active in Village	-0.135	-0.865
	(0.291)	(0.667)
Social groups (base: Higher Caste)		
Scheduled Caste	1.676***	3.834***
	(0.0298)	(0.0684)
Scheduled Tribe	-0.265***	-0.530***
	(0.0263)	(0.0588)
Other Backward Caste	1.176***	2.847***
	(0.0296)	(0.0666)
Education of HH head(base:Not-literate/Informal Edu)		
1. Secondary and Below	-0.217***	-0.488***
	(0.0234)	(0.0535)
2. Higher Secondary and Graduate	-1.481***	-3.272***
	(0.0250)	(0.0579)
Occupation of HH head(base:Casual work-Ag/others)		
1.Salaried workers - Ag/others	-0.571***	-1.419***
	(0.0339)	(0.0769)
2.Own business or Self-employed	-1.005***	-2.515***
	(0.0397)	(0.0884)

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Table 4.9 – *Continued from previous page*

	Days	Payment
3.Nonworking adults	-0.459***	-1.262***
	(0.0340)	(0.0765)
4.Common property resources, Livestock management	-0.166***	-0.536***
	(0.0390)	(0.0875)
5. Others	-1.919***	-4.586***
	(0.0308)	(0.0681)
Poorest of poor/poor(base: not so poor/not poor)	0.380***	0.895***
	(0.0184)	(0.0422)
Log Per Capita Consumption	-1.065***	-2.225***
	(0.00162)	(0.00364)
Rarely attend village meetings(base:Frequently attend)	0.0330***	0.108***
	(0.0122)	(0.0278)
Household Size	-0.0853***	-0.151***
	(0.00266)	(0.00598)
Household Head's Age	0.0573***	0.134***
	(0.000347)	(0.000784)
Household Head's Age Squared	-0.0009***	-0.0021***
	(6.36e-06)	(1.46e-05)
Log Land Holdings	0.0493	0.0924
	(0.0358)	(0.0819)
Log Land Holdings Squared	0.0437***	0.138***
	(0.0166)	(0.0379)
Constant	-9.470***	-23.43***
	(0.0143)	(0.0321)
Sigma	2.955***	6.707***
	(0.00671)	(0.0154)
Log pseudolikelihood	-1012.443	-1268.3895
Pseudo R2	0.1665	0.1356
Number of clusters	161	161
Observations	942	942

Note: Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include village fixed effects. Politically Active refers to intense party activities such as attending rallies, campaigning, attending meetings, giving speeches and writing pamphlets; Politically Inactive means that the household does not participate in political activities. The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to "Politically Inactive". Nonworking adults are pensioners/rentiers, dependents, students and those focusing on households chores.

Table 4.10: Tobit Regression of MNREGS benefits on Political Affiliation and Proportion of Politically Active Households, with Alternate Definitions of Political Activism

	Days	Payment
Household Political Affiliation (base: UPA)		
1. Unaffiliated	-0.112***	-0.498***
	(0.0394)	(0.0872)
2. UPA-Rival	0.351***	0.729***
	(0.0742)	(0.164)
Politically Very Active (base: Politically Less Active)	-0.0954**	-0.258***
	(0.0386)	(0.0850)
UPA-Rival X Politically Very Active	0.230**	0.823***
	(0.117)	(0.257)
Proportion Politically Active in Village	-1.812***	-3.706***
	(0.0327)	(0.0715)
Unaffiliated X Proportion Politically Active in Village	3.826***	8.698***
	(0.184)	(0.404)
UPA-Rival X Proportion Politically Active in Village	0.813***	1.384***
	(0.220)	(0.485)
Social groups (base: Higher Caste)		
1. Scheduled Caste	1.310***	2.889***
	(0.0252)	(0.0553)
2.Schuduled Tribe	-0.595***	-1.232***
	(0.0232)	(0.0499)
3. Other Backward Caste	0.943***	2.216***
	(0.0235)	(0.0516)
Education of HH head(base:Not-literate/Informal Edu)		
1. Secondary and Below	-0.0277*	-0.158***
	(0.0160)	(0.0350)
2. Higher Secondary and Graduate	-1.111***	-2.505***
	(0.0214)	(0.0479)
Occupation of HH head(base:Casual work-Ag/others)		
1.Salaried workers - Ag/others	-0.786***	-1.769***
	(0.0299)	(0.0647)
2.Own business or Self-employed	-1.066***	-2.429***

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Table 4.10 – *Continued from previous page*

	Days	Payment
	(0.0315)	(0.0681)
3.Nonworking adults	-0.698***	-1.632***
	(0.0309)	(0.0662)
4.Common property resources, Livestock management	-0.605***	-1.476***
	(0.0346)	(0.0738)
5. Others	-1.771***	-3.965***
	(0.0294)	(0.0633)
Poorest of poor/poor(base: not so poor/not poor)	0.723***	1.594***
	(0.0153)	(0.0339)
Log Per Capita Consumption	-0.878***	-1.695***
	(0.00129)	(0.00283)
Rarely attend village meetings(base:Frequently attend)	0.158***	0.298***
	(0.00888)	(0.0197)
Household Size	-0.0392***	-0.0659***
	(0.00218)	(0.00479)
Household Head's Age	0.121***	0.250***
	(0.000280)	(0.000618)
Household Head's Age Squared	-0.0016***	-0.0033***
	(5.48e-06)	(1.21e-05)
Log Landholdings	0.443***	0.852***
	(0.0353)	(0.0767)
Log Landholdings Squared	-0.208***	-0.360***
	(0.0152)	(0.0336)
Constant	-12.24***	-28.82***
	(0.0114)	(0.0249)
Sigma	2.842***	6.211***
	(0.00506)	(0.0114)
Log pseudolikelihood	-1362.7572	-1707.5677
Pseudo R2	0.1533	0.1242
Number of clusters	163	163
Observations	1076	1076

Note: Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include village fixed effects. In the alternate definition of political activism used in this regression, Politically Very Active refers to intense party activities such as campaigning, attending meetings, giving speeches and writing pamphlets; Politically Less Active refers to households attending rallies, and also not participating in political activities. The Unaffiliated category includes those not affiliated with any party or those affiliated with fringe parties that are non-UPA and non-UPA-rival. The involvement level of all unaffiliated households was set to ”Politically Inactive”. Nonworking adults are pensioners/rentiers, dependents, students and those focusing on households chores.

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