SHORT-TERM MIGRATION, RURAL PUBLIC WORKS, AND URBAN LABOR MARKETS: EVIDENCE FROM INDIA

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Abstract
This paper studies the effect of India's rural public works program on rural-to-urban migration and urban labor markets. We find that seasonal migration from rural districts that implemented the program decreased relative to those that were selected to, but did not implement it. We use a gravity model and find that real wages rose faster in cities with higher predicted migration from program districts. Since most seasonal migrants work outside of their district, urban wage increases were not limited to program districts, and may have attracted migrants from nonprogram districts. Difference-in-differences may hence be biased. Structural estimates indeed suggest that migration decreased by 22% in program districts, but also increased by 5% in nonprogram districts. As a result, urban wages increased by only 0.5%, against 4.1% if the program had been implemented in all selected districts. (JEL: O15, J61, R23, H53)

1. Introduction

Since rural and urban areas of developing countries are integrated via migration flows, rural development programs may have significant effects on urban labor markets (Harris and Todaro 1970). Specifically, a policy that improves employment opportunities in rural areas may reduce migration from rural to urban areas, and push up urban wages

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(Fields 2005). Providing empirical evidence on these spillovers is challenging, for at least three reasons. First, the rural development policy needs to be large enough to affect urban areas, and to be placed somewhat exogenously to allow for causal identification of its effects. Second, comprehensive data on labor reallocation between rural and urban areas is required. Migration flows may include long-term migration, which is usually available from population censuses, but also short-term (or seasonal) migration, which can only be measured with dedicated survey data. Third, standard empirical frameworks—such as a difference-in-differences approach that would compare towns located in rural areas with and without the policy—may not be able to capture spatial spillovers if they are not strictly local.

In this paper, we estimate the spatial spillover effects of India's National Rural Employment Guarantee Act (NREGA). The NREGA is a workfare program, which hires rural adults on local public works during the agricultural off-season.[1] It is a very large program, with close to 50 million household participants in 2013.[2] In previous work, we showed that it had significant impacts on rural labor markets (Imbert and Papp 2015). Here, we use variation in NREGA implementation across rural districts selected to receive the program to estimate its effect on rural to urban migration and urban labor markets.

Our measure of migration comes from the National Sample Survey (NSS). It reveals that seasonal flows play a major role in labor reallocation between rural and urban areas of India: 8.1 million adults left their village to work one to six months in urban areas in 2007. These flows are large when compared to the net flow of long-term migrants, who come to work and settle in urban areas (0.4 million). They are also large when compared to the number of urban residents engaged in unskilled wage work (14 million). Hence, small changes in seasonal migration may have large effects on urban labor markets.[3]

Our empirical strategy proceeds in three steps. First, among rural districts selected to receive the program by 2007 ("early districts"), we compare those located in states that actively implemented the NREGA ("star states") with the others, which received little public employment.[4] Difference-in-differences estimates show that public employment increased by 7.4 days per rural adult, wages increased by 5.7% and the prevalence of seasonal migration decreased by 50% in early districts of star states as compared to other early districts. One would expect such a large decrease in migration to affect urban labor markets. However, since 87% of seasonal migrants leave their district, the migration spillovers of the NREGA will not be felt in local towns, but in cities further away.

1. Workfare programs are common antipoverty policies. A report by The World Bank (2015) found them active in 94 countries in 2014.

2. Official reports available at http://nrega.nic.in.

3. Authors' calculations based on the NSS Employment-Unemployment Survey (July 2007–June 2008).

4. Our strategy differs from (Imbert and Papp 2015), in which we compared "early" and "late" districts. This is due to the fact that prevalence of short-term migration to urban areas is low in "late" districts (0.8%).

In the second step, we use a gravity model to predict seasonal migration flows into each urban center. We then compare wage trends in cities with high predicted migration rates from program districts to wage trends in other cities to identify urban spillovers. The results suggest that real wages rose faster in cities most exposed to the drop in seasonal migration due to the program (+2.4% on average). Reassuringly, these differential urban wage trends were not present before the program was implemented or after it was rolled out in all rural districts. They are also not concentrated in early districts or in star states, alleviating concerns that the states' decision to implement the NREGA was endogenous to urban outcomes. Overall, these results confirm that the program reduced migration from rural to urban areas and increased urban wages.

We also find evidence of lower wage growth in urban centers with higher predicted migration from nonprogram districts (−1.1% on average), which suggests that migration from nonprogram districts responded to the program. This casts doubt on the validity of our first difference-in-differences approach, which compares migration from rural districts with and without the program. To tackle this issue, we develop a spatial equilibrium model and show that in presence of spatial spillovers, difference-in-differences are indicative of the sign, but not the magnitude of the effect. The model also suggests how to adjust difference-in-differences by taking into account explicitly the structure of migration flows and the equilibrium effects. We derive from it two estimating equations that link rural wages, migration, and urban wages via three elasticities: the migration elasticity with respect to wages at home, the migration elasticity with respect to wages at destination and the urban labor demand elasticity.

In the third step of our empirical analysis, we structurally estimate these elasticities. The migration elasticity with respect to wages at destination is positive, large and significant (2.4). The migration elasticity with respect to wages at home is negative, significant and even larger in absolute terms (−5.6), which suggests a home bias among seasonal migrants. The estimated labor demand elasticity is −0.22, but imprecisely estimated. We use these estimates to compute the effect of the program on migration and urban wages. Our calibration implies that migration from program districts decreased by 22%, and migration from nonprogram districts increased by more than 5%, so that difference-in-differences overestimate the effect of the program by 20%. The implied increase in urban wages is small, 0.5%, but may have been as large as 4.1% if the NREGA had been implemented as planned in all "early" districts.

This paper contributes to the literature in three ways. First, we present evidence that local development policies can have substantial spatial equilibrium effects. The spatial equilibrium literature has provided abundant evidence that workers move in response to changes in employment opportunities (Glaeser 2008; Kennan and Walker 2011). However, most empirical studies that evaluate the effect of local development policies (Greenstone et al. 2010; Busso et al. 2013) or local labor demand shocks (Hornbeck 2012; Autor et al. 2013) compare changes in employment and wages between places that are affected by the policy or the shock to those that are not, and rule out the possibility of spatial spillovers. When spillovers are considered, they are assumed to be local: for example, Neumark and Kolko (2010) estimate spillover effects by comparing control units that are just next to treatment units with other control units that are further away. The same applies to the literature on rural development policies (Duflo and Pande 2007; Dinkelman 2011) and rural–urban linkages (Bustos et al. 2016; Santangelo 2016). Three papers closely related to ours are Monras (2018b) and Monras (2018a) who studies the spillover effects of Mexican migration and economic shocks across US labor markets, and Manning and Petrongolo (2017) who show evidence of job search across local labor markets in the United Kingdom. Our contribution is to show empirically that a place-based development policy that increases labor demand locally can have large far-reaching spatial spillover effects.

Second, we present evidence that a commonly used antipoverty policy significantly affects the extent of labor reallocation toward the urban nonagricultural sector. The development economics literature has been concerned with this issue since at least Harris and Todaro (1970), who considered the joint determination of the rural and urban labor markets equilibrium and the urban impact of rural development policies (Fields 2005). The recent literature on structural transformation identifies the lack of labor mobility as an important obstacle to development (Gollin and Rogerson 2014; Kraay and McKenzie 2014; Bryan and Morten 2017). Most empirical studies provide evidence on policies that help rural workers to leave their village: transport subsidies for seasonal migrants in Bangladesh (Bryan et al. 2014), cash-transfer programs for international migrants from Mexico (Angelucci 2015) or rural roads for commuters to local towns in India (Asher and Novosad 2018). We show that by improving alternative employment opportunities in the village, rural public works programs such as the NREGA reduce rural to urban migration.[5] We also estimate the effect of the induced change in migration on the urban sector. Recent papers have shown that rural development policies affect the nonfarm sector through capital, trade or labor flows, but these different channels are typically difficult to identify separately (Marden 2015; Bustos et al. 2016; Santangelo 2016).

Third, we estimate the labor market effects of changes in seasonal migration flows within a developing economy. The migration literature focuses heavily on the impact of international immigration on earnings and employment of natives in developed economies (Card 1990, 2001; Friedberg 2001; Borjas 2003). Some recent papers have estimated the effect of changes in within-country migration, driven by a productivity shock (El Badaoui et al. 2017; Kleemans and Magruder 2018), an inflow of international migrants (Monras 2018b), or the generosity of social programs (Boustan et al. 2010). This second set of studies typically finds larger negative effects on wages, which may be due to the fact that internal migrants are a better substitute to "natives" than international migrants. Most studies consider long-term movements of workers, except Dustmann et al. (2017), who estimate the effect of Czech commuters on German labor markets. We study the movement of workers who are neither commuters nor long-term migrants, but leave their village to spend the agricultural off-season working in urban

5. In a companion paper (Imbert and Papp 2018), we confirm the migration impacts of the NREGA using original survey data from a high-migration area and argue that migrants' decision to stay back for much lower NREGA wages is indicative of large migration costs.

areas. This type of migration is common in developing countries (Banerjee and Duflo 2007; Bryan et al. 2014; Morten 2016). Our contribution is to show that seasonal flows are highly reactive to changes in employment opportunities and can have large effects on labor markets at destination.

The following section describes the workfare program and presents the data set used throughout the paper. Section 3 provides a simple conceptual framework to guide the empirical analysis. Section 4 uses a reduced form approach to estimate the impact of the NREGA on migration from rural areas and on urban labor markets across India. Section 5 adopts a more structural approach to quantify direct and spillover effects of the program. Section 6 concludes.

2. Context and Data

In this section we describe employment provision under the National Rural Employment Guarantee Act. We next present the data we use in the empirical analysis.

2.1. The NREGA

India's National Rural Employment Guarantee Act (NREGA), passed in September 2005, entitles every household in rural India to 100 days of work per year at a state-specific minimum wage. The act was gradually introduced throughout India starting with 200 of the poorest districts in February 2006, extending to 130 additional districts in April 2007, and to the rest of rural India in April 2008. The assignment of districts to phases was partly based on a backwardness index computed by the Planning Commission, using poverty rate, agricultural productivity, agricultural wages, and the share of tribal population as poverty criteria (Planning Commission 2003). In the analysis we will call "early districts" the districts in which the scheme was implemented by April 2007 and "late districts" the rest of rural India.

The available evidence suggests substantial variation in the implementation of the program across states and even districts (Dreze and Khera 2009; Dreze and Oldiges 2009). Figure 1 shows the extent of cross-state variation in public works employment in 1999–2000 (before the NREGA) and 2007–2008 (when the NREGA was implemented in early districts). The graph suggests that the NREGA increased massively public employment in rural areas. It also makes clear that this increase was very uneven across states. As in Imbert and Papp (2015) we use the term "star states" to describe seven states that provided more than 3 days of employment per rural adult in 2007–2008, and were thus responsible for most NREGA employment provision. These states are Andhra Pradesh, Chhattisgarh, Himachal Pradesh, Madhya Pradesh, Rajasthan, Uttarakhand, and Tamil Nadu (see map in Figure 2). Dutta et al. (2012) argue that cross-states differences in NREGA implementation did not reflect underlying demand for NREGA work. States such as Bihar or Uttar Pradesh, which have a large population of rural poor, provided little NREGA employment.

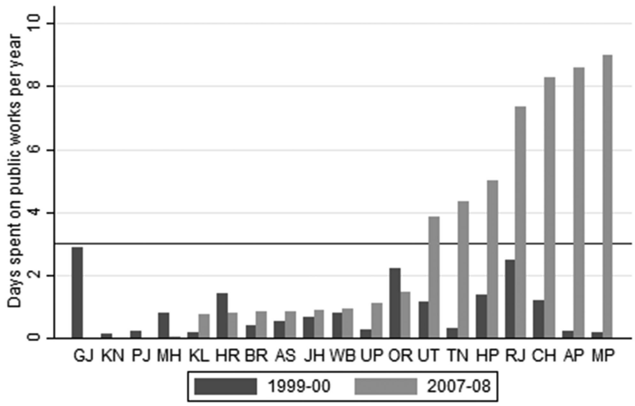

FIGURE 1. Cross-state variation in public employment provision. Source: NSS Employement survey 1999-00 and 2007-2008. Rural adults in early districts only. Star states are states which provide more than three days of employment per adults per year.

FIGURE 2. Map of star states.

Columns (1) and (2) in Table 1 present means of socioeconomic indicators in early districts of star and non-star states.[6] Early districts of star states do not seem to be systematically richer nor poorer than early districts of other states. Poverty rates are

6. Online Appendix B details how we construct these indicators.

TABLE 1. Characteristics of early districts in star and in other states (district controls).

	Star States (1)	Other States (2)	p-value (3)	Source (4)	Time-varying? (5)
Panel A: Controls for rural and urban areas					
Literacy Rate	57%	54%	0.06	2001 Census	No
Fraction Scheduled Castes (SC)	16%	18%	0.16	2001 Census	No
Fraction Scheduled Tribes (ST)	23%	15%	0.00	2001 Census	No
Log Population Density (per km^2)	0.69	1.41	0.00	2001 Census	No
Log Daily Wage for Salaried Labor	4.60	4.60	0.94	NSS 1999–2000	No
Employment Share in Agriculture	57%	43%	0.00	NSS 1999–2000	No
Employment Share in Construction	3%	2%	0.03	NSS 1999–2000	No
Employment Share in Manufacturing	4%	4%	0.83	NSS 1999–2000	No
Employment Share in Services	6%	7%	0.09	NSS 1999–2000	No
Poverty Rate in 2004–2005 (Tendulkar Poverty Line)	42%	46%	0.08	NSS 2004–2005	No
Agricultural Productivity p.c. in 2004–2005	7.81	7.52	0.00	Ag. Ministry	No
Election Year in 2007–2008	44%	16%	0.00	Gov Website	Yes
Alignment State-Central Government (2007–2008)	37%	48%	0.07	Gov Website	Yes
Panel B: Controls for rural areas only					
Fraction of Villages accessed by Paved Road	63%	64%	0.69	2001 Census	No
Fraction of Villages with Bus Service	55%	41%	0.00	2001 Census	No
Fraction of Villages with Education Facility	97%	92%	0.00	2001 Census	No
Fraction of Villages with Medical Facility	58%	46%	0.00	2001 Census	No
Fraction of Villages with Post and Telecom Facility	65%	56%	0.00	2001 Census	No
Fraction of Villages with Bank Facility	19%	17%	0.41	2001 Census	No
Fraction of Villages with Electricity	94%	73%	0.00	2001 Census	No
Irrigated Cultivable Land per Capita (ha)	0.10	0.07	0.00	2001 Census	No
Nonirrigated Cultivable Land per Capita (ha)	0.25	0.18	0.01	2001 Census	No
Cumulative Rainfall (normalized) in 2007–2008	0.10	0.75	0.00	TRMM	Yes
Log p.c. Spending on Rural Roads Program (2007–2008)	2.49	1.52	0.00	Gov Website	Yes
Log p.c. Spending on Watershed Programs (2007–2008)	3.66	1.94	0.00	Gov Website	Yes
Number of District Observations	93	198			
Number of Individual Observations (rural only)	34,409	84,900			

Notes: This table presents means of the controls used in the paper. Only rural areas of early phase districts are used. Column (1) restricts the sample to early districts of star states. Star states include Andhra Pradesh, Chhattisgarh, Himachal Pradesh, Madhya Pradesh, Tamil Nadu, Rajasthan, and Uttarkhand. Column (2) includes early districts in non-star states. Column (3) presents the p-values of the Student's t-test of equality of means in columns (1) and (2). The details of the construction of each control are given in Online Appendix B. For the Student's t-test in column (3) standard errors are computed assuming correlation of individual observations over time within each district.

lower in star states and literacy rates are higher, but population shares of scheduled caste are the same, and shares of scheduled tribes are higher. Early districts in star states have a larger fraction of the labor force in agriculture, and a higher agricultural productivity per worker, but the employment shares of manufacturing and services and wages for salaried labor are the same. Finally, they have similar access to paved roads and to banks, but better access to electricity, education, health and telecommunication facilities (according to 2001 census data). They also spend more per capita under the national rural road program (PMGSY) and under national watershed programs in 2007–2008, which suggests that they may be more effective in implementing public infrastructure programs.

An important question is whether differences in economic conditions or public service delivery can explain differences in public employment provision under the

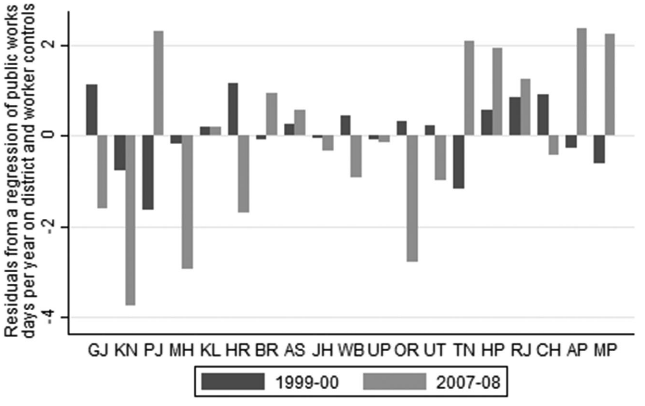

FIGURE 3. Unexplained cross-state variation in public employment provision. Source: NSS Employement survey 1999–00 and 2007–2008. Rural adults in early districts only. We compute state level average difference between observed and predicte public employment. Predictions are obtained by regressing public work days on district and workers and controls. District control are listed in table 1.

NREGA between star and non-star states. Figure 3 plots for each state the average residual from a regression of the fraction of time spent on public works by prime age adults on the whole list of district characteristics presented in Table 1 as well as worker controls.[7] The ranking of states in terms of public employment provision remains strikingly similar to Figure 1.[8] This provides support to the idea that differences in NREGA implementation are not mainly driven by differences in economic conditions or public service delivery, which could have independent effects on rural labor market outcomes and migration to urban areas.

Public employment provision is also highly seasonal. Local governments start and stop works throughout the year, with most works concentrated during the first two quarters of the year prior to the monsoon. The monsoon rains make construction projects difficult to undertake. Field reports further document government attempts to keep work-sites closed throughout the fall so they do not compete with the labor needs of farmers (Association for Indian Development 2009). According to the National Sample Survey 2007–2008, the average number of days spent on public works per rural adult was above one day during the first and second quarter of the year (January to June), and about a quarter of a day during the third and fourth quarter (July to December). This implies that public employment provision under the NREGA is highest during the agricultural lean season, when short-term migration is most prevalent (Coffey et al. 2015; Imbert and Papp 2018).

7. Worker controls include dummy variables for gender, age group, religion, caste group, education level, and marital status.

8. A notable exception is rural Punjab (PJ), which is much richer than the average rural Indian district. Punjab provides very little employment on public works, but given its high level of development it would be predicted to provide even less of it, hence the positive residual.

Work under the act is short-term, often on the order of a few weeks per adult. According to the National Sample Survey 2009–2010, participating households report a mean of only 37 days of work for *all* members of the household during that year, which is well below the guaranteed 100 days. Although this underutilization of the employment guarantee could also reflect low demand, work under the program is in fact rationed (Dutta et al. 2012). A World Bank report notes that "workers tend to wait passively to be recruited rather than actively applying for work" (The World Bank 2011). During the agricultural year 2009–2010, 45% of Indian households wanted work under the act but only 25% of Indian households benefited from the program. Despite rationing, the NREGA is well targeted toward poorer households (Dutta et al. 2014). In 2009–2010, 42% of Scheduled Tribes and 34% of Scheduled Caste households benefited from the program, against 15% for general caste households.[9] Because of its timing and its targeting, the NREGA may offer an alternative to seasonal migration, which is a common income smoothing strategy for poor households in India (Ashish and Bhatia 2009; Morten 2016).

2.2. Data

The main obstacle to studying migration is the scarcity of reliable data. The migration literature traditionally focuses on long-term migrants, who appear in population censuses. Studying short-term migration is more challenging, as it requires dedicated data collection efforts, which are often targeted to particular rural areas known to have high levels of seasonal migration (Bryan et al. 2014; Imbert and Papp 2018). Our primary source of information is the Employment and Unemployment Survey carried out by the National Sample Survey Organisation (here on, "NSS Employment Survey"). The NSS Employment Survey is a nationally representative household survey, which collects information on employment and wages in urban and rural areas, with one specialized module whose focus changes from round to round. For the purpose of our analysis, we use the 1999–2000, 2004–2005, 2007–2008, and 2011–2012 rounds, of which only the 1999–2000 and 2007–2008 rounds include questions on the migration history of each household member. NSS surveys are conducted from July to June and are implemented in each district throughout the year (National Sample Survey Office 2012).

Our analysis is at the individual level but the identifying variation is at the district-level.[10] The NSS Employment survey sample is stratified by urban and rural areas of each district. Our sample includes 504 districts that represent 97.5% of the population of India. It includes the twenty largest states of India, excluding Jammu and Kashmir. We exclude Jammu and Kashmir since survey data is missing for some quarters due to conflicts in the area. The NSSO oversamples some types of households and therefore

9. Author's calculations based on NSS Employment-Unemployment Survey (June 2009–July 2010).

10. Districts are administrative units within states. The median district in our sample had a rural population of 1.37 million in 2008 and an area of 1600 square miles (about 4100 km^2).

provides sampling weights. All statistics and estimates computed using the NSS data are adjusted using these sampling weights.[11] Finally, the NSSO interviews the same number of households in each strata during each quarter, so that the NSS Employment survey is representative of district outcomes for the whole year.[12]

2.2.1. Short-Term Migration. In order to measure short-term migration, we use NSS Employment surveys 1999–2000 and 2007–2008, which are the only two recent rounds that include a migration module. For each household member, NSS 2007–2008 asks whether each household member has spent between *one* and six months away from the village for work within the past year. We consider as short-term migrant anybody who answered yes to this question. The questionnaire is less straightforward in NSS 1999–2000. First, each household member is asked whether she stayed in the village for the last six months or more. If she answered positively, she is then asked whether she spent *two* to six months away from the village for work within the past year. We define as short-term migrant anybody who answered either negatively to the first question or positively to the second, excluding people who have moved into the household over the last six months (who changed their "usual place of residence").

The definition of short-term migration in NSS 1999–2000 is more restrictive than in NSS 1999–2000: trips shorter than two months that happened more than six months before the survey would not be counted. For this reason, one would expect 2007–2008 data to report higher levels of short-term migration than 1999–2000, even if migration patterns had not changed between the two periods.[13] Indeed, the percentages of short-term migrants among rural prime age adult is 2.6% in 1999–2000 and 2.8% 2007–2008.[14] National averages mask a considerable amount of spatial heterogeneity. Figure 4 draws the map of short-term out-migration across rural Indian districts. Short-term migration is not widespread, with most districts having out-migration rates lower than 1%. It is highly concentrated in poorer districts of the North-East (Bihar, Uttar Pradesh) and the West (Gujarat and Rajasthan), which report migration rates above 5%.

As discussed previously, NSS surveys are designed to have uniform coverage throughout the year. If in practice the timing of the survey was not uniform, and if reported seasonal migration varied during the survey year, then our measures of seasonal migration may be biased.[15] Online Appendix Figure A.1 suggests that

11. See National Sample Survey Organisation (2008) and Online Appendix B for details on the construction of sampling weights.

12. Since the quarterly samples are not randomly drawn, the NSS survey is not strictly speaking representative at the district × quarter level.

13. In their survey from Western India, Coffey et al. (2015) find 32% of adults were away from one to six months in the last 12 months and 23% were away for two to six months.

14. Authors calculation based on NSS Employment Surveys 1999–2000 and 2007–2008.

15. Since seasonal migration fluctuates from year to year (e.g., depending on the monsoon), reported seasonal migration may vary within a survey year because the reporting window (last 12 months) shifts.

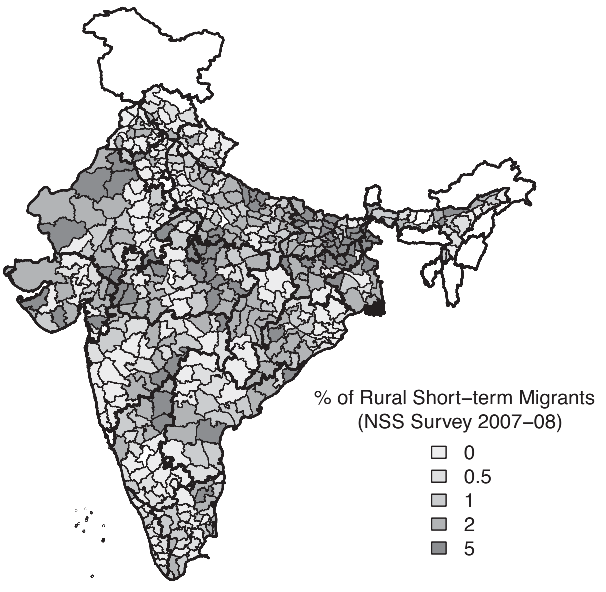

FIGURE 4. Map of seasonal migration rates across rural districts.

survey coverage in rural areas was perfectly uniform in NSS 2004–2005 and 2007–2008, but did fluctuate slightly across quarters in NSS 1999–2000, with a larger population covered in other states between July and September and in star states between April and June. Online Appendix Figure A.2 shows that reported seasonal migration declined throughout the survey year in NSS 1999–2000, and was mostly stable in NSS 2007–2008. Hence the differential coverage we observed in NSS 1999–2000 should lead us to overestimate short-term migration in other states and underestimate it in star states. Since our empirical strategy (see in what follows) compares changes in migration between the two survey years in star versus non-star states, the combination of these artifacts should lead us to underestimate the relative drop in migration in star states, which would go against us finding the effect we document.

Table 2 presents descriptive information about the migrants themselves. According to NSS 1999–2000 and 2007–2008 data, short-term migrants are mostly male. They also are younger than the average rural adult, but despite rising educational attainment in rural India have lower literacy rates. They are more likely to report doing casual (i.e., manual, unskilled) labor as their primary or secondary occupation. Finally, they are much more likely to belong to Scheduled Tribes, and come from poorer households.

NSS 1999–2000 has no information on migration trips, but NSS 2007–2008 does record the number of trips, the destination during the longest spell, and the industry in which they worked. The destination is coded in seven categories: same district (rural or urban), other district in the same state (rural or urban), another state (rural or urban),

TABLE 2. Short-term migration patterns.

	Year 1999–2000		Year 2007–2008	
	All	Migrants	All	Migrants
Short-term migrant?	2.77%	100%	3.52%	100%
Female	50%	36%	50%	13%
Age 18–30	63%	67%	52%	54%
Age 31–40	11%	10%	15%	18%
Illiterate	41%	49%	39%	53%
Primary education or below	25%	25%	24%	26%
Casual work as primary or secondary occupation	23%	21%	21%	24%
Scheduled Caste	14%	27%	14%	22%
Scheduled Tribe	33%	55%	30%	74%
Log deflated household monthly p.c. expenditure	3.14	3.07	4.93	4.77
Number of migration spells	–	–	–	2.22
Destination is in same district	–	–	–	13%
Destination is in another district of the same state	–	–	–	34%
Destination is in another state	–	–	–	52%
Destination is urban	–	–	–	72%
Worked in agriculture	–	–	–	20%
Worked in manufacturing and mining	–	–	–	18%
Worked in construction	–	–	–	46%
Worked in other sector (including services)	–	–	–	15%
Observations	131,920	3,763	119,309	10,311

Notes: The sample is composed of rural prime-age adults of early phase districts. Each statistic is computed using sampling weights. Source: NSS Employment-Unemployment Survey Round 55 and 64.

and another country. Seventy-two percent of rural short-term migrants go to urban areas, and 64% work in construction or manufacturing. Importantly, 87% migrate to another district and 52% to another state, which would often imply travelling long distances.[16]

2.2.2. Employment and Wages. We further use NSS Employment Surveys to construct measures of employment and wages at origin and destination. The NSS Employment Survey includes detailed questions about the daily activities of all persons over the age of four in surveyed households for the past seven days. We restrict the sample to persons aged 14–69. We then compute for each person the percentage of days in the past seven days spent in each of six mutually exclusive activities: public works, casual wage work, salaried wage work, self-employment, unemployment, and out of the labor force. The NSSO makes the distinction between two types of wage work depending on the duration and formality of the relationship with the employer:

16. Highly subsidized train fares are instrumental in getting poor workers from remote rural areas to seasonal jobs in urban centers. By contrast, rural workers who live close to a town may be able to commute by road (Asher and Novosad 2018).

salaried work is long-term and often involves a formal contract, and casual work is temporary and informal. In our analysis, we will focus on casual work, which is the dominant form of employment for short-term migrants from rural areas. We compute average earnings per day worked in casual labor (the "casual wage") and in salaried work (the "salaried wage"). Finally, in order to estimate the total number of workers engaged in casual work in each district we use the NSSO question on the occupation of each household member in the last year and categorize as "casual worker" every household member who reports casual work as her principal or subsidiary occupation.

Estimated wage levels may be biased if the timing of the NSS survey was not uniform and wages varied during the year. Online Appendix Figure A.4 shows that unlike rural areas, NSS survey coverage in urban areas did vary across quarters even in 2004–2005 and 2007–2008. There were also differences across states, with a higher coverage in the January–March period in 2004–2005 for other states and in 2007–2008 for star states. As Online Appendix Figure A.3, real wages increase throughout the survey year. Hence the increase in wages in cities of star states relative to other states may be underestimated, which will likely play against our finding that the NREGA increased urban wages.[17]

3. Model

In this section, we provide a conceptual framework to guide our empirical strategy. First, we outline a model of migration from rural areas to urban areas. Second, we consider the urban labor market equilibrium, and the effect of a change in migration from rural areas. Third, we analyze the effect of a public works program that increases the value of staying at home in some rural areas on urban labor markets. Finally, we derive the main estimating equations that we use in our empirical analysis.

3.1. Location Choice

Let us consider a rural worker i who supplies inelastically one unit of labor in a location j, which is either home r or an urban destination u from a discrete set $u \in \{1, ..., U\}$. The value of being in j is

$$v_{ij} = V_{rj}\varepsilon_{ij} = A_j w_j \tau_{rj} \varepsilon_{ij},$$

where A_j denotes amenities of location j, w_j the wage, τ_{rj} iceberg costs of migration (we assume $\tau_{rr} = 1$) and ε_{ij} an individual and location specific utility term. We assume

17. Our strategy does not strictly compare urban wages trends in star versus other states (see in what follows).

that the idiosyncratic utility terms ε are drawn from a generalized extreme value distribution:

$$F(\varepsilon_{ir}, \varepsilon_{i1}, \ldots, \varepsilon_{iU}) = \exp\left\{-\left[\varepsilon_{ir}^{-\theta_r} + \sum_{u=1}^{U} \varepsilon_{iu}^{-\theta_u}\right]\right\},$$

where θ_u and θ_r are dispersion parameters. Migrants are more sensitive to changes in conditions at home than at destination ("home biased" preferences) if $\theta_r > \theta_u$.[18] The probability p_r^u of migrating from r to a particular urban destination $u \in \{1, \ldots, U\}$ is

$$p_r^u = \frac{V_{ru}^{\theta_u}}{V_{rr}^{\theta_r} + \sum_{j=1}^{U} V_{rj}^{\theta_u}}.$$

Let N_r denote the population in rural origin r and M_{ru} the number of migrants from r to u. p_r^u is also the fraction of people who migrate from r to u so that

$$M_{ru} = p_r^u N_r.$$

Taking logs yields

$$\ln(M_{ru}) = \theta_u \ln(V_{ru}) - \ln\left[V_{rr}^{\theta_r} + \sum_{j=1}^{U} V_{rj}^{\theta_u}\right] + \ln(N_r). \tag{1}$$

We can use 1 to compute μ_{ru}^r, the elasticity of migration w.r.t. the home wage, μ_{ru}^u, the elasticity of migration w.r.t. the destination wage, and $\mu_{ru}^{u'}$ the elasticity of migration from r to u w.r.t. the wage in another urban destination ú (see Online Appendix A):

$$\mu_{ru}^r = -\theta_r p_r^r \quad , \quad \mu_{ru}^u = \theta_u - \theta_u p_r^u, \quad \text{and} \quad \mu_{ru}^{u'} = -\theta_u p_r^{u'}. \tag{2}$$

3.2. Urban Labor Market Equilibrium

Let us now consider urban areas. We assume that urban workers do not migrate to work and inelastically supply N_u days of work.[19] Let D_u denote labor demand in urban areas and M_u denote the labor supply of rural migrants. Assuming that urban labor markets are competitive and that residents and short-term migrants are perfect substitutes, the urban wage w_u clears the market:[20]

$$D_u = N_u + \sum_{r=1}^{R} M_{ru}.$$

18. This formulation is equivalent to a nested logit structure in which the upper nest is the decision of relocating and the lower nest the choice of destination as in Monras (2018a). Monras (2018a) demonstrates that the nested model is itself equivalent to a logit model with a fixed cost to relocating.

19. According to NSS Employment Survey 2007–2008, only 0.5% of urban adults were seasonal migrants.

20. According to NSS Employment Survey 2007–2008, only 3.9% of urban male adults were unemployed.

Let us consider the effect of an exogenous change in migration inflow from a rural origin r. To simplify notation, let $\alpha_u^r = M_{ru}/N_u$ denote the ratio of labor supply from rural migrants divided by the labor supply of urban workers. The higher α_u^r, the more the urban center relies on migrant labor from r to satisfy its demand for labor. Let ε denote the labor demand elasticity, which we assume constant across urban areas. One can express η_u^r, the elasticity of the urban wage with respect to migration from r, as a function of α_u^r and ε:

$$\eta_u^r = \frac{\partial \ln(w_u)}{\partial \ln(M_{ru})} = \frac{\partial \ln(w_u)}{\partial \ln(D_u)} \times \frac{\partial \ln(D_u)}{\partial \ln(M_{ru})} = \frac{1}{\varepsilon} \times \frac{\alpha_u^r}{\left(1 + \sum_{i=1}^{R} \alpha_u^i\right)}. \tag{3}$$

If the labor demand elasticity is negative, the elasticity of the urban wage with respect to migration is itself negative, that is, a decrease in migration from rural areas will increase urban wages. The elasticity of urban wages with respect to migration from r is decreasing in α_u^r, that is, the more an urban area relies on migrant labor from a rural area r, the more sensitive the wage will be to changes in migration inflows coming from r.

A simple calibration exercise may give an idea of the magnitudes. As numerator, we can use the estimated number of rural short-term migrants who worked in urban areas in 2007–2008, which is 8 million. As denominator, we can use the number of urban adults who declared doing casual labor as a primary or secondary occupation, which is 14.4 million. But we also need to account the fact that seasonal migrants only work in urban areas for part of the year. According to ARIS/REDS 2006 data, seasonal migrants who were away from one to six months during the last year spent on average 104 days at destination. Urban residents who did casual wage work as principal or secondary occupation supplied on average 265 days of work per year (NSS 2007–2008). This implies $\alpha_u^r \approx 0.22$ for urban India.[21] Let us now assume that the labor demand elasticity is -0.3. Then for $\alpha_u^r = 0.22$ the elasticity of urban wages w.r.t. changes in short-term migration from rural areas is -0.60, which is large, but in the same ballpark as other papers on internal migration in developing countries (El Badaoui et al. 2017; Kleemans and Magruder 2018). By contrast, in 2007–2008 the number of rural adults who declared doing casual labor as a primary or secondary occupation was 119 million, so that the elasticity of the rural wage w.r.t. changes in short-term migration to urban areas is small (-0.10). The elasticity of the rural wages to rural-to-rural short-term migration (only 28% of the flows) is even smaller (-0.5). One would hence expect small changes in seasonal migration to have large effects on urban wages and little effect on rural wages. This is why this paper focuses on rural-to-urban migration and on the urban labor market equilibrium.

21. Including casual work days by other urban residents, for example, self-employed or salaried workers, does not change this result. The probability that they did any casual work in a given week was lower than 0.1%.

3.3. *Effect of the Program*

We now consider the equilibrium effects of a public works program that is implemented in some rural areas $r \in R_1$ but not implemented in other rural areas $r \in R_2$. Consistent with the empirical evidence, we assume that the program increases labor earnings in rural areas R_1 (Imbert and Papp 2015).[22] We also assume that it has no direct effect on urban areas or untreated rural areas R_2. We use the subscript $i \in \{1, \ldots, R\}$ to denote rural areas and $j \in \{1, \ldots, U\}$ to denote urban areas. To simplify notation we denote by M_r total migration from r $\left(\text{i.e., } M_r = \sum_{j=1}^{U} M_{ru}\right)$ and by α_u the ratio of all migrants to residents in u (i.e., $\alpha_u = \sum_{i=1}^{R} \alpha_u^i$). In Online Appendix A.3 we show that the program effect on rural-to-urban migration and urban wages is

$$\frac{dM_r}{M_r} = \begin{cases} -\theta_r p_r^r \dfrac{dw_r}{w_r} + \theta_u \dfrac{p_r^r}{1-p_r^r} \displaystyle\sum_{j=1}^{U} p_r^j \dfrac{dw_j}{w_j} & \text{if } r \in R_1 \quad (4) \\ \theta_u \dfrac{p_r^r}{1-p_r^r} \displaystyle\sum_{j=1}^{U} p_r^j \dfrac{dw_j}{w_j} & \text{if } r \in R_2 \quad (5) \end{cases}$$

$$\frac{dw_u}{w_u} = \sum_{i \in R_1} \frac{\theta_r \alpha_u^i}{\theta_u \alpha_u - \varepsilon(1+\alpha_u)} p_r^r \frac{dw_r}{w_r} + \sum_{i=1}^{R} \frac{\theta_u \alpha_u^i}{\theta_u \alpha_u - \varepsilon(1+\alpha_u)} \sum_{j=1}^{U} p_r^j \frac{dw_j}{w_j}. \tag{6}$$

The program effect can be decomposed in the following sequence. First, an increase in wages in rural areas R_1 reduces migration from rural areas R_1 (first term on the right hand side of equation (4)). Second, the decrease in migration inflow increases urban wages (first term on the right hand side of equation (6)). Third, the rise in urban wages attracts more migrants from rural areas R_2 (equation (5)), and mitigates the drop in migration from rural areas R_1 (second term on the right hand side of equation (4)). Fourth, the migration response itself mitigates the rise in urban wages ($\theta_u \alpha_u$ in the denominators of equation (6)). However, since urban areas are competing for migrants, the fact that urban wages rise overall decreases migration to a particular destination, which increases urban wages further (second term on the right hand side of equation (6)).

The unique objective of this model is to guide the empirical strategy to estimate urban spillover effects, which we develop in the next sections. It does not explain why the program increases rural wages (see Imbert and Papp 2015). It does not cover all possible ways in which the program may affect migration either: for example, an employment guarantee may substitute for temporary migration as a risk coping strategy (Morten 2016). Finally, the model is not suited for a welfare analysis of the

22. The NREGA increases the value of working in rural areas in two ways, by providing employment at a wage higher than the prevailing wage, and by raising private sector wages (Imbert and Papp 2015).

employment guarantee. It does not factor in the value of rural public works as compared to the value of the urban private employment they displace. It also does not take into account the cost of migration for seasonal migrants who decide to stay at home and to forgo much higher wages in the city (Imbert and Papp 2018).

3.4. Empirical Strategy

For simplicity, let us assume that there are only two rural areas $r \in \{r_1, r_2\}$, such that the program is implemented in r_1 and not in r_2, and two urban areas $u \in \{u_1, u_2\}$, such that u_1 is closer to r_1 than to r_2 and u_2 is further away from r_1 than from r_2. The standard approach to estimating empirically the program effect on migration from rural areas would be to compare changes in migration from rural areas with the program and rural areas without the program.[23] In the context of our model, this means comparing M_{r_1} and M_{r_2}. In Online Appendix A.4 we show that this difference-in-differences estimate is

$$\frac{dM_{r_1}}{M_{r_1}} - \frac{dM_{r_2}}{M_{r_2}} = \underbrace{-\theta_r p_{r_1}^{r_1} \frac{dw_{r_1}}{w_{r_1}}}_{\text{Direct Effect}} + \underbrace{\theta_u \sum_{j=1,2} \left(\frac{p_{r_1}^{u_j} p_{r_1}^{r_1}}{1 - p_{r_1}^{r_1}} - \frac{p_{r_2}^{u_j} p_{r_2}^{r_2}}{1 - p_{r_2}^{r_2}} \right) \frac{dw_{u_j}}{w_{u_j}}}_{\text{Urban Wage Effects}} \quad (7)$$

equation (7) makes it clear that, in the presence of spatial spillovers, difference-in-differences will not in general identify the direct effect of the program on migration via an increase in rural wages, but will also pick up changes in migration due to urban wage effects. An important exception is if rural areas 1 and 2 have the same migration patterns at baseline, which may be the case if they are randomly selected. In our case however, as in most evaluations of place-based policies, areas with and without the program are not equally distributed across space. In that case the difference-in-differences estimate will be higher or lower than the direct effect, depending on the specific migration patterns between rural areas with and without the program and urban areas.

Studies that are interested in spillover effects of rural policies or productivity shocks on urban areas typically compare cities that are close to treated areas with cities that are close to control areas.[24] In the context of our model (see Online Appendix A.4), this approach consists in comparing changes in wages

23. This is the approach usually followed to identify the effect of place-based policies (Greenstone et al. 2010; Dinkelman 2011) or local labor demand shocks (Hornbeck 2012; Autor et al. 2013). We followed it ourselves to estimate the rural wage effects of the NREGA (Imbert and Papp 2015).

24. This is how, for example, Bustos et al. (2016) estimate the effect of agriculture productivity gains on industry growth and Santangelo (2016) estimate the effect of the NREGA on manufacturing firms.

in u_1 with changes in wages in u_2:

$$\frac{dw_{u_1}}{w_{u_1}} - \frac{dw_{u_2}}{w_{u_2}} = \left(\frac{\alpha_{u_1}^{r_1}}{\theta_u \alpha_{u_1} - \varepsilon(1+\alpha_{u_1})} - \frac{\alpha_{u_2}^{r_1}}{\theta_u \alpha_{u_2} - \varepsilon(1+\alpha_{u_2})} \right) \times \left[\theta_r p_{r_1}^{r_1} \frac{dw_{r_1}}{w_{r_1}} + \theta_u \sum_{j=1}^{U} p_{r_1}^{u_j} \frac{dw_{u_j}}{w_{u_j}} \right] + \left(\frac{\alpha_{u_1}^{r_2}}{\theta_u \alpha_{u_1} - \varepsilon(1+\alpha_{u_1})} - \frac{\alpha_{u_2}^{r_2}}{\theta_u \alpha_{u_2} - \varepsilon(1+\alpha_{u_2})} \right) \theta_u \sum_{j=1}^{U} p_{r_2}^{u_j} \frac{dw_{u_j}}{w_{u_j}}. \tag{8}$$

This equation makes it clear that difference-in-differences will not in general identify the effect of the program on urban area u_1 through a change in migration from rural area r_1, because all rural and all urban areas may be affected by the program. One exception is if spatial spillovers remain strictly local, for example, if rural area r_1 and urban area u_1 are so close to each other, and both so far from rural area r_2 and urban area u_2, that no migrant from r_1 goes to u_2 and no migrant from r_2 goes to u_1. Then changes in migration from r_1 only impact u_1, leaving wages in u_2 and migration in r_2 unchanged. In that case one can identify urban spillovers by comparing wage changes in u_1 and u_2 (see Online Appendix A.5 for more detail). In our context however, migration is not local: only 13% or seasonal migrants remain in the same district. Hence the difference-in-differences estimates commonly used in the literature will be biased and will not yield the magnitude of the program effects. They will be indicative of the sign of these effects as long as the direct effect from rising rural wages is first order relative to urban wage effects.

In the empirical part of this paper, we first compare changes in migration rates from rural areas with the program to changes in migration from rural areas without the program, which is the reduced form equivalent of equation (7). Second, we compare changes in wages in urban areas that rely more or less on migration from rural areas with and without the NREGA, which is the reduced form equivalent of comparing urban areas with high and low $\alpha_u^{r_1}$ and $\alpha_u^{r_2}$ in equation (8). Specifically, we predict migration flows based on a gravity model derived from equation (1) and baseline characteristics, and use these predicted values to estimate equation (8). Finally, we use a structural estimation based on equations (4)–(6) to recover the underlying parameters θ and ε. This allows us to compute the direct and spillover effects of the program on migration and urban wages, and to simulate its effect if it had been implemented uniformly across rural areas r_1 and r_2.

4. Difference-in-Differences

This section provides reduced form evidence on the spatial spill-over effects of the NREGA in three steps. First, we compare changes in migration from rural areas with and without the program. Second, we predict migration from each rural district to each city using a gravity model of migration flows. Third, we compare changes in unskilled wages in urban areas that attract more or fewer migrants from rural areas with and without the program.

4.1. Program Effect on Migration

4.1.1. Empirical Strategy. In order to estimate the impact of the program on migration and labor markets, we use variation in NREGA implementation documented in Section 2. When the NSS Employment survey was carried out between July 2007 and June 2008, NREGA was supposed to be implemented in 291 early districts.[25] However, as discussed in Section 2, the quality of NREGA implementation varied across states, with seven "star states" providing most of NREGA employment. Our empirical strategy builds on these observations and estimates the impact of the program by comparing changes in employment and migration between 1999–2000 and 2007–2008 in early districts of star states with other early districts.[26] Our outcomes of interest are the number of days spent on public works per year, the daily wage for casual work, and the fraction of adults who have done short-term migration trips during the past year.

We implement a difference-in-differences strategy that compares changes in rural outcomes in early districts of star states with changes in other early districts. Let Y_{irt} be the outcome for individual i in rural district of origin r in year t. Let $Star_r$ be a binary variable equal to one for early districts of star states. Let $Post_t$ be a dummy variable equal to one after 2007, once the program is implemented in early districts. Let $\boldsymbol{Z}_r$ denote a vector of district characteristics that do not vary with time, $\boldsymbol{X}_{rt}$ a vector of district characteristics that do vary with time. District controls are listed in Table 1. Let $\boldsymbol{H}_i$ be a vector of individual characteristics, including dummies for gender, education levels, caste, religion, and age ranges. Let η_t and μ_r denote time and district fixed effects, respectively. We use data from NSS 1999–2000 and 2007–2008 and estimate the following equation:

$$Y_{irt} = \beta Star_r \times Post_t + \delta \boldsymbol{Z}_r \times Post_t + \gamma \boldsymbol{X}_{rt} + \alpha \boldsymbol{H}_i + \eta_t + \mu_r + \varepsilon_{irt}. \quad (9)$$

25. The NREGA was extended to late districts on April 1, 2008. We do not include late districts in our analysis or rural outcomes. These districts have 18% higher casual wages and 40% lower short-term out-migration rates, they are hence less comparable to early districts.

26. Our empirical strategy is different from the one we used in Imbert and Papp (2015), in which we compare early and late phase districts. This is due to the fact that late phase districts have much lower seasonal migration rates (about 0.82%), and can hence not be used as a comparison group.

The main identifying assumption is that, absent NREGA, early phase districts of star states would have experienced the same trends in outcomes as early phase districts of other states. The three upper panels of Online Appendix Figure A.6 show trends in our main outcomes. Public employment did increase somewhat more in Star States between 1999–2000 and 2004–2005. This reflects the implementation of the National Food For Work Program (FWP), a precursor of the NREGA, in November 2004.[27] There is still however a steep increase in public employment provision when the NREGA was implemented. Reassuringly, there is no evidence of differential wage trends before the NREGA was implemented. Due to the lack of migration information in NSS 2004–2005 and 2011–2012, we cannot show pre-program trends in short-term migration. There is however a clear reversal between migration levels in star and non-star states between 1999–2000 and 2007–2008.

To further probe the validity of the common trends assumption, we provide two statistical tests. First, we test whether early districts in star and non-star states had different levels of outcomes before the program was implemented, and expect to find no significant differences between early districts of star states and non-star states. Using data from NSS 1999–2000, we estimate the following equation:

$$Y_{irt} = \beta Star_r + \delta \boldsymbol{Z}_r + \gamma \boldsymbol{X}_{rt} + \alpha \boldsymbol{H}_i + \varepsilon_{irt}. \tag{10}$$

Second, we test whether early districts in star and non-star states had different trends in outcomes before and after the program was implemented. For the preperiod, we redefine $Post_t$ is a dummy variable that equals to one after 2004 and estimate equation (9) using data from NSS 1999–2000 and 2004–2005. For the post-period, we redefine $Post_t$ as a dummy variable that equals to one after 2011 and estimate equation (9) using data from NSS 2007–2008 and 2011–2012. We would expect no differential trends in outcomes between early districts of star and non-star states.[28]

4.1.2. Results. Estimates of the program's impact on public employment are presented in panel A in Table 3. In 1999–2000, there are virtually no rural public works in early districts of non-star states: rural adults spend 0.7 days on public works per year on average. Between 1999–2000 and 2007–2008, public employment increased by 7.2 days more in early districts of star states than in early districts of non-star states (column (1)). When we include controls, the coefficient increases slightly to 7.4 days per adult per year (column (2)). By contrast, we find no significant differences in employment provision between early districts of star and non-star states in 1999–2000, seven years before the NREGA was implemented (column (3)). Due to the

27. Due to logistical issues, however, employment provision under the FWP was much lower than under the NREGA and the program was discontinued (Dreze 2005).

28. In Online Appendix Table A.6, we show that our results are also robust to excluding the last quarter of NSS 2007–2008 (April to June 2008), when the NREGA was rolled out everywhere.

TABLE 3. Impact of the NREGA on rural wages and migration to urban areas.

	1999–2000 2007–2008 (1)	1999–2000 2007–2008 (2)	1999–2000 (3)	1999–2000 2004–2005 (4)	2007–2008 2011–2012 (5)
Panel A: Public Employment					
Star State × Post	7.175***	7.438***		1.275**	− 1.907
	(1.483)	(1.426)		(0.498)	(1.778)
Star State			− 0.568		
			(0.540)		
Mean in non-Star States (1999–2000)	0.73	0.73	0.73	0.73	0.82
Observations	251,229	251,229	131,920	248,975	206,025
Panel B: Log Casual Wages					
Star State × Post	0.0569**	0.0551*		0.0108	0.0107
	(0.0286)	(0.0319)		(0.0324)	(0.0234)
Star State			0.0386		
			(0.0296)		
Mean in non-Star States (1999–2000)	2.38	2.38	2.38	2.38	2.38
Observations	52,652	52,652	27,237	44,553	36,986
Panel C: Short-term Migration					
Star State × Post	− 1.679***	− 1.790**			
	(0.559)	(0.900)			
Star State			1.061		
			(0.736)		
Mean in non-Star States (1999–2000)	2.53	2.53	2.53		
Observations	251,229	251,229	131,920		
Workers Controls	No	Yes	Yes	Yes	Yes
District Controls	No	Yes	Yes	Yes	Yes
District Fixed Effect	Yes	Yes	No	Yes	Yes

Notes: The sample is composed of rural adults from early phase districts surveyed in NSS: (i) from July 1999 to June 2000 and July 2007 to June 2008 (columns (1) and (2)), (ii) from July 1999 to June 2000 (column (3)), (iii) from July 1999 to June 2000 and July 2004 to June 2005 (column (4)), (iv) from July 2007 to June 2008 and from July 2011 to June 2012 (column (5)). The unit of observation is a rural adult. Each column presents results from a separate regression. All specifications include quarter fixed effects. In panel A the outcome is the estimated number of days spent on public works per adult per year. In panel B the outcome is log deflated daily wages for casual labor. In panel C the outcome is a binary variable that is equal to 100 if workers have spent one to six months away from the village to work during the last year and zero otherwise. Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu, and Uttarkhand. Worker controls include a set of dummy variable for age group, gender, education level, social group, and religion. District controls are presented in Table 1. In columns (1) and (2) Post is a time dummy equal to one for the period 2007–2008. In column (4) post is a time dummy equal to one for the period 2004–2005. In column (5) post is a time dummy equal to one for the period 2011–2012. Standard errors are clustered at the district level. *Significant at 10%; **significant at 5%; ***significant at 1%.

FWWP program we mentioned previously, we do find a small increase (1.3 days per adult per year) in public employment provision in early districts of star as compared to non-star states between 1999–2000 and 2004–2005 (column (4)). Finally, we estimate equation (9) using data from 2007–2008 and 2011–2012, and find no differential change in employment on rural public works after the initial roll-out (column (5)). These results confirm that the NREGA expanded dramatically employment on rural public works in early districts of the seven star states between 2004–2005 and 2007–2008 (see Section 2.1). This is where we expect to find an impact on rural wages and short-term migration.

Estimates of the program impact on rural wages for casual labor are presented in panel B in Table 3. Estimates in column (1) show that between 1999–2000 and 2007–2008, wages for unskilled, manual labor increased by 5.7% in early districts of star states, as compared to early districts of non-star states. The coefficient retains significance and remains virtually unchanged when we control for heterogeneity among workers and differences in district characteristics, which shows that the increase in rural wages is not driven by the selection of districts into the program (column (2)). Column (3) shows that wage levels were the same in star states in 1999–2000, and column (4) shows that there was no difference in wage trends between star and non-star states between 1999–2000 and 2004–2005, before the NREGA was implemented. Finally, we find no difference in wage trends between early phase districts of star and non-star states between 2007–2008 and 2011–2012, that is, after the NREGA was rolled out (column (5)). Taken together, these results provide solid evidence that the NREGA increased private sector wages in rural areas, which we also found in previous work (Imbert and Papp 2015).

Finally, panel C in Table 3 presents estimates of the program impact on short-term migration. Columns (1) and (2) show that between 1999–2000 and 2007–2008, short-term migration decreased in early districts of star states, as compared to other early districts. Once again, the inclusion of individual and district controls hardly changes the magnitude of the coefficient, if anything the estimated negative effect of the NREGA on seasonal migration becomes larger. The coefficients correspond to a 1.7 to 1.8 percentage point decrease in the probability of migrating, which is a large decrease (about 50%) in the prevalence of seasonal migration in early districts of star states (3.6% in 1999–2000). Column (3) presents estimates of equation (10) using data from July 1999 to June 2000 only. There is no significant difference in the probability of migrating at baseline between star and non-star states. This result provides reassurance that the relative decrease in migration in early districts of star states can be interpreted as a causal effect of the NREGA.[29] Taken together, our findings suggest that the NREGA increased the value of work in the village and reduced seasonal migration from rural areas. As the theoretical framework made clear, however, difference-in-differences estimates may be indicative of the sign of the effects but would be biased in the presence of spatial spillovers. We provide structural estimates of the direct and indirect effects of the program on migration in Section 5.

29. As explained in Section 2.2, there is no migration data for other years, which prevents us from testing the parallel trends assumption before and after the NREGA is implemented.

4.2. Predicting Short-Term Migration Flows

According to the model (Section 3.2), by reducing seasonal migration from rural areas, the NREGA can have substantial effects on urban labor markets. In order to estimate these effects, we first need to predict short-term migration flows, and construct for each urban center u the empirical counterpart of α_u^1 and α_u^2, that is, the number of rural migrants from program and nonprogram districts as a share of the urban workforce.

4.2.1. Strategy. Ideally, to predict exposure of urban areas to changes in seasonal migration due to the NREGA, we would want to use a bilateral matrix of short-term migration flows before the NREGA was implemented. Unfortunately, in 1999–2000, the NSS Employment survey did not collect any information on the destination of seasonal trips (see Section 2.2). The only information we have is from the NSS 2007–2008 survey. It is incomplete: for each district of origin we do not know the exact destination, but only the number of seasonal migrants who went to the same district, to another district of the same state or to another state. And it is collected after the NREGA was rolled out, which could have changed migration patterns. We tackle these two data limitations in two separate steps. First, we complete the migration matrix using information on long-term migration patterns from the 2001 census. Second, we predict migration flows using a gravity model based on district characteristics measured at baseline.

In order to construct a complete bilateral matrix of short-term migration flows, we first estimate the number of rural seasonal migrants from each early phase district who went to an urban area in the same district, in another district of the same state or in another state, according to NSS 2007–2008. We then allocate these flows across urban districts, using 2001 Census data on the fraction of rural long-term migrants from the same district who went to each urban district between 1991 and 2001, conditional on migrating to another district in the same state or to another state. This provides an approximation of M_{ru}, the number of short-term migrants from rural parts of each district r to urban parts of each district u in 2007–2008.[30]

This procedure relies on the assumption that conditional on going to another district of the same state or to leaving their state, short and long-term migrants choose similar destinations, which can be justified by the role of employer, family, village, and subcaste networks in "chain migration" (Card and DiNardo 2000; Munshi 2003). We provide some evidence that this is a reasonable assumption using the 2006 ARIS-REDS survey, which records both short and long-term migration flows for a representative sample of Indian villages.[31] Based on these data, we construct a bilateral matrix

30. The details of our method are described in Online Appendix B.2.

31. The 1999 ARIS-REDS survey did not collect information on short-term migration trips that prevents us from using these data to compare short-term migration trends between star and non-star states before the NREGA. We provide more information on REDS data in Online Appendix B

of short and long-term migration flows at the origin×destination district level, and implement two tests.[32] First, we regress short-term flows on long-term flows in REDS data. Second, we regress short-term flows in REDS data on migration probabilities from the Census 2001. In both regressions, we include origin fixed effects and control for whether origin and destination are in the same district or in the same state. For robustness, we specify the outcome variable either in log and use OLS or in levels and use Poisson regression. Despite the small sample size—57 origin×district pairs—the results shown in Online Appendix Table A.1 do support the assumption that conditional on staying in the same state or going to another state, short and long-term migrants from the same origin choose similar destinations.

We next predict migration flows based on district characteristics independent of the NREGA. The estimating equation builds on equation (1) and makes three simplifying assumptions (see Online Appendix A.6). First, we use population size N_u at baseline as a proxy for amenities $A_u = N_u^{\gamma_0}$. Second, we assume that the migration cost between r and u takes the form:

$$\tau_{ru} = \delta_{ru}^{\gamma_1} \times \exp(\gamma_2 I_{ru} + \gamma_3 SameState_{ru} + \gamma_4 SameDistrict_{ru}),$$

where δ_{ru} denotes distance between r and u, I_{ru} is the probability that a worker taken at random from r has a language in common with a worker taken at random from u, $SameState_{ru}$ and $SameDistrict_{ru}$ are dummy variables equal to one if r and u are in the same state and the same district, respectively. Finally, since the probability of migration is low, $V_{rr}^{\theta} + \sum_{j=1}^{U} V_{rj}^{\theta} \approx V_{rr}^{\theta}$. Then equation (1) becomes

$$\begin{aligned} \ln(M_{ru}) \approx\ & \beta_1 \ln(\delta_{ru}) + \beta_2 I_{ru} + \beta_3 SameState_{ru} + \beta_4 SameDistrict_{ru} \\ & + \beta_5 \ln(N_u) + \beta_6 \ln(w_u) + \beta_7 \ln(N_r) + \beta_8 \ln(w_r) + \varepsilon_{ru}. \end{aligned} \quad (11)$$

In order to minimize endogeneity concerns, we use measures of population and wages at origin and destination from the NSS employment survey 1999–2000, long before the NREGA was implemented. The model is estimated using Poisson-quasi maximum likelihood, which has the advantage of taking into account pairs of districts with no migrants, and has been shown to perform well for gravity models (Silva and Tenreyro 2006).

Finally, we construct for each urban center the empirical counterparts of α_u^1 and α_u^2 in our theoretical framework, that is, the measure of exposure to changes in migration from program and non-program districts. Let $\widehat{M_{ru}}$ denote the predicted short-term migration from rural district r to urban district u from estimating equation (11). Let L_u denote the number of casual workers living in urban district u in 2004–2005 (see

32. As Online Appendix Figure A.5 shows, short term migration is more geographically concentrated than long-term migration, both in terms of origin (poorer, remote areas) and in terms of destinations (richer, industrialized places). When focusing on the 25% largest long-term flows, however, long-term migrants also seem to be attracted to richer, industrialized destinations.

TABLE 4. Gravity model estimates of short-term migration flows.

	Number of migrants
Log Distance	− 1.491***
	(0.0713)
Log Destination Casual Deflated Wage	0.396***
	(0.130)
Log Origin Casual Deflated Wage	− 0.543***
	(0.188)
Log Destination Population	0.883***
	(0.0520)
Log Origin Population	0.337***
	(0.0658)
Language Proximity	0.557***
	(0.142)
Same State	0.147
	(0.140)
Same District	− 4.747***
	(0.399)
Observations	124,848
Pseudo *R*-squared	0.49

Notes: Estimates of a poisson regression. The unit of observation is a pair between the rural part of an early district and the urban part of a district. The outcome is the number of migrants going from one to another at baseline, constructed using NSS 2007–2008 and 2001 census data (see Online Appendix B.2). The specification is described in Section 4.2.1. All estimates are computed without sampling weights. Standard errors in parentheses are adjusted for correlation of the errors between state pairs. ***Significant at 1%.

Section 2.2). We compute

$$\widehat{\alpha_u^1} = \frac{\sum_{r \in StarEarly} \widehat{M_{ru}} \times 104}{L_u \times 265} \quad \text{and} \quad \widehat{\alpha_u^2} = \frac{\sum_{r \notin StarEarly} \widehat{M_{ru}} \times 104}{L_u \times 265},$$

where $\widehat{\alpha_u^1}$ and $\widehat{\alpha_u^2}$ are the predicted seasonal migration inflow into district u coming from early districts of star states and from early districts of other states, respectively. We take the ratio between seasonal migrant numbers M_{ru} multiplied by the number of days they spend on average at destination (from 2006 ARIS-REDS data), and the estimated number of casual workers living in u multiplied by the estimated number of days they spend doing casual work per year (from NSS 2007–2008).

4.2.2. Results. We first estimate equation (11) to predict migration flows between rural–urban district pairs. As Table 4 shows, the determinants of migration all have a significant impact on migration flows, and their coefficients have the expected signs. Distance negatively affects the number of migrants. Wages at destination and origin have a positive and negative impact on migration, respectively. We predict more migration between districts with a larger number of casual workers. Migrants are more likely to go to districts where more people have a language in common with them. Interestingly, rural short-term migrants are no more likely to migrate to urban centers in the same state, and less likely to migrate in the same district. This suggests that political borders per se do not matter for seasonal migrants, maybe because unlike long-term migrants they do not rely on state-specific benefits or jobs at destination (Kone et al. 2018).[33] These effects are robust to the model used, and to different definitions of the outcome variable.

We next use predicted migration flows to compute the two ratios α_1 and α_2, which measure the importance of migration flows from early districts in star states and from other rural districts, respectively, as a fraction of the urban casual labor force. Table 5 presents the weighted average of these estimates for each state. On average, urban areas of star states are more likely to receive migrants from early districts of star states than urban areas of other states (the migration rates are 7% and 4%, respectively). Conversely, urban areas of other states are more likely to receive migrations from early districts of other states than urban areas of star states (the migration rates are 20% and 6%, respectively). There is, however, a fair amount of heterogeneity due to the fact that half of short-term migrants cross state borders. Many star states (e.g., Himachal Pradesh or Madhya Pradesh) receive a large share of migrants from early districts of other states, and some other states (e.g., Delhi or Haryana) have high levels of migration from early districts of star states. In the next section, we use this geographical variation at the district level to estimate the impact of changes in migration due to the NREGA on urban wages.

Before we proceed to the next part of the analysis, two issues deserve discussion. First, because of measurement error in the denominator, some small urban districts have implausibly high values of $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$ (up to 14 and 34, respectively). To reduce the influence of these outliers in our regression analysis, we winsorize the top 1% of the distribution of $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$, which amounts to topcoding 4 districts out of 476. Second, the gravity model that we use to predict migration flows includes destination wages at baseline. This raises the concern that our migration predictions are endogenous to the urban wage trends that we want to explain. As robustness check, we estimate urban wage effects using migration predictions that are not based on wages at destination.

4.3. *Program Effect on Labor Markets*

4.3.1. Strategy. In order to estimate the effect of the NREGA on urban labor markets, we compare changes in labor market outcomes in cities that rely more on short-term migration from rural areas where the program is implemented (high α_u^1) to outcomes in cities for which migration is less important relative to the resident casual workforce (low α_u^1). For a given level of α_u^1, we further compare urban centers that attract migrants from rural areas without the program (high α_u^2) to other cities. We predict that, as compared to the average urban center, wages will increase in cities that rely more on migrants coming from rural areas where the program reduces migration,

33. Our method to impute the destination of short-term migrants in NSS 2007–2008 using long-term migrants in the 2001 Census does allow them to have different propensity to stay in the same district or in the same state (see previous section).

TABLE 5. Predicted migration rate from rural areas with and without NREGA employment.

	$\alpha_1 = \dfrac{\text{Number of rural migrants from early districts of star states} \times 104}{\text{Number of urban resident casual workers} \times 265}$ (1)	$\alpha_2 = \dfrac{\text{Number of rural migrants from early districts of other states} \times 104}{\text{Number of urban resident casual workers} \times 265}$ (2)
Panel A: Star States		
Andhra Pradesh	11%	4%
Chhattisgarh	8%	8%
Himachal Pradesh	6%	11%
Madhya Pradesh	8%	9%
Rajasthan	6%	8%
Tamil Nadu	3%	1%
Uttaranchal	2%	5%
All Star States	7%	4%
Panel B: Other States		
Assam	4%	36%
Bihar	5%	52%
Delhi	12%	31%
Gujarat	2%	6%
Haryana	8%	21%
Jharkhand	3%	21%
Karnataka	2%	5%
Kerala	2%	3%
Maharashtra	4%	10%
Orissa	4%	19%
Punjab	4%	13%
Uttar Pradesh	6%	24%
West Bengal	2%	26%
All Other States	4%	15%
All India	5%	10%

Notes: Column (1) present the ratio between the number of rural migrants from early districts of star states doing short-term trips to urban parts of a given state multiplied by the number of days rural migrants spend at destination and the number of casual workers living in these urban areas multiplied by the number of days that these workers spend doing casual wage work. Column (2) presents the ratio between the number of rural migrants from other rural districts doing short-term trips to urban parts of a given state multiplied by the number of days rural migrants spend at destination and the estimated number of casual workers living in these urban areas multiplied by the number of days that these workers spend doing casual wage work. Rural to urban migration flows are predicted using the gravity model presented in Table 4. Casual workers are prime-age adults who declared doing casual wage work as usual principal or subsidiary occupation in NSS 2007–2008. The number of days spent at destination by rural seasonal migrants is estimated using ARIS-REDS data.

and decrease in cities that rely more on migrants coming from rural areas where the program is not implemented. We estimate the following equation by ordinary least squares:

$$Y_{ut} = \beta_0 + \beta_1 \widehat{\alpha_u^1} \times Post_t + \beta_2 \widehat{\alpha_u^2} \times Post_t + \delta \boldsymbol{Z}_u \times Post_t + \gamma \boldsymbol{X}_{ut} + \alpha \boldsymbol{H}_i + \eta_t + \mu_u + \varepsilon_{ut}, \tag{12}$$

where Y_{ut} are wages earned by urban worker u deflated using urban prices.[34] As before $Post_t$ is a dummy variable equal to one after 2007, once the program is implemented in early districts, $\boldsymbol{Z}_u$ denotes a vector of district characteristics that do not vary with time, $\boldsymbol{X}_{ut}$ a vector of district characteristics that do vary with time. District controls are listed in panel A of Table 1. $\boldsymbol{H}_i$ is a vector of individual characteristics, including dummies for gender, education levels, caste, religion, and age ranges. η_t and μ_u denote time and district fixed effects, respectively. For inference purposes, we need to account both for the fact that regressors $\widehat{\alpha_u^1}$ and $\widehat{\alpha_u^2}$ are estimated from equation (11) and that error terms in equation (12) are likely correlated within district. Bootstrapped standard errors are obtained by repeating the estimation of models 11 and 12 on random district draws (with replacement).

A potential threat to our identification strategy is that urban centers that hire more migrants from early districts of star states may be on different economic trends, and hence would exhibit differential changes in labor market outcomes even without the NREGA. The raw trends, shown in the bottom two panels of Online Appendix Figure A.6, are very reassuring in that regard. Urban districts with high and low predicted migration from star states ($\widehat{\alpha_u^1}$) have very similar trends between 1999–2000 and 2004–2005, but in 2007–2008 wages suddenly grow faster in districts with a higher $\widehat{\alpha_u^1}$. Similarly, urban districts with high and low predicted migration from other states ($\widehat{\alpha_u^2}$) exhibit parallel trends until the NREGA is implemented, when wage growth in districts with a higher $\widehat{\alpha_u^2}$ slows down. We provide a statistical test of the existence of differential trends by estimating two placebo regressions, one using 1999–2000 and 2004–2005 data, before the NREGA was implemented, and another using 2007–2008 and 2011–2012 data, that is, after the NREGA was rolled out across India.

Another concern is that the states' decision to actively implement the NREGA may have been related to other state-level policies or economic trends that would also affect urban wages. To alleviate this concern, we take advantage of the fact that most seasonal migrants go beyond district and state borders, so that urban areas with high predicted migration from early districts of star states are not all in early districts, or even in star states. Specifically, we estimate equation (12) including dummies for early districts, star states, and early districts of star states interacted with $Post_t$. This robustness check also allows us to check that our findings are not driven by other effects of public employment provision on the local urban economy (e.g., higher consumption or investment).

4.4. Results

Table 6 presents the estimated effect of the NREGA on urban wages. We find that between 2004–2005 and 2007–2008, urban centers with higher predicted migration

34. We use the state-level price index for industrial laborers published by the Labour Bureau (http://labourbureaunew.gov.in).

TABLE 6. Impact of the NREGA on urban wages.

	Log Real Casual Wages			
	2004–2005 2007–2008		1999–2000 2004–2005	2007–2008 2011–2012
	(1)	(2)	(3)	(4)
$\widehat{a}_1 \times$ Post	0.598***	0.479***	−0.278*	−0.01
	(0.208)	(0.189)	(0.164)	(0.216)
$\widehat{a}_2 \times$ Post	−0.091**	−0.072**	0.036	−0.014
	(0.042)	(0.036)	(0.032)	(0.043)
Observations	16,338	16,338	20,301	14,598
Workers Controls	Yes	Yes	Yes	Yes
District Controls	Yes	Yes	Yes	Yes

Notes: Each column presents results from a separate regression. The outcome is log deflated casual earnings. All specifications include district and year fixed effects. The sample is composed of urban adults surveyed in NSS: (i) from July 2004 to June 2005 and July 2007 to June 2008 (columns (1) and (2)), (ii) from July 1999 to June 2000 and July 2004 to June 2005 (column (3)), (iii) from July 2007 to June 2008 and from July 2011 to June 2012 (column (4)). In panel A the sample is restricted to early districts. In panels B and C it excludes early districts. Star state is a dummy variable equal to one for Andhra Pradesh, Himachal Pradesh, Chhattisgarh, Madhya Pradesh, Rajasthan, Tamil Nadu, and Uttarkhand. In columns (1) and (2) post is a time dummy equal to one for the period 2007–2008. In column (3) post is a time dummy equal to one for the period 2004–2005. In column (4) post is a time dummy equal to one for the period 2011–2012. District controls are presented in Table 1. Worker controls include a set of dummy variable for age group, gender, education level, social group and religion. Standard errors are clustered at the district level. *Significant at 10%; **significant at 5%; ***significant at 1%.

rates from early districts of star states experienced a relative increase in wages. The estimated coefficient with controls suggests that in an urban district with a 10% higher migration rate from early districts in star states, wages would have risen by 4.8% more. We also find evidence of a mitigating impact through increased migration from rural districts that do not have the program. For a given migration rate from early districts of star states, an urban center with a 10% higher migration rate from other early districts would have had a 0.7% lower wage growth. As Table 5 shows, in the average urban district, the predicted migration rate from early districts of star states is 5% and the predicted migration rate from other early districts is 16%. Hence our estimates imply that for the average urban district the increase in wages (+2.4%) caused by a drop in migration from program districts was partially mitigated by an increase in migration from nonprogram districts (−1.1%). The net effect is a 1.3% increase in urban wages.

Columns (3) and (4) of Table 6 present the results of the first set of robustness checks. Reassuringly we find no evidence that the wage trends we document in cities with high migration from early districts of star or non-star states were present before or after the NREGA was rolled out. However, despite the fact that the raw trends seemed parallel (see Online Appendix Figure A.6), there is some evidence that urban districts with high migration from early districts of star states had lower wage growth before the NREGA was implemented. This raises the concern that our estimates pick up a temporary catch up ("Ashenfelter dip"). To alleviate this concern, we implement a second robustness check, and estimate our main specification controlling for the pre-NREGA wage trend interacted with time. The results, presented in Online Appendix Table A.2, suggest that our results are not driven by pre-existing trends. These robustness checks provide some reassurance that our findings are not driven by economic shocks or policies correlated with NREGA implementation. Online Appendix Table A.3 presents the results of the third robustness check. Wages did rise faster in urban areas of early districts and of star states between 2004–2005 and 2007–2008. However, even controlling for these trends we find that urban areas with higher predicted migration from early districts of star states experienced faster wage growth. This suggests that because of the relatively long distances traveled by short-term migrants, the spillover effects of the program on urban labor markets were not limited to districts or states with high NREGA employment. This alleviates the concern that states decided to implement the NREGA based on its expected effect on urban areas. This also suggests that the wage effects we document were due to reduced migration and not to rising local demand for urban goods (Santangelo 2016). As a fourth robustness check, we exclude destination wages from the gravity model and use these migration predictions instead: the estimated effects on urban wages are very similar (see Online Appendix Table A.4).[35] Finally, we also find similar results if we exclude the last quarter of the NSS 2007–2008 survey, which corresponds to the time when the NREGA was rolled out in all rural districts (see Online Appendix Table A.6)

5. Structural Estimates

Our reduced form estimates suggest that the NREGA reduced seasonal migration and increased urban wages. We also find that the urban wages effects were not limited to program districts but were geographically widespread. This raises the possibility that nonprogram districts were indirectly affected, so that difference-in-differences estimates are biased (see Section 3). In this section, we derive from the model two structural equations that allow us to quantify the direct and indirect effects of the program.

5.1. Strategy

In Online Appendix A.7, we derive from the model the two following equations:

$$\Delta_m = \theta_u a \Delta_{w_u} - \theta_r \Delta_{w_r}, \tag{13}$$

35. We also test whether the wage effects are concentrated in the peak migration season (January to June) by interacting the alpha $\times$ post dummies with two dummies for each half of the year. The estimates, presented in Online Appendix Table A.5 suggest that the urban wage effects are not significantly different across seasons. The results may not be however very reliable, given the fluctuations in NSS coverage for urban areas we document in Online Appendix Figure A.4.

$$\Delta_{w_u} = [I_u - \theta_u \varphi(\theta_u, \varepsilon) b]^{-1} \theta_r \varphi(\theta_u, \varepsilon) \Delta_{w_r}, \tag{14}$$

where the three parameters of interest are θ_u, the migration response parameter w.r.t. destination wages, θ_r the migration response parameter w.r.t. wages at origin, and ε, the labor demand elasticity in urban areas. Δ_m is the vector of observed changes in migration from rural districts, Δ_{w_r} is the vector of observed changes in casual wages in rural districts weighted by the probability of not migrating (p_i^i), and Δ_{w_u} is the vector of observed changes in casual wages in urban districts.[36] I_u is the identity matrix. The two matrices a and b can be constructed based on observed migration patterns. φ is a function of observed migration patterns and of the two structural parameters ε and θ_u. Specifically,

$$a = \left(\frac{p_i^j \, p_i^i}{1 - p_i^i} \right)_{\substack{1 \le i \le R \\ 1 \le j \le U}} \quad ; \quad b = \left(p_i^j \right)_{\substack{1 \le i \le R \\ 1 \le j \le U}} \quad ; \quad \varphi = \left(\frac{\alpha_j^i}{\theta_u \alpha_j - \varepsilon(1 + \alpha_j)} \right)_{\substack{1 \le j \le U \\ 1 \le i \le R}},$$

where p_i^j denotes the probability of migrating from rural district i to urban district j, p_i^i is the probability of staying in i, α_j is the in-migration rate for urban destination j, and α_j^i is the in-migration of migrants from rural district i into urban destination j.

We next translate equations (13) and (14) into a system of equations that we can use to estimate the three structural parameters θ_u, θ_r, and ε. Let $i \in \{1, R\}$ denote a rural district and $j \in \{1, U\}$ denote an urban district. Δ_i^m is the change in migration from i, $\Delta_i^{w_r}$ the change in casual wages in i and $\Delta_j^{w_u}$ the change in casual wages in j between 1999–2000 and 2007–2008. The system writes

$$\Delta_i^m = \theta_u \sum_{j=1}^{U} \frac{p_i^j \, p_i^i}{1 - p_i^i} \Delta_j^{w_u} - \theta_r p_i^i \Delta_i^{w_r} + C_r + \varepsilon_i, \tag{15}$$

$$\Delta_j^{w_u} = \frac{\theta_r}{\theta_u \left(\alpha_j - \sum_{j=1}^{U} \alpha_j^i p_i^j \right) - \varepsilon(1 + \alpha_j)} \sum_{i=1}^{R} \alpha_j^i p_i^i \Delta_i^{w_r} + C_u + \varepsilon_j, \tag{16}$$

where C_r and C_u are two constants that need to be estimated, and ε_i and ε_j are normally distributed error terms. p_i^i, p_i^j, α_j, and α_j^i are all based on the migration matrix in 2007–2008.

Equation (15) is linear in the parameters, and pins down θ_u and θ_r. Equation (16) is nonlinear, but pins down ε once θ_u and θ_r are known. We address the endogeneity in Δ^{w_r} by using the implementation of the NREGA as an instrument. Specifically, let T_r denote a vector of dummy variables equal to one for star states weighted by the probability of not migrating (p_i^i). Let $\widehat{p_i^i}$, $\widehat{p_i^j}$, $\widehat{\alpha_j^i}$, and $\widehat{\alpha_j}$ denote estimates of p_i^i, p_i^j, α_j, and α_j^i based on the migration patterns predicted by the gravity model estimated

36. All three vectors are normalized using the sample average.

in Section 4.2. In equation (15) we instrument

$$\begin{cases} \Delta_i^{w_r} & \text{with } \widehat{p_i^i} T_i \\ \sum_{j=1}^{U} \frac{p_i^j p_i^i}{1-p_i^i} \Delta_j^{w_u} & \text{with } \sum_{j=1}^{U} \frac{\widehat{p_i^j}\, \widehat{p_i^i}}{1-\widehat{p_i^i}} \Delta_j^{w_u}. \end{cases}$$

In equation (16) we instrument

$$\frac{\theta_r \sum_{i=1}^{R} \alpha_j^i p_i^i \Delta_i^{w_r}}{\theta_u\left(\alpha_j - \sum_{j=1}^{U} \alpha_j^i p_i^j\right) - \varepsilon(1+\alpha_j)} \quad \text{with} \quad \frac{\theta_r \sum_{i=1}^{R} \widehat{\alpha_j^i}\, \widehat{p_i^i}\, T_i}{\theta_u\left(\widehat{\alpha_j} - \sum_{j=1}^{U} \widehat{\alpha_j^i p_i^j}\right) - \varepsilon(1+\widehat{\alpha_j})}.$$

Identification relies on the model structure and on three assumptions. The first two were already needed in the reduced form approach: we assume that NREGA implementation is exogenous with respect to rural out-migration and that migration patterns predicted by the gravity model are exogenous with respect to changes in rural or urban outcomes. We make an additional assumption, that urban wage changes are exogenous with respect to changes in out-migration from a given rural origin. Since rural migrants go to cities far away, migration from a single district will have little impact on urban labor markets.

The structural estimation allows us to go beyond the difference-in-differences estimates of the program impact, which are likely to be biased if nonprogram areas are affected by the program (see Section 3). Based on our estimates, we can quantify the effect of the program on migration from both program and nonprogram areas, and the resulting impact on urban wages. Let $\widehat{\beta}$ denote the estimated program effect on rural wages in early districts of star states from equation (9). The estimated effects of the program on migration and urban wages are given by the following expressions:

$$\widehat{\Delta_m} = -\widehat{\theta_r}\widehat{\beta}T_r + \widehat{\theta_u}\left(\widehat{a}[I_u - \widehat{\theta_u}\widehat{\varphi}(\widehat{\theta_u},\widehat{\varepsilon})\widehat{b}]^{-1}\widehat{\theta_r}\widehat{\varphi}(\widehat{\theta_u},\widehat{\varepsilon})\right)\widehat{\beta}T_r, \tag{17}$$

$$\widehat{\Delta_{w_u}} = \left([I_u - \widehat{\theta_u}\widehat{\varphi}(\widehat{\theta_u},\widehat{\varepsilon})\widehat{b}]^{-1}\widehat{\theta_r}\widehat{\varphi}(\widehat{\theta_u},\widehat{\varepsilon})\right)\widehat{\beta}T_r, \tag{18}$$

where the first term on the right hand-side of equation (17) is the direct impact of the program on migration through a change in rural wages, and the second term is the indirect impact, through a change in urban wages. We also simulate the effect of the NREGA on migration and wages if the program had been implemented in all early districts with the same effect on rural wages, by replacing T_r in equations (17) and (18) with a vector of ones.

5.2. Results

Panel A in Table 7 presents our estimates. The estimated parameter that governs the migration response w.r.t. wages at destination is a highly significant 2.4, which also implies and elasticity of 2.4. Our point estimate is strikingly close to Monras's (2018a) 2.56 estimate of the same structural parameter for internal migration the United States.

TABLE 7. Structural estimates and calibration of the effect of the NREGA on migration and urban wages.

Panel A: Estimation of model parameters	
Migration response parameter w.r.t. wages at home (θ_r)	5.76
	(1.35)
	[2.79; 8.36]
Migration response parameter w.r.t. wages at destination (θ_u)	2.41
	(0.85)
	[0.91; 4.34]
Urban labor demand elasticity (ε)	– 0.22
	(0.66)
	[–1.96;0.18]
Panel B: Program effects, actual implementation	
Effect on rural wages, early districts of star states	5.7%
Effect on rural wages, early districts of other states	0.0%
Effect on migration, early districts of star states	– 22.6%
Effect on migration, early districts of other states	4.6%
Difference-in-differences estimate	– 27.2%
Bias of the difference-in-differences estimate	20.2%
Effect on urban wages	0.5%
Panel C: Program effects, full implementation	
Effect on rural wages, early districts of star states	5.7%
Effect on rural wages, early districts of other states	5.7%
Effect on migration, early districts of star states	– 11.8%
Effect on migration, early districts of other states	– 10.4%
Effect on urban wages	4.1%

Notes: Panel A presents the results of the estimation of the migration response parameter w.r.t. wages at origin (θ_r) and at destination (θ_u) for a given value of the elasticity of urban wages w.r.t. migration (ε). Bootstrapped standard errors are shown in parentheses and 5% confidence intervals in brackets. Panel B presents the results of the calibration of the program effects, using the increase in rural wages in early districts of star states estimated in Table 3 and the model parameters in Panel A. Panel C presents the results of a counterfactual calibration, assuming that the program is implemented in all early districts and has the same effect on rural wages as estimated in Table 3.

The estimated parameter that governs the migration response to wages at home is also highly significant and larger in magnitude 5.76, which suggests that migrants are indeed more sensitive to wages at home than at destination (home bias), even when one takes into account the fact that they are more likely to stay at home in general (p_i^i in the model). The implied migration elasticity w.r.t. wages at home is –5.6. In a companion paper (Imbert and Papp 2018), we show that once living costs and income risk are taken into account the difference between earnings per day migrated and daily NREGA earnings in the village is only 18%. Hence an 18% increase of rural wages may go a long way into closing the gap between earnings in the village and in urban areas, which is consistent with our migration elasticity estimate w.r.t. wages at home that migration should decrease by $18 \times -5.6 = -101\%$. The point estimate for ε is negative and reasonable in magnitude (–0.22), but insignificantly different from zero, which may be due to its estimation from a nonlinear function. In what follows, we will use the point estimates, with the caveat that these results can only be suggestive of the actual magnitudes. As we will see however, the implied migration and urban wage effects match our reduced form estimates quite well.

We next turn to the program impact on migration and urban wages implied by our estimates, using equations (17) and (18). As panel B shows, migration from early districts of star states experienced a large decline due to the increase in rural wages: about −22%. But at the same time, migration from early districts of other states increased by about 5%, in response to a change in urban wages. Hence difference-in-differences estimates that would compare changes in migration in rural districts with and without the program would be about −27%, which is in the same ballpark as the reduced form estimates presented in Section 4.1. Interestingly, these difference-in-differences estimates would overestimate the negative effect of the program on migration by 20%. Finally, our calibration shows that because the increase in migration from other states compensated the decline in migration from star states, the inflationary effect of the NREGA on urban wages has been relatively small, about 0.5%. Once again, the structural results are consistent both qualitatively and quantitatively with the reduced form estimates (see Section 4.3).

Finally, we simulate the effect of the program in the counterfactual case where all districts selected for the early implementation phase of the NREGA had indeed implemented the program. We assume that they would then have all experienced a 5.7% increase in rural wages, which is the estimated effect for early districts of star states from Section 4.1. As panel C shows, migration from early district would then have decreased by 11% overall, and urban wages would have increased by 4.1%. These estimates suggest that the effects of the program would have been much more dramatic if all early districts had implemented the program as in star states: they are close to the estimated effect of the program on rural wages (Imbert and Papp 2015). This is both because the direct negative effect of the program on migration would have been larger and because the indirect mitigating effect of increased migration would have been weaker.

6. Conclusion

This paper provides empirical evidence on the effect of a large rural development program, India's NREGA, on migration from rural to urban areas and on urban labor markets. Among rural districts that were selected to receive the program (early districts), we compare those where it was well implemented (star states) with the others, and find evidence that the NREGA increased rural wages and reduced short-term migration to urban areas. By comparing urban areas with higher/ lower migration rate from star states, we show that the decline in migration from program areas increased urban wages. We also find evidence of slower wage growth in cities that usually attract migrants from rural areas where the program was not implemented (other states).

A spatial equilibrium model suggests that in presence of far-reaching spatial spillovers, difference-in-differences estimates may be informative about the sign of the effect of the program on migration, but provide unreliable quantitative estimates. To address this issue, we derive and estimate a structural model that takes into account both the direct and the spillover effects of the program. We estimate elasticities of seasonal migration with respect to wages at home and at destination, which are significant and large (−5.6 and 2.4, respectively). They suggests that seasonal migrants are highly responsive to changes in earnings opportunities at origin and destination. We also estimate an urban labor demand elasticity that is reasonable in magnitude (−0.22), but imprecisely estimated.

We then use structural estimates to recover the direct and spillover effects of the program on migration, and to simulate the effect of the program if it had been implemented in all rural areas selected to receive it. We find that not only did migration from program areas decline (by 22%) but migration from nonprogram areas also increased substantially (5%), so that difference-in-differences overestimate the program effect on migration (by about 20%). The migration response from nonprogram areas mitigated the negative effect of the program on rural-to-urban migration and hence mitigated its inflationary effect on urban wages, which was only +0.5%. In contrast, urban wages would have increased by 4.1% if the program had been effectively rolled out in all districts selected to implement it.

Our results show that spatial spillover effects are not only qualitatively, but also quantitatively important in the evaluation of place-based policies. Our method also demonstrates how to leverage the structure of economic interactions between geographic units to estimate spillovers in the case where they are not strictly local.

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Supplementary Data

Supplementary data are available at *JEEA* online.