The Spillover Effects of Public Works on Labor Allocation and Wages: Evidence from National Rural Employment Guarantee Scheme, India

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Abstract

Public-works programs guaranteeing work at above-market wages are intended to provide security to the seasonally unemployed and are an increasingly used labor market and anti-poverty policy in developing countries. Impact evaluations of India’s National Rural Employment Guarantee Scheme (NREGS), the largest such program in the world, have estimated a variety of labor market effects, but this literature is agnostic about general equilibrium spillovers generated by the program, which could potentially bias these estimates. This paper tests for spillovers from NREGS to neighboring labor markets by exploiting plausibly exogenous variation in wage differentials and exposure induced by the program’s staggered rollout across contiguous districts. The results show that non-program districts exposed to program neighbors experienced an 8.7% rise in casual wages relative to unexposed districts and these spillovers are higher among women. These findings demonstrate that the impact of NREGS on the casual labor market is higher than previously estimated. They also provide empirical support for the theory that increased short-term migration to contiguous program areas is the mechanism generating spatial spillovers in neighboring areas which did not receive NREGS over the study period.

Keywords: Spillovers, labor markets, seasonal migration, public-works, safety nets, NREGS, India

JEL Classification: I38, J61, O15, O18, R23

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1. **Introduction**

Public works programs guaranteeing work at a pre-determined wage are intended to provide security to the unemployed and underemployed in the short-term and are an increasingly used feature of labor market policy for developing countries. Between 2007 and 2009, many countries started public works programs in response to the food, fuel and finance crises, with 24 being supported by the World Bank. Recent examples include flagship programs in Argentina, Ethiopia, and India, among others (Subbarao et al. 2012). Since long durations of guaranteed employment at close to the prevailing market wage are likely to put upward pressure on the local wage rate (Subbarao 2003), large-scale public works programs could widen regional wage differentials if implemented non-uniformly across proximate labor markets. In labor markets linked by migration, these wage differentials should equalize at equilibrium with corresponding changes in aggregate employment, thus leading to spillovers from areas assigned the intervention to areas which were unassigned. This type of spillover effect presents a challenge for the estimation of causal impacts through natural experiment approaches because it leads to a violation of SUTVA, i.e. Stable Unit Treatment Value Assumption (Imbens & Rubin 2009), and could result in biased estimates. Accounting for these spillovers is necessary for policy evaluation and is particularly important given the need for cost-benefit analyses of large-scale public works programs, which are increasingly also being used as anti-poverty schemes to provide higher and more stable incomes for the poor. Policy decisions about continuing, expanding, or restricting public-works programs depend on a precise estimation of their impacts, which could be understated in the presence of spillovers to non-participants (Murgai & Ravallion 2005).

India’s National Rural Employment Guarantee Scheme (NREGS), the largest public works program in the world, guarantees every rural household 100 days of employment at the state-specific minimum wage\(^1\),

\(^1\) In 2009, the central government uncoupled NREGS wages from state-level statutory minimum wages and set an all-India uniform wage of 100 rupees per day, but adjusted for state-specific inflation (Dutta et al 2014). Since this
and its impact on labor market outcomes has been subjected to scrutiny by a recent set of papers. On employment outcomes, the program has been attributed with increasing labor force participation (Azam 2012) and crowding out private sector work (Imbert and Papp 2015, Zimmerman 2013). In terms of wage outcomes, higher private sector (Imbert and Papp 2015), and unskilled labor wages (Azam 2012, Berg et al. 2012) have been estimated; Zimmerman (2013) has also found the program to have had no statistically significant impact on private wages. On migration, the slowing down of short-term migration from rural to urban areas has also been estimated (Imbert and Papp 2014, Bhatia & Ranjan 2009, Jacob 2008). The wider literature on NREGS has demonstrated the program’s ripple effects – increased use of labor-saving agricultural technology (Bhargava 2014), reduction in primary school enrollments (Li & Sekhari 2013), increase in child labor by older children (Islam & Sivasankaran 2014), positive impact on grade progression and test scores (Mani et al. 2014), and a rise in consumption, nutritional intake and asset accumulation (Liu & Deininger 2010).

The growing empirical literature on NREGS has frequently exploited its staggered rollout\(^2\) by employing quasi-experimental methods like difference-in-difference (Azam 2012, Berg et al. 2012, Imbert and Papp 2015, Liu and Deininger 2010) and regression discontinuity (Bhargava 2014, Zimmerman 2013) to identify its impacts on labor market outcomes. However, these studies are agnostic about the sign and magnitude of spillovers from program to non-program districts, reflecting the general paucity of studies that test for ‘between’ (Bayliss & Ham 2015) spillovers, a problem which exists in the experimental literature as well.\(^3\) Multiple randomized experiment based studies have estimated spillovers from treated peers to ineligible individuals or households within treated units.; examples include deworming

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\(^2\) The timeline of NREGA’s three-phase rollout was 199 districts in Phase I (Feb 2006), 128 districts in Phase II (April 2007) and the remaining 261 districts in Phase III (April 2008).

\(^3\) In the theoretical literature, Fields & Raghunathan (2014) have modeled the effect of NREGS on inter-temporal productivity spillovers as part of a two-period seasonal agriculture market.
externalities (Miguel & Kremer 2004), cash transfers effects of PROGRESA on ineligible households (Angelucci & De Maro 2015, Angelucci & De Giorgi 2009), information spillovers (Oster & Thornton 2012, Miller & Mobarak 2013), and general equilibrium effects of rainfall insurance (Mobarak & Rosenzweig 2013). The corresponding estimations of between spillovers in experimental designs are limited to cross-school deworming externalities (Miguel & Kremer 2004) and cross-village spillovers of PROGRESA on school participation (Bobba & Gignoux 2014).

Conceptually, both within and between spillovers lead to interference and violation of the SUTVA assumption, which requires that the treatment status of any unit does not affect the potential outcomes of other units, and is necessary for both experimental and quasi-experimental approaches to estimating causal impacts. In the NREGS context, quasi-experimental approaches to estimating the program’s causal impact assume that labor market outcomes of non-program districts are the appropriate counterfactual for the treated districts in absence of the public-works program, as a group (“parallel paths assumption” for DID estimators) or locally (for RDD estimators). This assumption is invalidated if changes in non-program districts’ outcomes occurred precisely because of exposure to program districts, leading to biased causal impacts (Duflo et al. 2007), incorrect cost-benefit calculations, and potentially flawed policy decisions about continuing or discontinuing the program. In this analysis, we test for the presence of between spillovers by exploiting plausibly exogenous variation in exposure to NREGS within the set of non-program districts. The comparison of wage and time allocation outcomes in exposed and unexposed districts enables us to compute spillover effects that we argue are driven by changes in labor flows between non-program and program areas. One of the major contributions of this paper is that it is the first known estimation of labor market spillovers from the world’s largest public-works program.

It is well-established that wage differentials across labor markets linked by migration should lead to equalization of wages in a competitive equilibrium. In fact, capital flows, migration, and goods trade are each, by themselves, sufficient for equalization of wages (Robertson 2000). Given that the study period
for this analysis is relatively short and that the demand for NREGS is seasonal in the agricultural labor market, it is unlikely that capital flows across neighboring districts in the form of lumpy, long-term investments in land and equipment would be the driving mechanism for equalization. The case for goods trade is even weaker because of the similarity in relative endowments and the mix of goods produced across neighboring districts. It must be highlighted here that in a long-run general equilibrium setting, nominal wage differentials could persist even in absence of capital flows and goods trade, if shocks to demand or supply of labor in a local market are fully capitalized in the price of land (Rosen 1979, Roback 1982), thus equalizing real wages spatially. While this result from the Rosen-Roback framework, the “workhorse of spatial equilibrium analysis” (Glaeser 2001), has limited applicability to this study’s context given the seasonality of NREGS and the relatively short study period, it does necessitate the use of real wages for the purposes of empirical analysis.

In principle, the enforcement of a mandated NREGS minimum wage in excess of market wage in some districts and its absence in neighboring districts would have created wage differentials across interlinked labor markets. Using NSS data from 2004-05, Murgai and Ravallion (2005) showed that 75% of all casual laborers in India, the group targeted by NREGS, worked for less than the state-specific minimum wage, making the program attractive to them. Even in 2009-10, when the program had been rolled out, two-thirds of agricultural labor days were paid less than the minimum wage for agricultural unskilled labor (Dutta et al. 2014). Given this differential, two kinds of migration-linked spillovers could affect residents of non-program districts. First, if the NREGS raised private sector wages in program districts, residents of non-program districts could seasonally migrate or commute to program districts if destination wages are higher, even without participating in the program⁴, thus lowering aggregate labor supply and raising

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⁴ Commuting to a program district in order to work in NREGS is ruled out in principle, by the rules of the program, which specify that only village residents are eligible for job cards and work allocation. This does not rule out long term in-migrants benefiting from the program but such migration is low and deterred by high costs.
wages in their home districts. Second, if NREGS lowered out-migration or commutes from program districts, non-program destinations would experience a reduction in labor supply. Together, these amplifying effects could raise wages in the non-program districts, thus resulting in wage spillovers for districts considered to be the control group in previous evaluations. In practice, there is

Previous estimations of NREGS’s labor market impacts have justified abstracting away from migration spillovers by citing the low fraction of rural, inter-district migrants in the population, but this reasoning is flawed on two counts. First, the relevant statistic for gauging the importance of migration spillovers is the fraction of mobile workers – short-term migrants and inter-district commuters – relative to total number of casual workers, not the entire population. Given that NREGS is designed to target unskilled labor with its timing, wage and type of work offerings, the size of inter-district labor flows relative to the market for unskilled labor is important. While the NSS definition of short-term migrant leads to an estimated 6.75% of all casual workers falling under the category, this is likely an underestimate. By other estimates, about 10% of agricultural laborers – could be seasonal migrants (Srivastava 2011). Further, inter-district commuters are unaccounted for in NSS, and there is no other nationally representative survey that records commuting data. Second, while the decline in migration from rural to urban areas dominates the popular discourse and empirical literature on NREGS’ effect on migration in India, inter-state rural-urban

5 This is similar to the effect on emigration on labor market outcomes in source countries, a question not given great attention in the empirical literature, with a notable exception being Mishra (2007), which estimated that the outflow of Mexican workers to the US between 1970 and 2000 has increased the wage of an average Mexican worker by about 8%. In related work, Robertson (2000) finds that U.S. wage shocks are transmitted from border to interior cities in Mexico by way of labor migration from interior to the border.

6 Author’s calculation using NSS 64 data.

7 NSS 64 asked individuals whether they had migrated for 1-6 months in the last 365 days. This is likely an underestimate because: i) in many cases, the seasonal/circular migration cycle is longer than six months, and ii) quite often, entire households and not individuals participate in seasonal migration (Srivastava 2011). In absolute terms, there were an estimated 15.2 million short-duration out-migrants, of whom 12.9 million (85.1 per cent) were male, and 13.9 million (71 per cent) were rural out-migrants. The overall out-migration rate was 1.33 - 1.72 for rural areas and 0.4 for urban areas.

8 Their salience to labor markets affected by NREGS is also reflected by the fact that in 2007-08, 56.6% of all seasonal migrants reported working in construction (36.2%) and agriculture (20.4%), sectors most likely to compete with the government program for workers.
migrants accounted for 36.4% of all short-duration migration in 2007-08 (Srivastava 2011). An almost equal amount of seasonal migration occurred across districts in the same state, which suggests that changes in cross-district wage differentials could have had a sizable effect on the labor markets in close proximity to NREGS districts.

This paper studies the labor market spillovers from NREGS to districts which did not receive the program during the study period (July 2005 to March 2008), by exploiting the plausibly exogenous variation in exposure to program neighbors. In spirit, this approach is similar to McKinnish (2005), which studied welfare migration in border counties of U.S. states with large cross-border benefit differentials for Aid to Families with Dependent Children (AFDC). The study found that border counties in the high-benefit state experienced higher program participation and expenditures relative to interior counties. It is also related to the estimation of spatial spillovers from natural resource booms to counties not experiencing booms (Allcott & Keniston 2014) and the effects of civil wars on economic outcomes in neighboring countries (Murdoch & Sandler 2002). Our results show that, conditional on not receiving the program, the real wage for casual labor increased by 8.7% in exposed districts relative to unexposed districts, with women experiencing larger wage increases than men. When heterogeneity of exposure intensity within exposed districts is accounted for, we estimate that a 10% increase in exposure intensity leads to a 1.03% rise in casual wage and an increase in weekly labor force participation. Lastly, we present evidence that short-term, short-distance migration to contiguous program areas is the mechanism generating between spillovers in districts which did not receive NREGS over the study period.

The rest of this paper is organized as follows. Section 2 provides a basic theoretical framework for the analysis and develops predictions for empirical estimation. Section 3 describes the measure of exposure intensity used in this analysis. Section 4 describes the data, with estimation strategy outlined in section 5. Section 6 presents the main results while section 7 discusses robustness checks. Section 8 presents
evidence of seasonal migration being the mechanism generating spillovers, and section 9 offers concluding remarks.

2. Model

This section presents a simple model motivating the optimization problem faced by an individual in a non-program district with an outside option of short-term migration or commute to a neighboring destination. Since the results can be extended to the case with many destinations without loss of generality, this model is presented to fix ideas. This individual has a utility function $u(c_i, l_i)$ over consumption and leisure, with the function increasing and concave over both arguments. Her time endowment, $T$, is split between leisure $l_i$ and either work within the home district ($L_i$) or work outside the home district ($L^{o}_i$). The home district wage is $w^d$, while both migrants and commuters earn $w^o$ outside the district. Work outside the home district is associated with an additional variable cost $v_i$, which is heterogeneous across individuals. While transportation cost is an example of a variable cost for commuters, it is fixed for seasonal migrants. Meanwhile, rent at destination is an example of variable cost for seasonal migrants but not for commuters. This model abstracts from the distinction between the variable costs faced by seasonal migrants and commuters because it does not change the individual’s problem. The marginal wage rate she faces depends on which wage rate is higher – home district wage ($w^d$) or the destination wage ($w^o - v_i$). Individuals also have non-labor income $y_i$, which can be thought of as profits from agricultural production in this setting. It is worth noting that the production function $f(D_i)$ only allows the use of labor input $D_i$, thus ruling out capital flows across labor markets by assumption. Individuals thus choose consumption and leisure to solve:

$$\max u(c_i, l_i) \quad \text{s.t.} \quad c_i + W_i l_i = y_i + W_i T$$ (1)

$$L^D_i + L^{o}_i + l_i = T$$ (2)

$$W_i = \max \{w^d, w^o - v_i\}$$ (3)
\[ y_i = \Pi_i = f(D_i) - w^d D_i \]  \hspace{1cm} (4)

Solving the first order conditions, the individual’s standard demand functions for leisure and consumption are given by:

\[ l^* = l^* (W_i, y_i + W_i T) \]  \hspace{1cm} (5)

\[ c^* = c^* (W_i, y_i + W_i T) \]  \hspace{1cm} (6)

In this model, it is optimal for an individual to either work in the home district or outside depending on the marginal wage rate, but not both. For a given \( \{w^d, w^o\} \) pair and wage differential \( (w^o - (w^d - v_i)) \) across districts, individuals with low variable costs \( (w^o - v_i > w^d) \) work outside the home district, henceforth termed “leavers.” On the other hand, individuals with high variable costs \( (w^o - v_i < w^d) \) optimally allocate their labor to the home district, hereafter referred to as “stayers.” The aggregate labor supply within home district is the sum of individual-level labor supply of \( S \) stayers and labor inflow from destination to home districts \( (L_o)\):

\[ L_{SD} = \sum_i S_i l_i^* (W_i, y_i + W_i T) + L_o \]  \hspace{1cm} (7)

while the aggregate labor supply at the destination is the sum of individual-level labor supply of \( L \) leavers and labor supplied by residents of destination districts \( (L_d)\):

\[ L_{SO} = \sum_j N_j l_j^* (W_j, y_j + W_j T) + L_d \]  \hspace{1cm} (8)

with \( (S+L) \) representing the total population of the home district. The labor market equilibrium conditions before the introduction of NREGS for home and destination districts can be written as:

\[ L_{SD} = \sum_i S_i D_i^* (w^d) \]  \hspace{1cm} (9)

\[ L_{SO} = \sum_j N_j D_j^* (w^o) \]  \hspace{1cm} (10)
where home district wage $w^d$ and out of district wages $w^o$ clear the respective labor markets.

2.1 Introduction of NREGS

In this setup, we assume that only destination districts can receive NREGS. If the destination district receives the program, the guaranteed employment at above-market wage $^9 (G(w^o))$ raises aggregate labor demand and destination wage $(w^o)$.

$$L_s^o = \sum_{j}^N D_j^o(w^o) + G(w^o)$$

As $w^o$ increases at destination, the inflow of labor to home districts, $L_o$, would decline because of the high program wage being offered by NREGS. The rising destination wage $w^o$ simultaneously changes the labor allocation decision of home district residents. As the wage differential $(w^o - (w^d - v))$ widens, previously marginal stayers would choose to allocate their labor to the program neighbor and leave, unless $v_i$ is too high for all stayers. The amplifying effects of reduced inflow and increased outflow of labor lead to an inward shift in aggregate labor supply of home districts $(L_s^D)$, which continues until $w^d$ rises sufficiently and equalizes the wage differential for remaining stayers (eq. 7). The rising home district wage could induce the remaining stayers to either supply more labor or buy more leisure at the individual-level, with this ambiguity being the result of offsetting income and substitution effects. It is noteworthy here that if the destination district does not receive NREGS, the labor market equilibrium characterized by equations (9) and (10) remains unchanged. In other words, $w^o$ remains unchanged and the home district experiences no spillovers to wage and aggregate employment if it is not ‘exposed’ to a program neighbor.

2.2 Exposure Intensity and Non-Program Labor Markets

We can now extend the model outlined above to multiple destinations to allow greater variation in exposure, i.e. number of program neighbors for home districts. We also assume that for a given $w^o$, the

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$^9$ This is supported by empirical evidence on the minimum wage guaranteed by the program exceeding the prevailing market wage for casual labor in fifteen of the eighteen states in India in 2007 – 08 (Azam 2012).
effective out of district wage \( w_{E}^{o} \) for home district residents is a monotonically increasing function of exposure intensity \( E \), a measure of linkages between home and destination labor markets where the program is implemented.

\[
w_{E}^{o} = g(w^{o}, E), \quad g_{E}(w^{o}, E) \geq 0
\]

It is axiomatic that as the choice set of program destinations expands for home districts, the highest \( w^{o} \) offered outside the district is non-decreasing. It is noteworthy that this assumption might not hold in practice if neighboring districts are subject to different policies designed to stop the movement of labor, i.e., ones that keep labor markets segmented, thus delinking the relationship between the number of program neighbors and the maximum market wage offered outside a non-program district. Since the introduction of NREGS was not conditioned on any mobility restrictions for non-participants and this model aims to capture intra-country mobility within India, which constitutionally guarantees the right to move and reside in any part of the country (Part III, Constitution of India), there is little evidence of market segmentation and thus minimal cost to making this assumption. Given that the new wage differential \( (w_{E}^{o} - (w^{d} - v_i)) \) is an increasing function of exposure intensity, the following predictions are generated from this model:

**Prediction 1:** For a given shock to out-of-district wage \( w^{o} \), growth in \( w^{d} \) for non-program districts is increasing in exposure intensity \( E \).

**Prediction 2:** For a given shock to out-of-district wage \( w^{o} \), aggregate employment for non-program districts is decreasing in exposure intensity \( E \).

**Prediction 3:** For a given shock to out-of-district wage \( w^{o} \), change in individual-level labor supply has an ambiguous relationship with higher exposure intensity \( E \).
It is evident from the discussion above that the problem is symmetric for program districts, where the introduction of NREGS would lead to a reduced outflow and increased inflow of labor. Aggregate employment and market wage would increase as is to be expected with a shock to labor demand at a guaranteed minimum wage above prevailing market wage. In practice though, there is evidence that the employment guarantee offered by NREGS is fuzzy, with extensive rationing of work and significant unmet demand for it in some states (Dutta et al. 2014). It is worth emphasizing here that labor market spillovers to non-program districts, like private sector labor market impacts in program districts, will be decreasing in the level of rationing. Hence, the extent of spillovers generated by the program is fundamentally an empirical question.

3. Exposure and Exposure Intensity

Enacted as law in September 2005, NREGS guarantees 100 days of work annually at a state-level minimum wage to every rural household. In 2010-11, NREGS provided 2.27 billion person-days of employment to 53 million households, and its budget represented 0.6% of India’s GDP. Rolled out non-randomly in 199 of the most “backward”\textsuperscript{10} Indian districts in February 2006, the act was gradually extended to 128 districts in April 2007 and to the rest of rural India in April 2008 (Table 1).

<table>
<thead>
<tr>
<th>Table 1: NREGS Rollout</th>
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<tbody>
<tr>
<td><strong>Phase</strong></td>
</tr>
<tr>
<td><strong>Rollout date</strong></td>
</tr>
<tr>
<td><strong>Number of Districts</strong></td>
</tr>
<tr>
<td><strong>Study Classification</strong></td>
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</tbody>
</table>

Table 2: NSS Survey Rounds & NREGS Rollout

\textsuperscript{10} The Planning Commission used district-level data on caste composition, agricultural productivity and agricultural wage rates from the mid-1990s to calculate a “poverty index” and ranking for 447 districts in 17 states (Planning Commission 2003). This index was then combined with state poverty headcounts, which are not publicly available, to allocate early phase districts to states, with each state receiving at least one district in Phase I. Comparing the list of 199 Phase I districts with only the poverty index ranking, it is clear that higher ranked districts of richer states received the program because of the imperative to introduce the program in at least one district of each state, thus leading to a wider geographic spread than warranted by only the index.
This analysis is restricted to Phase III districts which received NREGS last, henceforth referred to as “late” districts (Phase I and II will be referred to as “early” districts). The study period is from July 2004 – March 2008, when late districts had not yet received the program. However, late districts were exposed to it from February 2006 onwards by virtue of proximity and labor market linkages to neighboring early districts. Since this analysis is conditioned on being a late district, the non-random rollout of the program is not inherently a threat to its internal validity, unless proximity to early phase districts is systematically correlated with unobservable individual and district-level characteristics, an issue which is addressed in the next two sections of the paper. Using data from two rounds of the nationally representative National Sample Survey’s (NSS) conducted before and after introduction of NREGS (Table 2), the spillover impacts of NREGA on wages and labor allocations in late districts can be estimated. The maps shown in Figures 1 and 2 in the appendix visually depict the spatial distribution of districts across NREGS phases and the classification of early and late phase districts used in this analysis.

3.1 Exposure as Binary Indicator

In order to capture exposure, the following binary measure is computed for each late district:

\[ E_1 = \begin{cases} 1 & \text{if at least one contiguous neighbor is "Early"} \\ 0 & \text{otherwise} \end{cases} \]

In other words, a late district is considered exposed if it shares a border with one or more early district neighbors and is classified as unexposed if surrounded by late district neighbors. It is noteworthy that in principle any two districts or, for that matter, any two points in space can be considered neighbors, depending on how neighborhood is defined. Given the absence of theory about the geographic scale of
labor markets, empirical choices in the literature have largely been driven by data constraints and the objective of the analysis. While spatial data on a finer scale identifying smaller administrative units is available, the NSS data used to construct outcomes in this analysis is only identified up to the district level, making finer measures of neighborhood redundant. Additionally, since the objective of this exercise is to capture spillover impacts driven by variation in proximity to NREGS, in otherwise similar labor markets, first-order contiguity is used as the criterion for neighborhood (see Murdoch & Sandler 2002, Robertson 2000 for similar criteria). It is possible that some distant labor markets are better linked by idiosyncratic transport or social networks than adjacent districts, but this study abstracts from those linkages because on average, first-order contiguity enables greater comparability of exposed and unexposed districts similar and in close proximity to each other. The map in Figure 3 of the appendix highlights all districts that are classified as exposed using this measure.

3.1 Exposure Intensity as Ratio

Since $E_1$ constrains exposure to being a binary variable and does not capture heterogeneity across exposed districts, the following measure of exposure intensity is also computed for late phase districts.

$$E_2 = \frac{\text{Number of contiguous "Early" neighbors}}{\text{Total number of contiguous neighbors}}$$

$E_2$ takes on fractional values ($E_2 \in [0, 1]$) and increases with every additional contiguous early district, assuming that the total number of contiguous neighbors does not change. This measure gives higher weight to districts with more early neighbors that the binary measure of exposure, but also penalizes large districts which might have more adjacent neighbors by virtue of size, by adjusting the ratio downward. It also enables this analysis to investigate the robustness of spillover effects to an alternative measure of exposure which captures intensity.

4. Data
As outlined in section 2, this analysis utilizes two sources of data: i) two rounds of employment surveys – NSS 61 (July 2004 – June 2005) and NSS 64 (July 2007 – June 2008) and ii) spatial data on district boundaries based on the Indian Administrative Census (2001). The individual is the primary unit of analysis, and the sample is restricted to adults aged 15 to 59\textsuperscript{11} with secondary education or less in the 215 late districts\textsuperscript{12}. The NSS survey is comprised of four sub-rounds designed to coincide with \textit{rabi} and \textit{kharif}, the two growing seasons in Indian agriculture, as well as post-harvest quarters. The study period for this analysis is restricted to July 2004 -March 2008 by dropping the last sub-round from NSS 64, which ensures that labor market changes in late districts after they received the program in April 2008 do not contaminate the working sample. Since the survey is uniformly distributed across sub-rounds by design, this does not systematically change the working sample. Together, seven sub-rounds of data drawn from NSS 61 and 64.

In the NSS surveys, employment was measured in three different approaches: i) \textit{usual status} with a reference period of one year, ii) \textit{current weekly status} with a one-week reference period and iii) \textit{current daily status} based on the daily activity pursued during each day of the week preceding the survey. This analysis utilizes the \textit{current daily status} measure to construct weekly time allocation for each individual in three mutually exclusive and exhaustive categories: work days (casual labor, salaried work, domestic work, public sector work and self-employment), unemployment, and non-labor force participation (NLFP)\textsuperscript{13}. We also compute daily wages for individuals who worked as casual laborers since this segment of the labor force is most likely to be directly impacted by spillover from public sector casual labor

\textsuperscript{11} National Sample Survey Organization (NSSO), the agency which carried out the NSS, defines individuals aged 15 to 59 as the “economically active population” and uses this sample to calculate employment and unemployment rates. This analysis adopts the same convention.

\textsuperscript{12} The sample drops union territories, the conflict affected state of Jammu & Kashmir, and small, sparsely populated north-eastern states. Completely urban districts are also dropped from the sample.

\textsuperscript{13} NSS 61 and 64 recorded the time disposition of respondents during the week preceding the interview, coding the intensity of their activities as 0.5 or 1 for each day. In this analysis, these activities are classified in one of the four categories and the intensity of that category is summed across the week to get weekly time allocations.
offered by NREGS. Daily wages for individuals who worked as salaried laborers is also used as an outcome variable to validate this assumption and ensure that our analysis captures spillovers induced by NREGS and not unrelated trends correlated with exposure. Both wages have been inflation-adjusted using quarterly CPI for agricultural workers. The table below summarizes individual-level statistics for all the dependent variables used in the analysis and salaried days in unexposed ($E_i = 0$) and exposed ($E_i = 1$) late districts, before the introduction of the program. While the allocation of weekly days to work, casual days, salaried days and non-labor force participation is similar across exposed and unexposed districts, weekly unemployment accounts for 0.9 more days for the average economically active adult in exposed districts. In terms of wages, salaried wage is similar across both categories but casual wage is lower in exposed districts.

**Table 3: Pre-Exposure Outcomes in Late Districts**

<table>
<thead>
<tr>
<th></th>
<th>Unexposed</th>
<th>Exposed</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Days</td>
<td>0.28</td>
<td>0.37</td>
<td>0.049</td>
</tr>
<tr>
<td>NLFP Days</td>
<td>2.92</td>
<td>2.89</td>
<td>0.687</td>
</tr>
<tr>
<td>Work Days</td>
<td>3.80</td>
<td>3.74</td>
<td>0.512</td>
</tr>
<tr>
<td>Casual Days</td>
<td>0.87</td>
<td>0.93</td>
<td>0.501</td>
</tr>
<tr>
<td>Salaried Days</td>
<td>0.78</td>
<td>0.61</td>
<td>0.136</td>
</tr>
<tr>
<td>Casual Labor Wage (Real)</td>
<td>65.17</td>
<td>55.49</td>
<td>0.012</td>
</tr>
<tr>
<td>Salaried Labor Wage (Real)</td>
<td>110.74</td>
<td>108.63</td>
<td>0.678</td>
</tr>
</tbody>
</table>

Note: These estimates were computed using NSS 64 (July 2004 – June 2005). Casual Labor Wage and Salaried Labor Wage are reported in Rupees/Day (July 2004 prices)

Although these pre-exposure differences in unemployment days and casual labor wage are significant across exposed and unexposed districts, they do not invalidate the difference-in-difference estimation strategy undertaken in this analysis, which instead relies on the identifying assumption of parallel trends in outcomes. While this assumption cannot be directly tested with the two rounds of data used in our study sample, we graph the annual evolution of casual wage through two 1993 – 1994 and 1999 – 2000 (NSS 50 and 55 respectively) along with the study period survey rounds (2004 – 2005 and 2007 – 2008) in Fig. 4 below. As mentioned earlier, the last quarter from 2007 – 2008 has been dropped to exclude the post-Phase III period when late districts receive the program. Visually, it is quite evident that the casual
wage trends in exposed and unexposed late districts run parallel between 1999 and 2005 and then their gap narrows after introduction of the program in the first two phases (PI and PII in the figure). This increases our confidence that pre-existing difference in casual wage across exposed and unexposed districts documented in Table 3 is not necessarily an indicator of pre-existing non-parallel trends for this outcome.

Fig. 4: Annual Casual Wage Trends in Exposed and Unexposed Districts

Note: Casual Wage is inflation-adjusted using the state-level Consumer Price Index for Agricultural Labor (CPI – AL) from the Indian Labour Bureau and reported in base year (1986-87) prices. The reference markers PI (Feb 2006) and PII (April 2007) indicate the first and second phase rollouts of NREGS.

Next, it is instructive to compare observable characteristics across late districts to explore if the non-random rollout of the program necessarily implied systematic differences across exposed and unexposed districts. In order to do so, Table 4 reports averages for individual and household-level characteristics
during the pre-exposure period. It also reports averages for demographic variables using district-level data from the 2001 Census. It is clear from the Census statistics that unexposed districts are larger, more rural and have a higher proportion of Scheduled Tribe residents than exposed districts. However, they do not differ from exposed districts in terms of Scheduled Caste proportion of population, sex-ratio (overall and caste-differentiated), literacy (overall and gender-differentiated) and household size. Since the Census is decadal, we do not have information on these characteristics for the post-exposure period in our sample (July 2007 – March 2008) to explicitly control for them. If time-invariant though, these district-level characteristics are accounted for by including district fixed effects in our regression specification. On the other hand, the comparison of means for individual and household-level variables using NSS data has much higher power given the large size of our study sample. It shows that in the pre-exposure period, the economically active population of unexposed districts was younger, less likely to belong to Scheduled Tribes or Other Backward Castes, and more likely to be male and belonging to the other caste category. In terms of land possession, literacy and likelihood of belonging to Scheduled Castes, there is no statistical difference between unexposed and exposed districts. All these variables as well are controlled for in our regression specifications. It is also possible that other time-varying individual, household or district-level unobservables are correlated with exposure. We carry out robustness checks by way of an out of study sample placebo analysis and impose sample restrictions in order to investigate the effect, if any, of these unobservables.

<table>
<thead>
<tr>
<th>Controls</th>
<th>Unexposed</th>
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<tr>
<td>Age</td>
<td>31.8</td>
<td>32.4</td>
<td>0.019</td>
<td>NSS 61</td>
</tr>
<tr>
<td>% Male</td>
<td>51.3</td>
<td>49.8</td>
<td>0.015</td>
<td>NSS 61</td>
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<td>% Scheduled Caste (SC)</td>
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<td>19.2</td>
<td>0.993</td>
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<td>% Scheduled Tribe (ST)</td>
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<td>4.9</td>
<td>0.000</td>
<td>NSS 61</td>
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<tr>
<td>% Other Backward Caste</td>
<td>40.7</td>
<td>45.9</td>
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<td>NSS 61</td>
</tr>
<tr>
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</tr>
<tr>
<td>% Literate</td>
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<td>NSS 61</td>
</tr>
<tr>
<td>% Land Possessed &lt; 1ha</td>
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<td>% Rural Population</td>
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<td>71.4</td>
<td>0.024</td>
<td>2001 Census</td>
</tr>
<tr>
<td>Sex Ratio (per 1000 men)</td>
<td>931.3</td>
<td>940.3</td>
<td>0.443</td>
<td>2001 Census</td>
</tr>
</tbody>
</table>
% Literacy | 59.1 | 60.4 | 0.414 | 2001 Census
% Female Literacy | 58.5 | 60.0 | 0.453 | 2001 Census
% Male Literacy | 79.6 | 80.3 | 0.608 | 2001 Census
% Scheduled Caste (SC) | 16.2 | 17.2 | 0.406 | 2001 Census
% Scheduled Tribe (ST) | 4.5 | 1.7 | 0.042 | 2001 Census
Sex Ratio (SC) | 930.4 | 941.8 | 0.256 | 2001 Census
Sex Ratio (ST) | 799.3 | 724.8 | 0.190 | 2001 Census
Household Size | 5.43 | 5.41 | 0.894 | 2001 Census
Number of Districts | 49 | 166

Note: The NSS 61 sample consists of late phase individuals between the ages of 15 and 59, interviewed from July 2004 to June 2005, before the introduction of NREGS. The estimates for late phase district-level characteristics are taken from 2001 Census, which is representative of the entire district population.

5. Estimation

In our strategy, we compare changes in outcomes of exposed late districts to unexposed late districts in order to calculate NREGS induced spillovers from early districts. In other words, the spillover effects on casual wages and weekly time allocations are estimated by exploiting the plausibly exogenous shock to variation in exposure across late districts due to introduction of the program in contiguous early neighbors. In the first set of estimated specifications, a difference-in-difference approach is employed and Exposure_j is the binary measure of exposure used, i.e. “treatment” is defined as having at least one contiguous early neighbor. Post_jt is an indicator variable which is 0 for all late districts in the first four quarters predating the program (July 2004 – June 2005) and is 1 in the post-exposure quarters (July 2007 – March 2008). The variable of interest is the interaction term, Post_jt*Exposure_j, and the parameter β3 estimates the impact of exposure on individual level time allocation and wage variables. This impact of exposure is a “treatment effect” which captures labor market spillovers in exposed districts relative to unexposed districts, conditional on not receiving NREGS. Inflation-adjusted daily wage for casual labor, salaried labor and time allocations and serve as the dependent variables (Y_ijt) in separate regressions. These regressions are implemented at the individual-district-quarter level of analysis. There are two main advantages to this approach, as compared to a household-district-quarter level approach: i) individual
level factors like age, education, and gender which are correlated with seasonal migration\textsuperscript{14}, can be controlled for in addition to household level factors like caste and land possessed and ii) greater efficiency of estimates due to higher number of observations. The full specification is:

$$Y_{ijt} = \alpha + \beta_1 Post_{jt} + \beta_2 Exposure_j + \beta_3 Post_{jt} \times Exposure_j + \beta_4 TrendFE_i + \beta_5 DistrictFE_j + \Theta X_{ijt} + \epsilon_{ijt}$$ (1)

where \(i\) indexes individual, \(j\) indexes district, and \(t\) indexes quarter-year, while \(X_{ijt}\) represents individual, household, and district-level controls. The sampling weights provided in the surveys are used to weight these estimates. Season-quarter fixed effects are included to control for seasonal and secular changes in labor market outcomes through the study period. Since the exposure variation being exploited in this estimation is at the district-level, district fixed effects, which account for pre-existing, time-invariant district characteristics, are also included. The error term \(\epsilon_{ijt}\) captures individual level heterogeneity in the variable costs associated with working outside the home district. Given that the shock to exposure is at the district-level, the individual level errors within a district may be correlated. To account for intra-district correlation, standard errors are clustered at the district-level for all reported results.

While the results for the specification in (1) are intuitive and relatively easy to interpret, they are presented with the caveat that heterogeneity of exposure intensity across exposed districts is not accounted for. The second class of specifications (2) estimated in this analysis employs the ratio-based measure of exposure intensity, \(ExposureIntensity_i\), which takes on fractional values between 0 and 1. \(\beta_3\) is again the parameter of interest but the interpretation of its estimate is different from specification (1) because of this range. While the previous estimate represented the effect of being exposed to at least one early phase neighbor relative to none, this parameter can be used to compute the linear, marginal effect of

\textsuperscript{14} “The socioeconomic profile of the short-duration/seasonal out-migrants is very different from the other migrants. These migrants are much more likely to be from socially deprived and poorer groups, have low levels of education, less land and more likely to be engaged in casual work. They are also more likely to be of prime working age (two-thirds are 15-29 years old) and are predominantly male” (Srivastava 2011).
increased exposure intensity. In its most basic interpretation, $\beta_3$ is the effect of being surrounded by early phase neighbors, relative to having no early phase neighbors.

$$Y_{ijt} = \alpha + \beta_1 Post_{jt} + \beta_2 ExposureIntensity_i + \beta_3 Post_{jt} \times ExposureIntensity_i + \beta_4 TrendFE_t + \beta_5 DistrictFE_j + \Omega X_{ijt} + \varepsilon_{ijt}$$

(2)

5.1 Plausible Exogeneity of Exposure

Irrespective of measure, the main source of potential bias in employing this econometric strategy is a violation of the identifying assumption that district level exposure is quasi-random across pre- and post-NREGS quarters, conditional on quarter-year and district fixed effects and individual and household-level controls. If exposure is actually a proxy for some other unobservable, and is correlated with differential district-level trends in outcomes, then the estimates of spillover impacts on late districts are likely be biased. In other words, our confidence in the study sample results would be weakened if we estimated similar impacts during a pre-period when late districts did not have program neighbors. In order to carry out this check formally for all outcome variables, specifications (3) and (4) are implemented using a placebo sample consisting of two rounds of NSS conducted before the introduction of NREGS. These results are reported in section 7. A visual representation of this placebo test can be seen in Figures 5 and 6 of the appendix, which show the quarterly evolution of inflation-adjusted casual wage in the placebo and study sample respectively. While the line marker partitions pre and post-exposure periods in the study sample, it separates periods before and after “fake” exposure in the placebo sample. It is clear that while the gap between exposed and unexposed districts narrows in the last two of three post-exposure quarters for the study sample, it fluctuates in both directions in the placebo sample, thus suggesting that differential trends are related to actual exposure.

There are two other threats to exposure being plausibly exogenous. Firstly, if late districts were able to manipulate their exposure to the program, then it could be the case that exposure is correlated with other
unobserved variables that differentially affect outcome trends for exposed districts. Here, it must be emphasized that our analysis is restricted to late districts and is thus conditioned on receiving NREGS last. While late district administrators may have tried to manipulate early reception of the program, it is not clear how they would have influenced being exposed to early district neighbors, given that they were unsuccessful. Since the central government’s selection of early districts was non-random with “backward” districts being selected first, our sample of late districts is definitely richer than early districts¹⁵, but this is not the comparison being made in our analysis. Unless exposure is systematically correlated with differential outcome trends within the sample of late districts, the non-random rollout of the program does not threaten the internal validity of this analysis. As discussed earlier, the balance between exposed and unexposed districts for five of the seven outcomes used in this paper and the absence of pre-existing non-parallel casual wage trends increases our confidence that the two groups of late districts do not experience differential outcome trends, even if they are systematically different from early districts as a group.

A second, less serious source of bias is that if late district residents correctly anticipated the program rollout and the identified early districts which would receive NREGS before their home district, their behavioral response could be to migrate to NREGS districts before the shock, thus resulting in diminished or no spillover effects on labor markets being estimated. In fact, a large scale migration of this sort would be a threat to any evaluation of the program’s impact, not just the estimation of spillovers associated with it. Given that the assignment of early phase districts is imperfectly predicted even using the index made publicly available after the introduction of the program (Zimmerman 2013), it is quite improbable that individuals would have correctly anticipated which districts would receive the program early and migrate

¹⁵ Zimmerman (2013) has reconstructed this two-step algorithm using state poverty headcounts from the 2001 Census to imperfectly predict assignment for a RD design based impact evaluation of NREGS. Since poverty index and corresponding rank is missing disproportionately for late phase districts, this analysis cannot utilize these ranks as additional controls.
to them. In the unlikely case of this concern being valid, our estimates simply serve as a lower bound for spillover effects.

6. Main Results

6.1 Exposure and Spillovers

The results from estimation of specification (2) are presented in Table 5. The dependent variables in the first two columns are inflation-adjusted daily casual and salaried labor wages, while the next three columns are weekly time allocations for unemployment, work, and non-labor force participation days, which are mutually exclusive and exhaustive of time endowment. We estimate that, on average, spillovers from NREGS resulted in inflation-adjusted daily casual wage increasing by 8.7% (significant at 5%) more in exposed districts, relative to the increase in unexposed districts. This result provides empirical support to the prediction of home wages rising faster with exposure in late phase districts. The absence of a similar effect on salaried wage supports our conjecture that the relevant market for measuring spillovers from NREGS is the casual labor market and that our results reflect the impact of exposure to the program. There is no statistically significant effect of exposure on weekly time allocation variables as well. Given the limitations of repeated cross-section data, which does not track leavers in both rounds, the absence of predicted impacts on employment can be attributed to the changing composition of the sample. In particular, since leavers are likely to be concentrated in exposed districts during the post-period, the estimated effects of exposure on aggregate employment are attenuated. Further, the small fraction of casual workers relative to the overall sample could contribute to small effects not being detected. Although the contexts are not strictly comparable, the basic result is similar to the Alcott & Keniston (2014) finding that earnings spillovers from natural resource booms were concentrated in nearby counties, relative to faraway counties.
6.2 Exposure Intensity and Spillovers

When specification (3) is implemented, we estimate that, on average, spillovers from NREGS resulted in inflation-adjusted daily casual wage increasing by 1.03% with every additional 10% increase in exposure intensity (significant at 5%). For example, a late district with ten neighbors would experience a 1.03% increase in casual wage with every additional neighbor receiving the program early. The change in log daily salaried wage remains statistically insignificant, corroborating the result from Table 5 and increasing our confidence that the estimated impacts on casual wages are not a reflection of secular wage increases across all labor markets in exposed districts, relative to unexposed districts. Interestingly, the time allocation results differ across exposure and exposure intensity, with labor supply changes increasing with exposure intensity. The weekly decrease of 0.21 non-labor force participation days (at 5% level of significance) for completely exposed districts relative to completely unexposed districts is accompanied by positive but insignificant increases in work days and unemployment days. Since the survey does not track leavers, this result should be interpreted as the effect of exposure intensity on the average labor supply responses of stayers, and not on aggregate district-level labor supply. Given that the model’s predicted effect on individual-level labor supply of stayers is ambiguous (as discussed in section 2), rising casual wages accompanied with increased labor force participation by stayers is indicative of an upward sloping labor supply curve in this wage range. Further, the estimation of this additional time allocation effect suggests that while the dichotomous exposure variable performs fairly well in terms of approximating exposure intensity impacts on casual wages, there are efficiency gains when heterogeneity of exposure is accounted for.

6.3 Spillovers by Gender

Given that seasonal migrants who leave for employment purposes are overwhelmingly male in India, it is of interest to evaluate whether spillovers due to exposure are gender-differentiated. In order to estimate these gender-differentiated impacts, indicators for men and women are interacted with the $\beta_3 Post_{jt} \times Exposure_j$ term in specification (2) and the coefficients are reported in Table 7. Additionally, we
report effects on time allocated to casual labor, a subset of workdays, in order to focus on the gender specific labor responses of stayers in this particular market. We estimate that, on average, casual wage for women increased by 9.3% more in exposed districts relative to the increase in unexposed districts. On the other hand, the increase in casual wage for men was estimated to be 8.5%. If NREGS raised women’s wages more than men’s on account of a bigger differential between program and private sector wages for women, as the findings from Azam (2012) suggest, it follows that the wage differentials across program and non-program districts would also be higher for women. Higher casual wage spillovers for women in exposed districts despite seasonal migrants being predominantly male, thus also support the prior that given relatively low labor force participation, even small flows of female migrant labor could have had large impacts on home district casual labor markets. On the other hand, weekly male labor force participation increased by 0.19 days in exposed districts and almost all of it translated into an increase of time allocated to casual labor, i.e. 0.17 days. Weekly unemployment days for men also rose by 0.08 days even as changes in time allocations for women are not statistically significant. The presence of time allocation spillovers among men despite higher wage spillovers among women, suggests that the elasticity of labor supply is positive among male stayers while income and substitution effects induced by higher wages could be offsetting each other for women. Lastly, the simultaneous increases in male unemployment, labor supply and casual wage, signals the presence of search costs or wage rigidities which prevent the labor market from clearing in late phase districts.

7. Robustness Checks

7.1 Placebo Analysis

The Act mandates that one-third of workers be women and equal wages be paid to men and women (Dutta et al. 2014). It is also attractive to women because of the mandated local provision of work (within 5 kilometers of residence) and child care facilities at worksites.
In order to ensure that the effects estimated for late districts are genuinely spillovers and not being driven by a correlation between unobserved variables and exposure, a placebo analysis is carried out, and the effects of fake exposure to early program districts are estimated. In other words, if the parallel paths assumption underlying the difference-in-difference estimation is violated, differential trends in outcomes unrelated to exposure would be reflected in the placebo sample as well. In particular, the impacts on casual wages, for which positive and significant effects have been estimated in the main sample, would be replicated even with fake exposure if this concern was valid. To carry out the placebo analysis, specifications (2) and (3) are implemented using two rounds of data – NSS 50 (July 1993 – June 1994) and NSS 55 (July 1999 – June 2000) – which preceded the introduction of NREGS. In order to make the sample comparable with the study sample, the last sub-round of NSS 55 is dropped from the analysis. Since no districts received the program during this period, a priori, exposure to contiguous neighbors which received the program more than a decade later should have no effect on casual wages. In the results reported in Table 8, we observe that changes in inflation-adjusted casual labor wage are statistically insignificant in exposed late districts, relative to unexposed late districts. Similarly, there is no significant effect of exposure intensity on casual labor wage in Table 9. These results validate the interpretation that the study sample results are not being driven by a spurious correlation across exposed and unexposed districts but are instead genuine spillover effects generated by exposure-induced seasonal migration. Additionally, Tables 8 and 9 (see Appendix) show that time allocation changes in the placebo sample are not statistically significant like the main sample results, but since predictions from theory cannot be tested for these variables, no conclusion can be drawn from this similarity between placebo and study sample results.

7.2 Sample Restriction

**Low Coverage States:** Since early phase districts were concentrated in eastern and central Indian states, the late phase districts in these states have a higher likelihood of exposure and higher exposure intensity than late phase districts in western and southern India. It could be the case that the spillover effects
estimated in the study sample are driven by “high coverage” states where late district individuals have greater choice in terms of migration destinations with higher wages than their home districts. To test this hypothesis, specifications (2) and (3) are estimated on a restricted sample consisting only of late districts in large, “low coverage” states, defined as having less than half of their districts receiving the program early. The results in Tables 10 and 11 (see Appendix) follow the same pattern qualitatively observed in study sample results, but with larger magnitudes of increases in casual wage due to exposure (13.5%) and exposure intensity (18.3%). The effects are significant at 1% and 10% levels of significance, respectively, despite the reduced sample size. Estimating larger impacts in “low coverage” states relative to the original sample suggests that there may be diminishing returns to exposure and exposure intensities in terms of casual wage spillovers. Changes in salaried wage and time allocations continue to remain insignificant.

8. **Seasonal Migration and Exposure Intensity**

Although the spillover impacts on casual wages estimated in this analysis are motivated as resulting from changes in flows of seasonal migrants to and from late phase districts, the direct impact of exposure on seasonal migration has not been estimated because migration information was not collected in NSS 61 (the round immediately preceding NREGS). While this information was collected in NSS 55 (July 1999 – June 2000) and NSS 64 (July 2007 – June 2008), differences in the definition of short-term migrants across rounds prevent comparability and thus, direct estimation of exposure’s direct impact on seasonal migration. However, some inferences can be drawn about the empirical relationship between exposure intensity and seasonal migration by exploiting the temporal dimension of NSS 64’s survey design, which comprises four quarterly sub-rounds (July – Sep 2007, Oct – Dec 2007, Jan – Mar 2008, and April – June 2008), broadly coinciding with the agricultural cycle.

As a first step, it is useful to visually observe the relationship between short-term migration and exposure intensity, and explore if the distance of destination from home districts. Figures 7 and 8 in the appendix
graph two measures: i) the percentage of short-term migrants in the population, and ii) the percentage of short-term migrants in the population who moved to a destination outside the district, within the same state. Both measures are graphed across three exposure intensity terciles, before and after the introduction of NREGS in late districts (April 2008). While Fig. 7 shows these changes for early districts, Fig. 8 demonstrates the same for late districts. It is evident that in early districts, where program was active in both periods, both measures increased with exposure intensity (Fig. 7). Further, in the April – June 2008 quarter which is the pre-monsoon dry season, short-term migration from early districts to all destinations as well as within state districts increased across exposure intensity terciles. This increase fits in with the view of short-term migration serving as a coping strategy for the poor even in districts where the employment guarantee had been implemented.

In contrast, Fig.8 shows that late districts exhibited different patterns from early districts. While short-term migration to any destination increased in the dry season like early districts, short-term migration to districts within the state declined in the dry season across all exposure terciles. Since the dry season quarter (April – June 08) coincided with the introduction of NREGS in late districts, this decline reflects the well-documented migration-reducing impact of the program. More significantly, this decline indicates that short-term, short-distance migration was the relevant form of labor movement previously induced by exposure to the program, conditional on not receiving it. In other words, exposure and the resultant short-term, short-distance migration to nearby program areas substituted for actual assignment in the period when late districts did not receive NREGS (pre-April 2008). As an additional note, the relationship between short-term, short-distance migration and exposure intensity is U-shaped in both periods, supporting the higher wage spillovers estimated for low-coverage states relative to the entire sample, in the previous section.

9. Conclusion
The findings from this analysis demonstrate that exposure to NREGS produced significant spillover effects in the form of higher real casual labor wage in districts where it was not rolled out during the study period. Comparing the magnitude of these spillovers to previous evaluations of the program, it is striking that the impact of exposure (8.7%) is higher than the 4.7% and 5.1% increases in casual wages in program districts estimated by Imbert and Papp (2015) and Berg et al. (2012), respectively. These spillovers are marginally higher among women than men and are stronger in large, low-coverage states, indicating a diminishing return to exposure for late districts. Given the presence and magnitude of these spillovers, it is evident that the gains from public works programs are not completely accrued by the jurisdictions in which they are implemented. Since public works programs are often started at the level of sub-national governments -- the precursor to NREGS was the state of Maharashtra’s Employment Guarantee Scheme, started in early 1970s (Murgai & Ravallion 2005) -- there is a strong incentive to free-ride on a neighboring state or district’s program given its spillover benefits. Conversely, if a state chooses to discontinue a public works program, district-level labor markets in neighboring states will also experience the end of spillover benefits. In either case, policymakers need to know the relevant parameters estimated in this paper to assess how their jurisdiction is likely to be impacted by public works programs in adjoining jurisdictions. The political economy dimension of these findings is that in periods of economic distress when the stabilization benefits of public works programs are most needed, government revenues also decline, thus making them less likely to be enacted given the benefit to waiting for a neighboring jurisdiction to start the program.

References


Appendix
Figure 1: Program Rollout
Figure 2: Early vs Late Districts
Figure 3: Exposure in Early and Late Phase Districts
Figure 5: Quarterly Casual Wage and fake Exposure in Placebo Period

Figure 6: Quarterly Casual Wage and Exposure in Study Period
Figure 7: Short-term Migration & Exposure Intensity in Early Districts

Figure 8: Short-term Migration & Exposure Intensity in Late Districts
### Table 5: Exposure induced Spillovers to Late Districts

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<tr>
<th></th>
<th>Log deflated casual wage</th>
<th>Log deflated salaried wage</th>
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<th>NLFP Days</th>
<th>Work Days</th>
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<td>17,513</td>
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</table>

Note: Each column represents results from a separate regression. The sample consists of late phase individuals between the ages of 15 and 59, interviewed from July 2004 to June 2005 and from July 2007 – March 2008. Unemployment days, non-labor force participation days and work days are calculated using time allocation responses for the week preceding interview. Log casual wage and log salaried wage is the log of earnings per day worked for people who report working in casual labor and salaried work respectively. Daily casual wage and salaried work wage are deflated using the monthly, state-level price index for agricultural laborers from the Indian Labour Bureau. Exposure is an indicator for whether district has at least one contiguous early-phase neighbor. Individual-level controls (age, age squared, gender, indicators for literacy, land possessed, and caste group), rural fraction of district population, year-quarter and district fixed effects are included in all regressions. All estimates are computed using sampling weights. Standard errors are clustered at district level to control for intra-district correlation. ***Significant at 1% level, **Significant at 5% level, *Significant at 1% level.

### Table 6: Exposure Intensity induced Spillovers to Late Districts

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<th>Log deflated salaried wage</th>
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<th>NLFP Days</th>
<th>Work Days</th>
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</tbody>
</table>

Note: Each column represents results from a separate regression. The sample consists of late phase individuals between the ages of 15 and 59, interviewed from July 2004 to June 2005 and from July 2007 – March 2008. Unemployment days, non-labor force participation days and work days are calculated using time allocation responses for the week preceding interview. Log casual wage and log salaried wage is the log of earnings per day worked for people who report working in casual labor and salaried work respectively. Daily casual wage and salaried work wage are deflated using the monthly, state-level price index for agricultural laborers from the Indian Labour Bureau. Exposure is the ratio of the number of contiguous early-phase neighbor to number of contiguous neighbors. Individual-level controls (age, age squared, gender, indicators for literacy, land possessed, and caste group), rural fraction of district population, year-quarter and district fixed effects are included in all regressions. All estimates are computed using sampling weights. Standard errors are clustered at district level to control for intra-district correlation. ***Significant at 1% level, **Significant at 5% level, *Significant at 1% level.
<table>
<thead>
<tr>
<th>Post<em>Exposure</em>Women</th>
<th>Log deflated casual wage</th>
<th>Unemployment Days</th>
<th>NLFP Days</th>
<th>Work Days</th>
<th>Casual Days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.093***</td>
<td>0.031</td>
<td>0.077</td>
<td>-0.108</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.035)</td>
<td>(0.096)</td>
<td>(0.098)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>Post<em>Exposure</em>Men</td>
<td>0.085**</td>
<td>0.075*</td>
<td>-0.188**</td>
<td>0.113</td>
<td>0.169**</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.041)</td>
<td>(0.089)</td>
<td>(0.087)</td>
<td>(0.076)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>District FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>19,677</td>
<td>192,124</td>
<td>192,124</td>
<td>192,124</td>
<td>192,124</td>
</tr>
</tbody>
</table>

Note: Each column represents results from a separate regression. The sample consists of late phase individuals between the ages of 15 and 59, interviewed from July 2004 to June 2005 and from July 2007 – March 2008. Unemployment days, non-labor force participation days and work days are calculated using time allocation responses for the week preceding interview. Log casual wage and log salaried wage is the log of earnings per day worked for people who report working in casual labor and salaried work respectively. Daily casual wage and salaried work wage are deflated using the monthly, state-level price index for agricultural laborers from the Indian Labour Bureau. Exposure is an indicator for whether district has at least one contiguous early-phase neighbor. Individual-level controls (age, age squared, gender, indicators for literacy, land possessed, and caste group), rural fraction of district population, year-quarter and district fixed effects are included in all regressions. All estimates are computed using sampling weights. Standard errors are clustered at district level to control for intra-district correlation. ***Significant at 1% level, **Significant at 5% level, *Significant at 1% level.
### Table 8: Exposure induced Spillovers in pre-study period (Placebo Test)

<table>
<thead>
<tr>
<th></th>
<th>Log deflated casual wage</th>
<th>Log deflated salaried wage</th>
<th>Unemployment Days</th>
<th>NLFP Days</th>
<th>Work Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post*Exposure</td>
<td>-0.045</td>
<td>-0.023</td>
<td>0.075*</td>
<td>0.013</td>
<td>0.183</td>
</tr>
<tr>
<td></td>
<td>(0.137)</td>
<td>(0.064)</td>
<td>(0.043)</td>
<td>(0.147)</td>
<td>(0.221)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>District FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>12,936</td>
<td>8,423</td>
<td>165,267</td>
<td>165,267</td>
<td>165,267</td>
</tr>
</tbody>
</table>

Note: Each column represents results from a separate regression. The sample consists of late phase individuals between the ages of 15 and 59, interviewed from July 2004 to June 2005 and from July 2007 – March 2008. Unemployment days, non-labor force participation days and work days are calculated using time allocation responses for the week preceding interview. Log casual wage and log salaried wage is the log of earnings per day worked for people who report working in casual labor and salaried work respectively. Daily casual wage and salaried work wage are deflated using the monthly, state-level price index for agricultural laborers from the Indian Labour Bureau. Exposure is an indicator for whether district has at least one contiguous early-phase neighbor. Individual-level controls (age, age squared, gender, indicators for literacy, land possessed, and caste group), rural fraction of district population, year-quarter and district fixed effects are included in all regressions. All estimates are computed using sampling weights. Standard errors are clustered at district level to control for intra-district correlation. ***Significant at 1% level, **Significant at 5% level, *Significant at 1% level.

### Table 9: Exposure Intensity induced Spillovers in pre-study period (Placebo Test)

<table>
<thead>
<tr>
<th></th>
<th>Log deflated casual wage</th>
<th>Log deflated salaried wage</th>
<th>Unemployment Days</th>
<th>NLFP Days</th>
<th>Work Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post*Exposure</td>
<td>0.044</td>
<td>0.104</td>
<td>0.021</td>
<td>0.222</td>
<td>-0.132</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.152)</td>
<td>(0.077)</td>
<td>(0.190)</td>
<td>(0.286)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>District FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>12,936</td>
<td>8,423</td>
<td>165,267</td>
<td>165,267</td>
<td>165,267</td>
</tr>
</tbody>
</table>

Note: Each column represents results from a separate regression. The sample consists of late phase individuals between the ages of 15 and 59, interviewed from July 2004 to June 2005 and from July 2007 – March 2008. Unemployment days, non-labor force participation days and work days are calculated using time allocation responses for the week preceding interview. Log casual wage and log salaried wage is the log of earnings per day worked for people who report working in casual labor and salaried work respectively. Daily casual wage and salaried work wage are deflated using the monthly, state-level price index for agricultural laborers from the Indian Labour Bureau. Exposure is the ratio of the number of contiguous early-phase neighbor to number of contiguous neighbors. Individual-level controls (age, age squared, gender, indicators for literacy, land possessed, and caste group), rural fraction of district population, year-quarter and district fixed effects are included in all regressions. All estimates are computed using sampling weights. Standard errors are clustered at district level to control for intra-district correlation. ***Significant at 1% level, **Significant at 5% level, *Significant at 1% level.
Table 10: Exposure induced Spillovers to Late Districts in Low Coverage States

<table>
<thead>
<tr>
<th></th>
<th>Log deflated casual wage</th>
<th>Log deflated salaried wage</th>
<th>Unemployment Days</th>
<th>NLFP Days</th>
<th>Work Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post*Exposure</td>
<td>0.135***</td>
<td>-0.001</td>
<td>0.015</td>
<td>0.066</td>
<td>-0.081</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td>(0.080)</td>
<td>(0.051)</td>
<td>(0.114)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>District FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>8,029</td>
<td>8,013</td>
<td>69,352</td>
<td>69,352</td>
<td>69,352</td>
</tr>
</tbody>
</table>

Note: Each column represents results from a separate regression. The sample consists of late phase individuals between the ages of 15 and 59, interviewed from July 2004 to June 2005 and from July 2007 – March 2008. Unemployment days, non-labor force participation days and work days are calculated using time allocation responses for the week preceding interview. Log casual wage and log salaried wage is the log of earnings per day worked for people who report working in casual labor and salaried work respectively. Daily casual wage and salaried work wage are deflated using the monthly, state-level price index for agricultural laborers from the Indian Labour Bureau. Exposure is an indicator for whether district has at least one contiguous early-phase neighbor. Individual-level controls (age, age squared, gender, indicators for literacy, land possessed, and caste group), rural fraction of district population, year-quarter and district fixed effects are included in all regressions. All estimates are computed using sampling weights. Standard errors are clustered at district level to control for intra-district correlation. ***Significant at 1% level, **Significant at 5% level, *Significant at 1% level.

Table 11: Exposure Intensity induced Spillovers to Late Districts in Low Coverage States

<table>
<thead>
<tr>
<th></th>
<th>Log deflated casual wage</th>
<th>Log deflated salaried wage</th>
<th>Unemployment Days</th>
<th>NLFP Days</th>
<th>Work Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post*Exposure</td>
<td>0.183*</td>
<td>-0.020</td>
<td>0.031</td>
<td>-0.079</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.091)</td>
<td>(0.083)</td>
<td>(0.218)</td>
<td>(0.238)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>District FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>8,029</td>
<td>8,013</td>
<td>69,352</td>
<td>69,352</td>
<td>69,352</td>
</tr>
</tbody>
</table>

Note: Each column represents results from a separate regression. The sample consists of late phase individuals between the ages of 15 and 59, interviewed from July 2004 to June 2005 and from July 2007 – March 2008. Unemployment days, non-labor force participation days and work days are calculated using time allocation responses for the week preceding interview. Log casual wage and log salaried wage is the log of earnings per day worked for people who report working in casual labor and salaried work respectively. Daily casual wage and salaried work wage are deflated using the monthly, state-level price index for agricultural laborers from the Indian Labour Bureau. Exposure is the ratio of the number of contiguous early-phase neighbor to number of contiguous neighbors. Individual-level controls (age, age squared, gender, indicators for literacy, land possessed, and caste group), rural fraction of district population, year-quarter and district fixed effects are included in all regressions. All
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