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## The distributional impact of structural transformation in rural India: Model-based simulation and case-study evidence

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WIDER Working Paper 2019/33

# **The distributional impact of structural transformation in rural India**

Model-based simulation and case-study evidence

Chris Elbers and Peter Lanjouw<sup>\*</sup>

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**Abstract:** The North Indian village of Palanpur has been the subject of close study over a period of six decades from 1957/8 to 2015. Himanshu et al. (2018) have documented the evolution of the village economy over this period in an exhaustive study entitled *How Lives Change: Palanpur, India and Development Economics*, and point to two distinct, and staggered, drivers of growth and distribution of income. An early period of agricultural intensification associated with the green revolution saw an expansion of irrigation and the introduction of new agricultural technologies, leading to rising incomes accompanied by falling poverty and fairly stable, or even declining, income inequality. Subsequently, from about the mid-1970s onwards, a cumulative process of non-farm diversification took hold, and was accompanied by further growth and poverty decline, but also a significant rise in income inequality. This process of structural transformation is likely to be occurring more broadly in rural India. In this paper, we construct a simple model of a village economy that captures several of the salient elements of the Palanpur economy and society. We show that this basic model is readily able to reproduce the distributional outcomes observed in the village. We suggest that to the extent that there exist other villages in rural India with such features, similar distributional outcomes might be expected. We indicate, further, that while the non-farm diversification phase of the village growth story was accompanied by rising inequality, the counterfactual of no diversification might well have been associated with an even greater increase. We suggest that non-farm diversification has arguably helped to contain growth in inequality and has played a particularly pronounced role in reducing poverty.

**Keywords:** income inequality, non-farm employment, poverty, rural diversification, simulation model, village study

**JEL classification:** O18, O15, I32, C51

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## 1 Introduction

Rural India is home to 70 per cent of the nation's population and about the same proportion of poor people in the country. This rural population resides mainly in villages—the 2011 Census reports roughly 800 million people living in more than 600,000 villages. Most of rural India's workforce (60 per cent) remains primarily involved in agriculture, but in recent decades this sector's growth has lagged other sectors in the economy. The deceleration in agricultural growth has been offset by the emergence and expansion of the non-farm sector; in 2011/12 non-farm workers accounted for 40 per cent of the workforce, nearly double that observed only ten years earlier (Himanshu et al. 2018).

The aim of this paper is to study the impact of this structural transformation of the rural Indian economy at the village level. In particular, our focus is on the impact of this process on village-level income inequality. Recent years have seen growing interest and analysis of income inequality in India, with, in particular, concerns being voiced about a significant increase in inequality over time (Chancel and Piketty 2017; Crabtree 2018). Himanshu and Murgai (2018) survey the evidence from secondary data and suggest that although there are clear signs of rising inequality in certain dimensions, this not universally the case. Notably, while estimates of income inequality show a clear rise, the evidence from India's consumption surveys conducted by the National Sample Survey Organization is less clear-cut. Common to most of the discussions of inequality in the literature is a focus on inequality at the all-India level. This is a natural place to look and is clearly relevant when comparing India internationally. However, aggregate national-level inequality can readily mask inequality outcomes and trends at the sub-national level. At the village level, inequality could be rising while national-level inequality is stable or even falling. This could occur if the underlying processes were leading to rising within-village dispersion of income, but accompanied by convergence across villages of average income. Recent analysis by Mukhopadhyay and Garces (2018) points to the possibility that such a process is indeed underway in parts of rural India.

Conventional survey data are not able to monitor inequality trends at the village level in India; their sampling design does not permit such a fine level of disaggregation. It is therefore difficult to monitor inequality in a given village, much less to make broad statements about village-level trends (although see Mukhopadhyay and Garces 2018). And yet, there are grounds for interest in such local-level inequality outcomes. In rural areas, the village population likely serves as reference group against which villagers compare themselves. Attitudes about the magnitude and direction of change in inequality are likely to be heavily influenced by village-level trends. For example, Luttmer (2005) documents that in the United States, controlling for income, subjective welfare of individuals is lower in more unequal neighbourhoods. Similarly, Lentz (2007) finds that in Ghana, subjective welfare falls when neighbours become richer. Further, Araujo et al. (2008) document that in rural Ecuador, 'elite capture' of community-driven development projects is more likely in high-inequality communities. In general, rising inequality is likely to put pressure on village solidarity and the functioning of village-level institutions (Himanshu et al. 2018).

In this paper, we report on the findings from a study of long-term economic development in a single village, Palanpur, located in western Uttar Pradesh. This village study, by Himanshu et al (2018), points to two key drivers of economic development over the six decades between 1957/8 and 2008/9: agricultural intensification associated with the green revolution, and a cumulative process of rural non-farm diversification. These drivers have combined to generate rising per capita incomes and falling poverty rates (notwithstanding steady population growth and falling per capita landholdings). Their association with income inequality appears to have been distinct, however. Agricultural intensification, which began in the 1960s, was associated with the expansion

of irrigation and the adoption of new farming technologies and techniques. Income inequality in Palanpur was broadly stable and even showed some decline during the period up to the mid-1970s. In the subsequent decades, rural non-farm diversification increasingly took hold in the village, alongside further agricultural intensification. Although per capita income continued to grow, and poverty fell, income inequality rose significantly.

We borrow elements of Palanpur’s economic structure and society to construct a simulation model of a small village economy. We impose on it the exogenous forces of demographic change, technological change, and non-farm diversification to which Palanpur has been exposed over time. We show that allowing this simple model to run over a five decade period returns a time series of inequality change and poverty decline that mimics reasonably closely that which was observed in Palanpur. We suggest, therefore, that other Indian villages—with similar economic and social structures, and facing similar exogenous forces of change—might also be experiencing rising inequality alongside a general rise in living standards.

Further, we study how inequality in a village such as Palanpur might have evolved if the non-farm sector had not emerged. Conventional inequality decomposition analysis suggests that non-farm incomes have become the main contributor to overall inequality in Palanpur. Yet, such decomposition techniques do not address the counterfactual of how inequality might have evolved in the absence of diversification. Our simulation model indicates that if the village had remained an agricultural economy the rise in income inequality during the latter half of the study period could well have been even more pronounced. Seen this way, non-farm diversification may thus have acted to attenuate an even sharper underlying trend of rising inequality. The model suggests, further, that the distributional impact of non-farm diversification was manifested most clearly via the upward mobility it has offered the poorest villagers.

In the next section, we offer an abridged description of economic development and distributional change in Palanpur. We base this on the detailed analysis presented in Himanshu et al. (2018). We then present our simulation model and results in Section 3. Section 4 offers concluding remarks.

## **2 Economic development and welfare trends in Palanpur: 1957/8–2015**

### **2.1 The village setting**

Palanpur is a small village located in Moradabad District in west Uttar Pradesh. It has been the subject of close study since 1957/8, when it was first surveyed by the Agricultural Economics Research Centre (AERC) of the University of Delhi. A subsequent survey was fielded by the AERC in 1962/3. In 1974/5, Christopher Bliss and Nicholas Stern spent nearly a year in the village collecting data; their fieldwork culminated in the publication of a book on the Palanpur economy (see Bliss and Stern 1982). The village was next surveyed in 1983/4 by Jean Drèze and Naresh Sharma, in collaboration with Stern, and they visited the village again in 1993 for a quick resurvey. Findings from these data collection efforts were reported by Lanjouw and Stern (1998). In 2008 and 2009, Himanshu and collaborators conducted fieldwork over two consecutive years and then returned again in 2015 for a quick resurvey. Analysis of the complete dataset, covering all of the survey years, was reported by Himanshu et al. (2018). Enquiring into the evolution and determinants of distributional outcomes has been a central theme in both the studies by Lanjouw and Stern (1998) and Himanshu et al. (2018). Scrutiny of trends in income inequality and of

mobility patterns is possible with the Palanpur data because the data collection efforts covered the entire village population—not just a sample.<sup>1</sup>

The village is located in the plains of the Ganges river and is located near the town of Chandausi, and large city (and district headquarter) of Moradabad. A railway line connects the village to these urban centres, as well as to Delhi, some 220 kilometres away. This railway line has been the primary means of access to the outside world over the study period, although in recent years road access has also improved. Palanpur's population density, and proximity to urban centres, is not atypical in this part of northern India. Access to non-farm jobs often occurs through commuting; although migration rates have risen in recent years, it remains a relatively uncommon occurrence.

In early 2008 (the year for which the richest data are available), Palanpur had a population of 1,255 persons, divided into 233 households (Table 1). Overall population growth was slightly above that for India in the 1950s and 1960s but substantially lower than that during the last 25 years. However, after adjustment for out-migration, the population growth rate in Palanpur is very similar to India for the same 25-year period.

Table 1: Basic population indicators of Palanpur

	Year						
	1957/8	1962/3	1974/5	1983/4	1993	2008/9	2015
Population	528	585	790	960	1133	1255	1299
Number of households	100	106	117	143	193	233	224
Average household size	5.3	5.5	6.8	6.7	5.9	5.4	5.6
Female–male ratio	0.87	0.87	0.85	0.93	0.85	0.98	0.94
Annual growth rate of population	—	2.2	2.5	2.2	1.7	0.74	0.58
Migration-adjusted growth rate	—	2.3	2.7	1.9	2.2	1.9	1.8
Age (in years) distribution of the population (%)							
0–14	39	38	46	44	41	38	36
15–24	21	19	15	20	21	21	20
25–44	23	25	25	23	22	26	27
45–64	14	13	12	10	12	11	13
65+	3	5	2	3	4	4	4

Source: This table also appears in the study by Himanshu et al. (2018), and is reproduced here with permission from the copyright holder.

The caste composition of Palanpur is presented in Table 2. Although there are eight caste groups in the village, and a few additional individual caste households, the three main castes in the village are the Thakurs, Muraos, and Jatabs. Thakurs are the largest caste in the village numerically and they continue to be powerful economically. They were the first to move into the non-farm sector in a major way but have now been joined by other castes. Muraos, on the other hand, are seen as a cultivating caste and take pride in their agricultural skills. Jatabs, at the bottom of the village hierarchy, remained economically and socially marginalized until around 2005, but are now seen as an increasingly important community within the village.

One of the key findings emerging from the 2008/9 survey data is that the circumstances of the Jatabs is showing significant improvement, both absolutely and relative to the rest of the village. This process is paralleled by a clearly discernible expansion of non-farm employment in the village economy. Jatabs appear now to be enjoying greater access to non-farm opportunities than in the

<sup>1</sup> Comprehensive income data are not available for all survey years. The 1993 and 2015 rounds did not collect the detailed information needed to produce income data that are comparable with the other survey years. Discussion of findings related to incomes will thus not pertain to those survey years.

past, and this is translating into rising per capita incomes and upward mobility. We provide a cursory documentation of these trends in the sections to follow.

Table 2: Distribution of households and population by caste

Caste group	Year						
	1957/8	1962/3	1974/5	1983/4	1993	2008/9	2015
	Population (N)						
Thakur	104	125	174	217	283	287	302
Murao	117	133	178	217	294	304	345
Dhimar	56	53	59	74	82	113	106
Gadaria	42	45	68	83	89	91	89
Dhobi	6	2	22	27	31	46	59
Teli	47	57	71	92	109	143	148
Passi	56	70	63	79	62	20	27
Jatab	71	71	97	118	133	203	201
Others	29	29	58	53	50	48	22
Total	528	585	790	960	1133	1255	1299

Source: This table also appears in the study by Himanshu et al. (2018), and is reproduced here with permission from the copyright holder.

## 2.2 Agriculture

Throughout the survey period, the economy of Palanpur has essentially been one of small farmers. The proportion of landless households is relatively small by Indian standards and there are no clearly outstanding large farmers. The bulk of economic activity is in agriculture, and since the late 1950s the village has seen agricultural practices transformed in connection with the spread of irrigation, the introduction of new seed varieties, fertilizers and pesticides, the emergence of rental markets for agricultural equipment, and the introduction of new crops. Nonetheless, in the face of ongoing population growth and roughly constant village land availability (village lands cover roughly 400 acres, or about 160 hectares), a growing share of village income comes from non-agricultural wage employment outside the village.

At the all-India level, agricultural gross domestic product grew at an average rate of 2.8 per cent since the early 1950s, with rates above 3 per cent per annum after the 1980s (Himanshu et al. 2018). Agricultural growth rates in Palanpur have mirrored the national income growth rates in India for most of the period post-Independence. Agriculture remains of great importance to village livelihoods, notwithstanding the growth of non-farm activities in recent decades. Eighty-four per cent of Palanpur's households reported income from agriculture in 2008/9, although only 23 per cent were dependent on agriculture alone. Key to the agricultural development process over the survey period has been the expansion of irrigation from around half of village land at the beginning of the survey period to 100 per cent by the 1974/5 survey years as well as the intensification of farm capital in the form of farm mechanization that has been both land-augmenting and labour-saving. While farm mechanization has raised agricultural productivity, it has also played a role in enabling the release of labour to non-farm activities. Additional forces of agricultural change have been the shift of cropping patterns towards higher value crops, such as *mentha*, as well as improvements in farming practices. Table 3 documents the increase in yields over the survey period. Although costs of cultivation also rose during this time period, the rising yields were sufficient to ensure that village cultivation income in Palanpur grew over time in real terms.

Table 3: Yields (quintals per *bigha*) of major crops in Palanpur, 1957/8–2008/9

Year	Major crop			
	Wheat	Paddy	<i>Bajra</i>	Sugar cane
1957/8	0.37	0.14	0.38	11.46
1962/3	0.39	0.31	0.33	13.86
1974/5	1.40	0.93	0.50	15.33
1983/4	1.01	1.30	0.48	12.30
2008/9	2.90	1.90	0.95	24.70

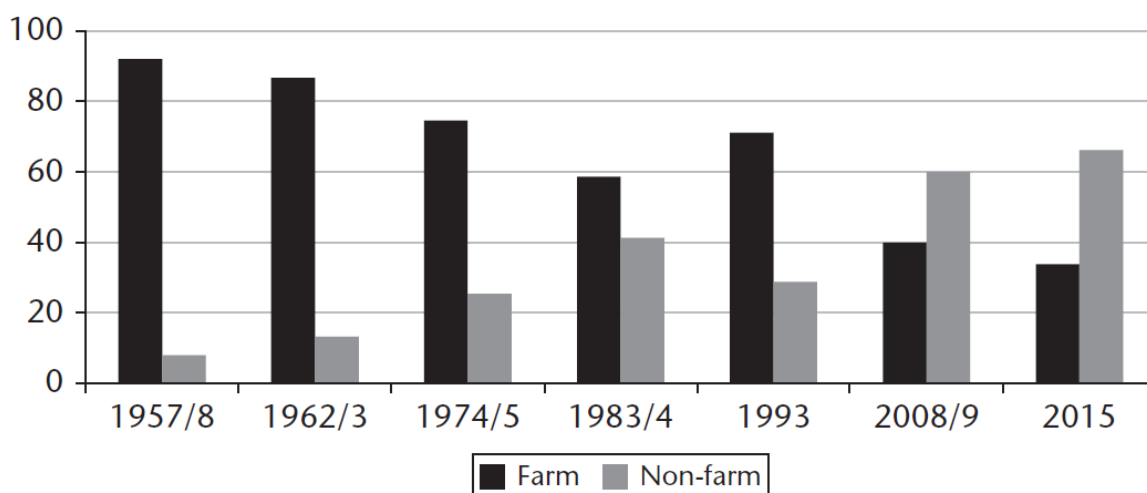
Notes: One quintal is 100 kg. There are approximately 6.4 *bighas* in an acre.

Source: This table also appears in the study by Himanshu et al. (2018), and is reproduced here with permission from the copyright holder.

### 2.3 Expansion of non-farm employment

Non-farm activities represented roughly two-thirds of total primary employment in Palanpur by 2015 and accounted for nearly 60 per cent of average household income in 2008/9 (see Figure 1 and Table 4). This compares to less than 10 per cent of employment and 20 per cent of income in 1957/8. In Palanpur, the increase in the population, the decline in per capita landholdings, and the release of agricultural labour through mechanization has prompted the take-up of non-farm activities by the labour force. Better access to towns and cities via improvements in railways and communications infrastructure, particularly mobile phones, has helped villagers find jobs and has assisted in this process and has led to a growing numbers travelling outside Palanpur for their employment.

Figure 1: Share of the farm and non-farm workforce (%)



Source: This figure also appears in the study by Himanshu et al. (2018), and is reproduced here with permission from the copyright holder.



Table 4: Income shares in Palanpur over time (%)

Income source	Year				
	1957/8	1962/3	1974/5	1983/4	2008/9
Household income					
Cultivation	58.5	56.7	58.4	50.2	30
Livestock income	19.8	21.5	22	13.7	10.4
Non-cultivation (see breakdown)	21.7	21.8	19.6	35.4	59.6
Total income share	100	100	100	100	100
Breakdown of non-cultivation income (% contribution to total income)					
Agricultural labour income					
Casual labour—farm	7.3	3.5	1.8	1.5	0.9
Other non-cultivation income					
Other farm income	1.2	0.6	0.1	2.7	10.7
Rental	0	0.2	0.6	0	1.6
Non-farm income					
Casual labour—non-farm	1.1	1	0	7	6.1
Self-employment	1.3	3.5	1	3	19.8
Regular employment	7.5	8.9	15.7	20	16.1
<i>Jajmani</i> income	1.3	0.6	0.4	1	0.2
Remittances	2	1.9	0	0.2	3.6
Other non-farm	0	1.7	0	0.2	0.6

Source: This table also appears in the study by Himanshu et al. (2018), and is reproduced here with permission from the copyright holder.

Over time, there has been substantial change in the range and nature of non-farm jobs available. While these jobs were restricted mainly to traditional caste-based *jajmani* services and a few regular jobs in the railways during the first two survey years of the 1950s and 1960s, there has been a significant expansion over time beyond the network of traditional services. Non-farm employment is now found in a range of establishments located in the vicinity, such as a cotton factory, a sugar mill, a paper factory, marble polishing units, casual labour in brick kilns, and so on.

The jobs in the non-farm sector can largely be categorized into two kinds: low-paying casual wage and menial activities and more attractive and higher-income opportunities. The latter category would comprise both well-paid regular jobs (often government provided) as well as some profitable self-employment units. But even the lower-paying jobs are more remunerative than agricultural labour, and offer more frequent days of employment while also offering the flexibility to maintain some involvement in agriculture.

The casual non-farm sector has registered the highest growth in employment in recent decades, notably in activities related to the construction sector. The rate of growth in casual employment has been followed in employment terms by self-employment. Self-employment has seen the fastest income growth in Palanpur by a substantial margin. Regular wage jobs have declined both relatively and absolutely; there has been very little growth in the number of such jobs after the early 1990s

In the face of declining per capita landholdings and lower cultivation incomes, households have pursued a broad spectrum of livelihood strategies. Himanshu et al. (2018) indicate that participation in the non-farm sector varies across households depending on the size of their landholdings and caste affiliation. Casual non-farm employment is the primary source of employment for the landless and the near-landless as the rewards from agricultural labour become less attractive relative to the opportunities outside. For households with landholdings above 30 *bighas* (slightly less than 5 acres) non-farm participation remains less common, although there are a number of villagers engaged in relatively high-earning, regular employment or particularly remunerative self-employed enterprises.

A majority of households in Palanpur now belong to the small and marginal farm category and, for these, non-farm activities are playing an important role in increasing income and diversifying risk. Dependence on cultivation has declined and the constraints on income related to land have loosened. Although households rarely exit fully from cultivation, the extent of participation in it is determined by opportunities in the non-farm sector. Those with well-paid regular jobs reduce their involvement in cultivation significantly while those with casual sector jobs remain more dependent on cultivation in order to maintain levels of income and to manage variability.

While land endowment plays a role in the basic occupational decision concerning participation or not in non-farm activities, access to these jobs, especially regular jobs, is also influenced by the caste affiliation of an individual. Access to regular jobs is often determined by an ability to pay bribes, as well as influence, contacts, and networks based on caste and kinship. As a result, such jobs tend to be held by relatively advantaged caste groups such as the Thakurs. The historically disadvantaged Jatavs, on the other hand, are poorly placed to find regular non-farm employment.

Recent decades have seen a marked increase in participation by Jatavs in the casual wage non-farm labour force, where there are few barriers to entry. This process has led to improvements in their economic circumstances: almost all Jatavs owned proper houses in 2008/9, whereas almost all their houses had been mud huts in the earlier decades of the surveys; many have moved out of poverty as conventionally measured (see Section 2.4).

The traditionally cultivating caste of Muraos originally displayed some resistance to non-farm participation, preferring to focus efforts and attention on cultivation. But declining agricultural incomes over time (due to declining per capita landholdings) has led some of them to belatedly pursue opportunities in the non-farm sector.

There is little evidence to show that education plays a key role in determining access to non-farm jobs. Most of the jobs available in the non-farm sector are unskilled in nature and formal education does not appear to be essential. Women are greatly under-represented in the non-farm labour force of Palanpur, and indeed in the entire labour force of the village. There are examples where women work alongside their husbands in non-farm activities—for example, as part of a family group in the brick kilns—but it appears that social restrictions on women working for wages as non-farm labourers, salaried employees (except for some government jobs), or entrepreneurs continue to hold. In the same way, economic activities in agriculture within the village are also circumscribed for women, although there is some indication of increasing cultivation activity for Murao women as participation in non-farm activities by Murao men starts to increase.

While full migration from Palanpur is not particularly common and is not yet increasing as a proportion of households, the related practice of villagers commuting from Palanpur on a daily basis, or for periods of short duration, is both common and increasing over time. Commuting permits villagers to continue to reside in Palanpur, and maintain some involvement in cultivation, while they access an ever wider range of non-farm job opportunities in the surrounding area and in nearby towns and cities.

## **2.4 Poverty, inequality, and income mobility**

The richness of data covering all households in Palanpur for a span of many decades permits an analysis of the dynamics of poverty, inequality, and mobility at a level of detail not normally available from secondary data sources. Poverty in Palanpur was very extensive in the early survey years: over 80 per cent of the population was classed as poor during the first two rounds (Table 5). The growth in incomes associated with expanding irrigation in the late 1950s and 1960s, and the green revolution technologies and methods in the late 1960s and early 1970s, led to a sharp

decline in poverty, with the headcount ratio falling to less than 60 per cent by 1974/5, and remaining at roughly that level in 1983/4. Poverty then fell again sharply after 1983, with non-farm employment playing an important role in improving the fortunes of many, including those at the bottom of the distribution. A similar picture emerges with mean consumption expenditure estimates that changed only moderately in the first two decades but increased strongly by 2008/9.

Table 5: Estimates of poverty headcount rates in Palanpur

Year	Poverty headcount ratio		Mean income/consumption (annual; per capita, in rupees)	
	Income	Consumption	Income	Consumption
1957/8	85.1	80.4	5,774	7,357
1962/3	83.6	74	6,010	8,079
1974/5	56.7		8,954	
1983/4	58.3		8,309	
2008/9	38.3	38.3	13,628	12,788

Notes: Mean income/consumption data are at 2008/9 prices deflated by consumer price index for agricultural labour (CPIAL) for respective years. The poverty line used here is based on the official poverty line for rural Uttar Pradesh from the Planning Commission (2009). This line yields a consumption–poverty rate of 38.3 per cent in Palanpur in 2008/9. To determine a comparable income–poverty line, the per capita income level associated with a poverty rate of 38.3 per cent in 2008/9 was obtained and then deflated back using CPIAL price indices to obtain the income poverty rates for the earlier years.

Source: This table also appears in the study by Himanshu et al. (2018), and is reproduced here with permission from the copyright holder.

Thakurs and Muraos have historically seen the lowest poverty rates (Table 6). The relative prosperity of Thakurs and Muraos increased after the expansion of irrigation and the green revolution, with both caste groups showing a sharp decline in poverty between 1962/3 and 1974/5. By 1983/4, Muraos were the least poor caste group, better off even than the Thakurs. At the other end of the distribution, the expansion of irrigation and the green revolution did little to lift the Jatabs out of poverty. The most recent interval—between 1983/4 and 2008/9—saw some decline in poverty among the Jatabs, although 70 per cent remain in poverty, considerably higher than any other group. On the other hand, with the declining rate of agricultural growth, Muraos have not seen any significant further decline in poverty since the late 1980s. Indeed, the Thakurs have regained their pole position in terms of lowest poverty and have been joined by the Telis and Gadarias, two groups that have also seen a particularly sharp reduction in poverty in the last three decades. These latter two caste groups were also among those with the highest involvement in non-farm employment in 2008/9, including in self-employment and starting small businesses.

Table 6: Poverty by caste (%)

Caste group	Year				
	1957/8	1962/3	1974/5	1983/4	2008/9
Thakur	73.1	81.6	45.7	46.9	22
Murao	78	70.7	37.4	33.3	32.2
Dhimar	98.2	100	70.7	60	47.8
Gadaria	95.2	57.8	64.6	61.9	25.3
Teli	100	100	59.2	74.2	23.9
Passi	75.8	85.7	44.1	55.2	40
Jatab	94.4	95.8	82.3	100	72.4
Total	85.1	83.6	56.7	58.3	38.3

Source: This table also appears in the study by Himanshu et al. (2018), and is reproduced here with permission from the copyright holder.

Table 7 presents various measures of inequality calculated on the basis of per capita income, for each of the survey years. Between 1957/8 and 1962/3, the Gini coefficient rose from 0.336 to 0.353 and then fell back sharply by 1974/5. The remarkable decline between 1962/3 and 1974/5 accompanied, and was likely shaped by, three principal factors. First, there was a significant expansion in irrigation in the 1960s and in the use and application of modern agricultural

technologies. The distributional ‘incidence’ of the expansion of irrigation was particularly progressive in that whereas previously only a few better-off farmers had been in a position to irrigate their land (using ‘Persian wheel’ lifting technologies that required digging and maintaining a large well and complementary draught animal power), the decade of the 1960s saw irrigation spread to all farmers. By 1974/5 all village land was irrigated. Second, that year was also a particularly good agricultural year in terms of harvest quality in Palanpur. As a result, those who had spent less on inputs were less at risk from lower or negative incomes in the face of a bad harvest. And ‘errant’ farming practices were likely to have been punished less in a good year.

Table 7: Inequality of individual incomes

Measures of inequality	Survey years				
	1957/8	1962/3	1974/5	1983/4	2008/9
Gini coefficient	0.336	0.353	0.272	0.310	0.379
Coefficient of variation	0.650	0.755	0.530	0.578	0.769
Atkinson index					
$e = 1$	0.173	0.191	0.137	0.170	0.229
$e = 2$	0.319	0.344	0.206	0.366	0.444
Theil $L$ measure					
$GE(0)$	0.19	0.213	0.147	0.186	0.26
No. of observations	529	585	750	977	1255
No. of households	100	106	112	143	233
No. of individuals (households) with missing income	0	0	5 (1)	8 (3)	37 (12)

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Finally, the distribution of land cultivated in Palanpur was more equal in 1974/5 than in other years. This was in part a result of a fall in the proportion of land owned by Thakurs due to a few land sales. In addition, during this year tenancy and sharecropping practices displayed a clear pattern of large landowners leasing-out their land to those with smaller landholdings. In later years that pattern became more mixed, with also cases of ‘reverse tenancy’: households with smaller holdings leasing-out to those with larger ones.

Between 1974/5 and 1983/4, inequality increased but remained lower than its 1957/8 and 1962/3 levels. With the ongoing intensification of agriculture, the Muraos as a group, already with the Thakurs among the more prosperous groups, experienced improved relative prosperity due to higher returns from cultivation.<sup>2</sup> By 1983/4, the Muraos had even surpassed the Thakurs in terms of per capita income. In addition, in 1983/4, new non-farm employment opportunities were becoming increasingly available, and were taken up mostly by villagers from economically better-off backgrounds. Due to a disappointing harvest in 1983/4, the income gaps were further widened between those who derived some earnings from outside and those who were entirely dependent on agriculture. And there was wider dispersion within cultivator incomes, influenced by spending on inputs and the relative impact of the poor harvest.

In the most recent survey for which income data are available, conducted in 2008/9, the Gini index, at 0.379, was at its highest level compared with all other survey years. The sharp increase in inequality between 1983/4 and 2008/9 merits further examination. While changes in inequality across the early survey rounds can be understood in terms of the impact of expanding irrigation and green revolution technologies and methods on agricultural incomes, as well as the varying efforts or abilities of Palanpur households to create improvements in agricultural productivity, the distribution of income in later survey rounds was also influenced by the expanding rural non-farm

<sup>2</sup> Muraos, a traditional cultivator caste, were, on average, among the earlier to take advantage of the green revolution technologies and methods.

sector. One window on this process is offered by income inequality decompositions that assess the contribution of different sources of income to overall income inequality.

Table 8 reports results from a decomposition of the Gini by income sources (see Shorrocks 1982). The share of income from non-farm sources in total income has increased over the survey period, from 13 per cent in 1957/8 to 46 per cent in 2008/9. In contrast, the share of cultivation income has declined from almost 50 per cent in 1983/4 to 30 per cent in 2008/9. In addition, there has been increasing divergence in non-farm incomes which can be observed from the rise in the non-farm income source Gini ( $G_k$ ). It increased from 0.59 in 1983/4 to 0.64 in 2008/9. These two factors, along with the Gini correlation coefficient, give the ‘contribution’ of various income sources to overall inequality. In 2008/9, the contribution of cultivation income was 20 per cent while that of non-farm income was 58 per cent. The corresponding figures in 1983/4 were 63 per cent and 22 per cent, respectively. The rise in the contribution of non-farm income to inequality, as suggested by this decomposition, is dramatic in those 25 years.

Table 8: Inequality decomposition by factor components

Year	Inequality in source of income $k$ (Gini coefficient ( $G_k$ ))			
	Cultivation income	Non-farm income	Other sources	Total
1957/8	0.468	0.825	0.539	0.336
1962/3	0.475	0.836	0.576	0.354
1974/5	0.434	0.685	0.450	0.272
1983/4	0.529	0.598	0.510	0.310
2008/9	0.499	0.645	0.598	0.379
Share of total income ( $S_k$ ) (%)				
1957/8	58.5	13.3	28.2	1
1962/3	56.7	17.5	25.8	1
1974/5	58.4	17.0	24.6	1
1983/4	49.9	31.7	18.5	1
2008/9	30.0	46.4	23.6	1
Contribution to overall Gini coefficient (%)				
1957/8	63.9	8.7	27.4	1
1962/3	55.0	19.2	25.8	1
1974/5	76.6	3.7	19.8	1
1983/4	63.9	22.9	13.3	1
2008/9	19.7	58.4	21.9	1

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The Palanpur data can be further analysed to study patterns of mobility. Over the entire survey period since the 1950s there is evidence of increasing mobility of households across income quintiles, with the share of households ranked in the same quintile between two rounds, falling from 28 per cent in 1957–62 to 20 per cent in 1983–2008. Among the factors that seem to have contributed are the decline in landholding and the relatively weak role played by agriculture compared with non-farm work, which has emerged as a new source of potential income increase. While access to non-farm jobs has been uneven, with the relatively affluent and socially networked being more successful in finding regular, high-paying jobs, the spread of non-farm activities to lower-ranked households in more recent years has also allowed at least some of those at the bottom to improve their fortunes.

The long-time horizon covered by the Palanpur study offers an opportunity to look beyond intragenerational mobility to intergenerational mobility, and indeed to compare changes in intergenerational mobility. Himanshu et al. (2018) broach this question by looking at the father–son intergenerational income elasticity between two 25-year intervals: 1957/8–1983/4 and 1983/4–2008/9. They identify father–son pairs, where sons in the latter period belong to the 25–30-year age group, and consider the per capita income of the household in the initial period as the father’s income. Following Atkinson et al. (1983), they then regress the log of the son’s income on

the log of his father's income, and denote the resulting parameter estimate on the father's income as the intergenerational income elasticity. Table 9 reveals that this elasticity has increased over time, suggesting a decline in intergenerational mobility: the father's income is a better predictor of his son's income in the 1983/4–2008/9 interval than the preceding interval. The degree of intergenerational mobility measured in this way is fairly close to the estimate obtained by Atkinson et al. (1983) for the town of York between 1950 and 1957/8, and is also not far off from the association that has been observed between fathers' height and that of their sons.

Table 9: Intergenerational elasticity in earnings and inequality, 1958–2009

	1958–84	1984–2009	1958–74 (1984)	1974 (1983)–2009
	(1)	(2)	(3)	(4)
Number of observations (in the age group 25–35 years)	58	100	58	100
Gini coefficient in terminal year	0.336	0.379	0.235	0.379
Intergenerational elasticity	0.328	0.396	0.294	0.441

Notes: Columns 3 and 4 represent the elasticity replacing the income for 1983/4 by an average of 1974/5 and 1983/4, because 1974/5 was a good agricultural year and 1983/4 was a bad year.

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Himanshu et al. (2018) stress that although non-farm employment opportunities in the village have become available to a wider population, the importance of networks and assets has not disappeared and may well have increased. In particular, access to regular, well-paying, on-farm jobs remains concentrated among Thakur and other advantaged households who have better access to networks and can finance 'entrance fees' where these are necessary. The finding of declining intergenerational mobility is thus not inconsistent with increased intragenerational mobility of Jatab and other caste groups. Broadly speaking, the new non-farm opportunities do open up possibilities for upward mobility and within any group some move to take these opportunities more quickly than others. Nevertheless, income and social status increase the likelihood of obtaining these non-farm jobs, and this effect becomes more important as the number of non-farm opportunities rises.

### 3 A simulation model for tracking distributional outcomes

The distribution of income, however defined and assessed, is a highly derived concept, with multiple determinants. Conversely, inequality, or some other measure of the distribution of welfare, is likely to affect many socioeconomic variables. In this section, we build a relatively simple model of a village economy that highlights some of the determinants of inequality (but ignores the influence of inequality on those determinants). Our objective is to develop a model where the impact of drivers of inequality can be studied in isolation, with a view to acquiring a better understanding of inequality trends in the particular contexts that can be represented by the model's parameters and assumptions.

Here, we describe the building blocks of the model and its calibration on data from Palanpur. Inspiration for the model comes from the Lewis model, which can be seen as a simple explanation of a trend in inequality that follows the Kuznets hypothesis. As described in Section 2, powerful forces of change have shaped the distribution of income in the village. Technological change in agriculture, the expansion of non-farm employment opportunities, and demographic change have been influential but largely exogenous to the village. We are interested not only to scrutinize further how the distribution of welfare in Palanpur has been shaped by these factors but also to examine a few counterfactual scenarios, to gauge how welfare might have evolved in their absence.

We conclude by assessing how our model-based simulations have informed our understanding of economic development in Palanpur. Pointing to the likely general applicability of the model's structure to other villages in this part of Uttar Pradesh, and perhaps beyond, we suggest that our findings may well be of broader relevance.

### 3.1 Model description

The model has an annual recursive structure. The unit of time is a year, which simplifies calibration of the model to the data from Palanpur.

#### *Population dynamics*

We assume people live for exactly 70 years. They live in single-person households, so no distinction is made between individuals and households. Between ages 15 and 51 years (not included) they individually produce offspring (with constant probability per year). Those aged 15 years and over earn an income. For implementation, we generate a population with an age distribution that is more or less in equilibrium, while at the same time producing the population growth rate observed in Palanpur (1958–2009) (i.e. 2 per cent per year).<sup>3</sup> The model allows for three ‘castes’ (representing the three largest castes in Palanpur: Thakurs (‘T’), Muraos (‘M’), and Jatabs (‘J’)); in the current version of the model, the population dynamics for all three castes are the same.<sup>4</sup>

#### *Economic dynamics*

Economic dynamics are a combination of occupational and income dynamics. For income earners (adults between 15 and 70 years of age) incomes evolve according to an autoregressive process:

$$\log y_{t+1} = \alpha + \beta \log y_t + \sigma \varepsilon_{t+1},$$

where  $\varepsilon_t$  is standard normal (independent across time and across castes or individuals). The parameters of this process ( $\alpha$ ,  $\beta$ ,  $\sigma$ ) are specific for caste, occupation, and epoch, as further explained later in this section. The year before children enter adulthood we initiate them with an income that is related to their parent's income according to

$$\log y_t^{\text{[age is 14]}} = a + b \log y_{\text{parent},t} + s \varepsilon_t.$$

They start earning incomes from 15 years onwards.

An individual's occupation is determined by a Markov transition process. Each caste has a set of occupations (with corresponding parameters for the income process) and transitions between occupations are determined by caste- and occupation-specific probabilities. The full model is depicted in Figure 2.

Figure 2 indicates that the model ‘produces’ individuals from different castes with their occupations and incomes, as well as their offspring. Thus, the model can be used to analyse the interplay of population, occupation and income dynamics, and derivatives of those, like inequality. In the implementation, we take the parameters of population and occupation and income dynamics

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<sup>3</sup> Given our interest to examine trends in the distribution of income, we do not incorporate data and village features from the 2015 survey.

<sup>4</sup> Bliss et al. (1998) find little in the way of a discernible relationship between population growth and its caste status in Palanpur.

as exogenous. For a small village, such extreme assumptions seem justifiable. As noted, there is no feedback of inequality or other model outcomes to the model's parameters.

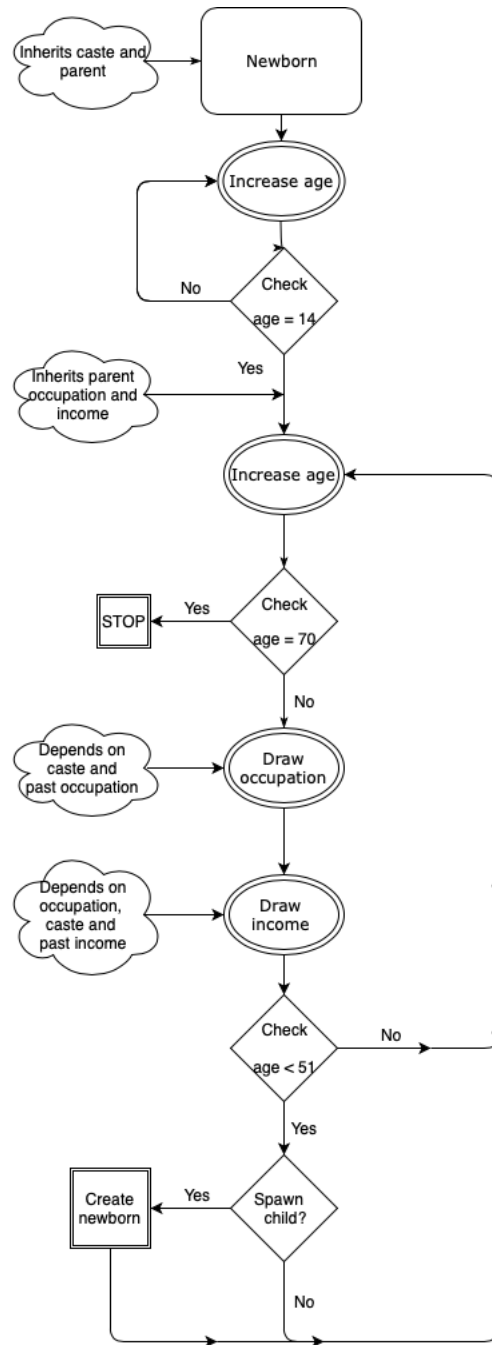
### *Calibration*

Many steps in the model involve random variables. In this particular model implementation, we have fixed these underlying random variables (by setting the 'seed' of the random number generators). Therefore, unless stated otherwise, model outcomes should not be looked at as 'expected' or average model outcomes; they are the outcome of a particular simulation path.

*Population:* As described, the model is calibrated on data from Palanpur. A population growth rate of 2 per cent is assumed (informed by the data) for all three castes ('J', 'M', 'T') starting from an age distribution that is approximately in equilibrium. In this paper, we do not explore the possible effect of differential population growth on inequality.



Figure 2: Model summary



Source: Authors' compilation.

*Occupation dynamics:* Individuals from each of the three castes earn either agricultural or non-agricultural incomes. With three castes this would amount to  $3 \times 2 = 6$  occupations, but we have pooled the agricultural and non-agricultural occupations of the 'M' and 'T' castes, resulting in a total of four occupations. Classification of a household's total income in a particular year as agricultural or not has been based on whether the total from agricultural income components exceed the non-agricultural income components in the data from Palanpur. All income components that are directly related to agriculture have been classified as agricultural, including a number of categories termed 'non-cultivation' in Table 4 earlier. This then allows estimation of occupation transition probabilities. For instance, Tables 10 and 11 (absolute numbers and transition probabilities, respectively) describe transitions for the 'J' caste in the period 1974–83. In

a few cases, the raw transition numbers had to be adjusted to allow derivation of annualized transition probabilities.<sup>5</sup>

Table 10: Occupation dynamics: Jatabs, 1974–83

1974	1983	
	Agriculture	Non-agriculture
Agriculture	11	10
Non-agriculture	0	0

Source: Authors' calculations based on simulation and Palanpur survey data.

Table 11: Transition probabilities (annualized) occupation dynamics: Jatabs, 1974–83

T+1		
	Agriculture	Non-agriculture
Agriculture	0.931	0.069
Non-agriculture	0	1

Source: Authors' calculations based on simulation and Palanpur survey data.

*Income dynamics:* The first step in setting the parameters of the income-generating process is a regression, per caste–occupation combination, of a household's log per capita income in a particular survey round to log per capita income in the previous round, linking households through their ancestor's household number.

$$\log y_{\text{round } n, h} = \alpha + \beta \log y_{\text{round } n-1, h} + \sigma \varepsilon_{\text{round } n, h}$$

This amounts to 4 (transition periods) times 4 (caste–occupation combinations) regressions. After this step the results of the regressions are annualized. It can be verified that parameter estimates  $\hat{\alpha}, \hat{\beta} > 0, \hat{\sigma}^2$  based on a period covering  $k$  years can be annualized to parameters  $\alpha, \beta, \sigma^2$  as follows:

$$\begin{aligned}\beta &= \hat{\beta}^{\frac{1}{k}} \\ \alpha &= \hat{\alpha} \frac{1 - \beta}{1 - \hat{\beta}} \\ \sigma^2 &= \hat{\sigma}^2 \frac{1 - \beta^2}{1 - \hat{\beta}^2}\end{aligned}$$

We illustrate the procedure in Table 12. Complications arise if the regression coefficient on lagged log income is negative. In those cases we have set the coefficient to zero, amounting to annual independent lognormal draws representing the end-period income distribution for all in-between years. Table 13 shows that negative autoregressive parameters are found in half of the regressions, suggesting that intergenerational and intragenerational income mobility is considerable. Further, we explore an altogether different approach by setting the annual autoregressive parameter to an a priori value.

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<sup>5</sup> This was necessary when the matrix of transition probabilities had negative eigenvalues. Tables 10 and 11 also show that in the absence of data on transitions from the non-agricultural occupation we have modelled it as an absorbing state.

After having thus obtained annualized regression parameters, in the next step we have calibrated  $\alpha$ ,  $\beta$ , and  $\sigma^2$  to better match the overall Gini and the caste- and occupation-specific income distributions.

Table 12: Muraos and Thakurs, 1974–83, agriculture

	1974–83	Annualized
$\alpha$	6.0977	1.3170
$\beta$	0.1683	0.8204
$\sigma$	0.6170	0.3579

Source: Authors' calculations based on simulation and Palanpur survey data.

The resulting fit of the model can be gleaned from Appendix Figures A1 and A2. The match between data and model outcomes should not come as a surprise: it only shows that the model is flexible enough to fit the income data from the Palanpur surveys well. For instance, the model has enough degrees of freedom to exactly replicate the Gini coefficients from the survey in the baseline scenario.

Table 13: Estimated autoregressive parameters

Period	Jatab—agriculture	Jatab—non-agriculture	Other—agriculture	Other—non-agriculture
1958–64	0.93**	(2 cases)	0.4077*	(1 case)
1964–74	(No cases)	0.0874	–0.1442	–1.8720
1974–83	0.2360	–0.2660	0.1683	0.1100
1983–2009	–0.1346	–0.3217	0.1606	–0.2280

Source: Authors' calculations based on simulation and Palanpur survey data.

Recall that model simulations are outcomes depending on a particular, fixed, set of draws for the underlying random variables. To gauge the importance of random drivers of outcomes in the model, Table 14 gives the mean and standard deviation of the baseline simulation, when using other sets of draws.<sup>6</sup> They suggest that for such a small population as Palanpur, changes in the Gini between 1958 and 1983 could very well reflect short-run rather than structural fluctuations. On the other hand, the increase in inequality between 1983 and 2009 clearly stands out as a significant change compared with the period before 1983.

Table 14: Gini coefficients: Mean and standard deviation of simulated baseline scenario

Year	Baseline data	Mean baseline simulations	Standard deviation, baseline simulations
1958	0.3270	0.3396	0.0194
1964	0.3378	0.3496	0.0170
1974	0.2959	0.3153	0.0126
1983	0.3145	0.3005	0.0141
2009	0.3750	0.3900	0.0147

Source: Authors' calculations based on simulation and Palanpur survey data.

Table 15 shows results for the poverty headcount rates in the baseline run. The close match between baseline headcount rates and the data is the result of calibrating each year's poverty line to reproduce the poverty headcount data (up to rounding error due to finite population size). To gauge the possible role of short-term fluctuations, mean and standard deviations of a series of runs with different underlying random variables have been added. Data and model outcomes suggest that poverty decline was fastest in the 1964–74 period, at almost 3 percentage points per year.

<sup>6</sup> The standard deviations are similar to those obtained from bootstrapping the Palanpur data. Note that the Gini coefficients from column 'Baseline data' in Table 14 differ from the Gini coefficients in Table 7. This is because we have considered only households from the Jatab, Muraos, and Thakur castes.

Table 15: Poverty headcount: Data and baseline scenario outcomes

Year	Data	Baseline	Mean	Standard deviation
1958	0.8510	0.8513	0.8115	0.0206
1964	0.8360	0.8333	0.8218	0.0268
1974	0.5670	0.5673	0.5740	0.0272
1983	0.5830	0.5816	0.5602	0.0299
2009	0.3830	0.3832	0.3728	0.0210

Source: Authors' calculations based on simulation and Palanpur survey data.

### 3.2 Counterfactual simulations

In this section, we perform a few simulations to interpret trends in the income distribution. In all simulations, we have fixed the underlying random variables for better comparability. However, it should be kept in mind that small differences in the order of 1 to 2 percentage points could be the result of short-term variability.

#### *Occupational dynamics*

In the first simulation we keep households in their (or their ancestor's) occupation in the year 1957/8. This amounts to setting all occupations to 'agriculture' since only one of the 1957/8 households (a Thakur household) was classified as non-agricultural in that year. As can be seen from the aggregate results in Table 16, this scenario almost reproduces the baseline Gini values, although it points to a somewhat larger increase in inequality between 1983/4 and 2008/9. The same conclusion holds for headcount rates except for the final year 2009, with considerably higher poverty, suggesting that moving out of agriculture has contributed to poverty reduction, especially after 1983. Again, these overall trends are confirmed by the actual data for Palanpur, with a Gini coefficient among agricultural earners of 0.372 in 2009 against 0.338 for non-agricultural households.

Table 16: Simulation results: Baseline and no occupational change (NOC) scenarios

Year	Baseline Gini	NOC	Baseline headcount	NOC
1958	0.3270	0.3270	0.8513	0.8513
1964	0.3378	0.3315	0.8333	0.8611
1974	0.2959	0.2886	0.5673	0.5636
1983	0.3145	0.2919	0.5816	0.5638
2009	0.3750	0.3908	0.3832	0.4655

Source: Authors' calculations based on simulation and Palanpur survey data.

#### *Technological change*

The model also permits simulating the effects of technological change. We present two scenarios. In the first scenario, the income processes are kept at their 1974 specification: independent annual lognormal draws, specific for each of the four occupation groups (Jatabs: agriculture and non-agriculture; Muraos and Thakurs: agriculture and non-agriculture).<sup>7</sup> In the second scenario, we fix agricultural incomes to their 1958 specification, while increasing the mean to reflect overall income growth. We therefore interpret this scenario as simulating 'neutral' technological change in agriculture. The findings are presented in Tables 17 and 18.

<sup>7</sup> Recall that only a single (Thakur) household was classified as non-agricultural in 1958. Therefore, we could not simulate what would have happened under the 1958 income-generating processes.

Table 17: Gini coefficients: Baseline and various income scenarios

Year	Baseline	Income 1974	Neutral agriculture
1958	0.3270	0.2921	0.3270
1964	0.3378	0.3054	0.3524
1974	0.2959	0.2901	0.3301
1983	0.3145	0.3105	0.3527
2009	0.3750	0.3816	0.3360

Source: Authors' calculations based on simulation and Palanpur survey data.

Table 18: Headcount rates: Baseline and various income scenarios

Year	Baseline	Income 1974	Neutral agriculture
1958	0.8513	0.5897	0.8513
1964	0.8333	0.5370	0.7778
1974	0.5673	0.5418	0.4727
1983	0.5816	0.5697	0.4599
2009	0.3832	0.5849	0.2723

Source: Authors' calculations based on simulation and Palanpur survey data.

The outcomes can be interpreted as the result of occupational mobility, net of changes in income processes. They suggest that by itself the increase in the number of households classified as non-agricultural has not led to major changes in inequality or poverty. This seems to contradict the previous results (see Table 16), which suggested that staying in agriculture would have led to less poverty reduction over the period 1983–2009 (and a somewhat larger increase in inequality). The reason is that in the current set of scenarios the parameters of the income process have been kept at their 1974 value, while in fact non-agricultural incomes have especially increased in the 1983–2009 period. For instance, for the Jatabs incomes (in current prices) earned in agriculture grew 5 percentage points slower than non-agricultural incomes. The outcomes of Table 16, therefore, seem driven by ‘price changes’, not quantity changes.

### 3.3 Alternative approach

As mentioned earlier in reference to Table 13, the autoregressive parameter of the income-generating processes is only imprecisely estimated and often found to be negative. Here, we consider the alternative approach of setting the parameter representing annual income autoregression to an arbitrary but reasonable seeming value ( $\beta=0.9$ ) and then using the method of moments to derive an intercept and standard deviation for the error term. Since the data show first a declining trend in inequality and then an upward trend, we do this separately for the periods 1958–83 and 1983–2009. For the initial year 1958 we use the same outcomes as in the earlier model simulations. For simplicity, we also adjust the occupation dynamics to these epochs. Standard deviations of the autoregressive processes had to be tweaked slightly to reproduce Gini coefficients for 1983 and 2009. Poverty lines have been set to reproduce actual observed headcount rates (up to deviations due to finite counts). Table 19 indicates that the most important difference between the real data and model results occurs for the Gini in 1964.<sup>8</sup> Given that in 1983 the actual Gini was approximately back where it was in 1958 (around 0.32), and given that the income-generating processes in this set of simulations do not change between 1958 and 1983, this suggests that the decline in inequality observed between 1958 and 1974 could be related to changes in the distribution of occupations.

<sup>8</sup> The data for 1964 show a *decline* in per capita income, whereas under the alternative approach considered here 1964 takes a third of the aggregate growth between 1958 and 1983.

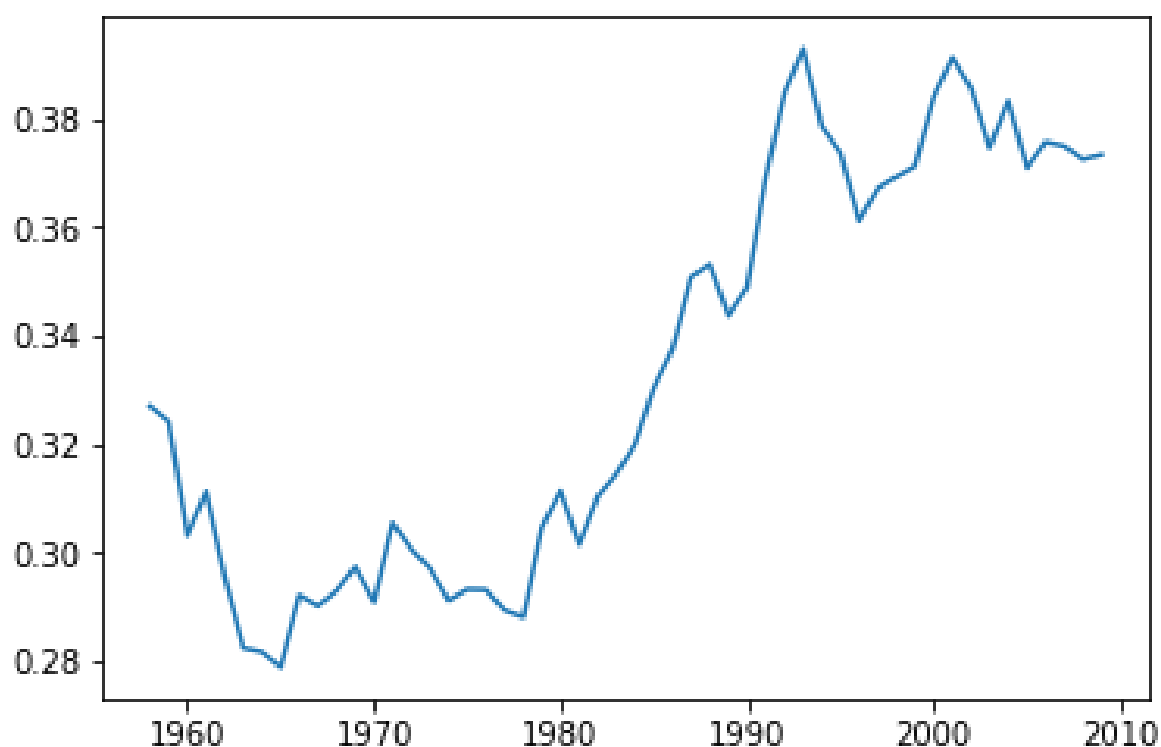
Table 19: Alternative approach: Results from baseline scenario

Year	Gini data	Gini model	Headcount data	Headcount model
1958	0.3270	0.3270	0.8510	0.8513
1964	0.3378	0.2816	0.8360	0.8333
1974	0.2959	0.2911	0.5670	0.5673
1983	0.3145	0.3145	0.5830	0.5816
2009	0.3750	0.3750	0.3830	0.3832

Source: Authors' calculations based on simulation and Palanpur survey data.

Figure 3 shows the path of Gini coefficients in the baseline simulation, in particular its volatility. If the random model elements are correctly reflecting real world uncertainty one should be careful not to draw too strong conclusions from small changes in inequality or poverty seen in the data.

Figure 3: Alternative approach: Simulated path of Gini coefficients



Source: Authors' calculations based on simulation and Palanpur survey data.

### *Counterfactual scenarios*

For comparison, we repeat the counterfactual scenario 'no occupational change' (NOC) which keeps occupations as in 1958. Table 20 shows the results. Comparison with Table 16 marks 1964 as a special year as also noted in the discussion of Tables 6 and 7. By assuming constant income generating processes between 1958 and 1983, the trends in agricultural incomes are effectively smoothed. Calibrating the model to observed Gini coefficients then puts the burden of the inequality increase between 1958 and 1964 on the expansion of non-agricultural occupations. This contrasts with the earlier discussion of Tables 6 and 7 which maintains that the increase in inequality in 1964 is related to unequal access to irrigation, i.e. an agricultural phenomenon. In this case, the alternative approach misrepresents developments in Palanpur.

Table 20: Alternative approach: NOC scenario

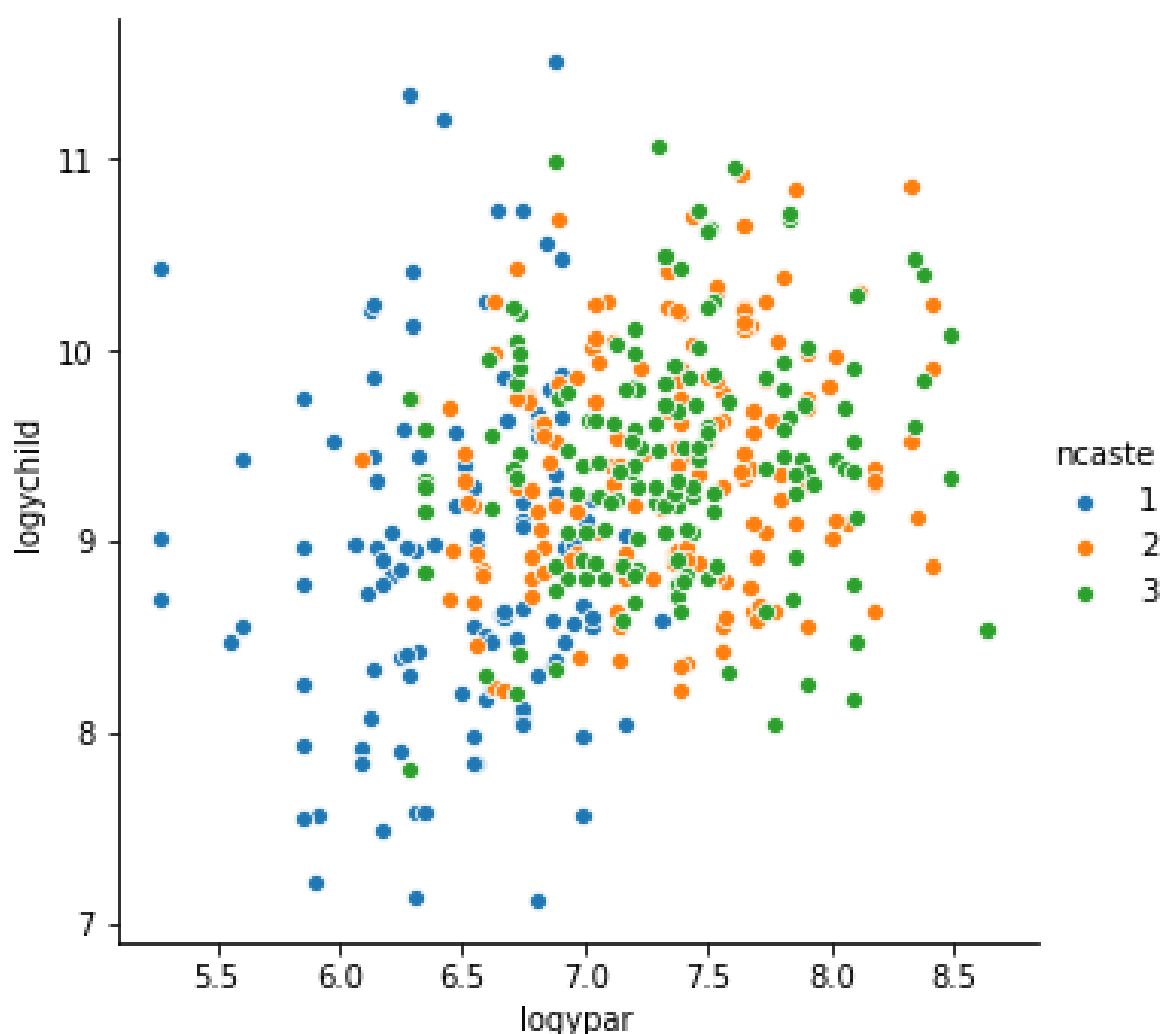
Year	Baseline Gini	NOC	Baseline headcount	NOC
1958	0.3270	0.3270	0.8510	0.8513
1964	0.3378	0.2807	0.8360	0.8241
1974	0.2959	0.2891	0.5670	0.5537
1983	0.3145	0.3100	0.5830	0.5638
2009	0.3750	0.3632	0.3830	0.4437

Source: Authors' calculations based on simulation and Palanpur survey data.

### *Intergenerational income mobility*

The alternative model also allows us to look at intergenerational mobility. Parents' and children's' incomes are linked by the income autoregression parameter, together with the model assumption that at 14 years of age a next-year income earner is endowed with their parent's income. With an autoregression parameter of  $\beta=0.9$ , is a link still discernible over the period of a generation? Figure 4 plots simulation outcomes for the period 1983–2009.

Figure 4: Alternative approach: Parent (1983) and child (2009) income pairs by caste



Notes: Caste 1, Jatab; 2, Murao; 3, Thakur. Parent log income on the horizontal axis.

Source: Authors' calculations based on simulation and Palanpur survey data.

We show results of two kinds of intergenerational regression: one that links a model person's 1983 (2009) income to that of their parent in 1958 (1983); and one that links a model person's 1983 (2009) income to that of their parent when she was of the same age as the child in 2009 (1983). Both regressions are carried out conditional on caste and unconditionally. The estimated coefficients turn out to differ considerably across simulation runs. Therefore, in Table 21 we report the average and standard deviation of the estimated autoregression parameters  $\beta$  for the regressions, based on 200 simulation runs. The last row in the Table, with unconditional coefficients linking incomes of parent and child at the same age, can be compared with the intergenerational elasticities of Table 9. However, note that in Table 21 a parent can have several offspring, while a parent's income is compared to the income of only a single son (the successor) in Table 9. Contrary to Table 9, the simulation results do not support a conclusion of decreasing inter-generational mobility. With  $\beta=0.9$  and simulation epochs of 25 and 26 years, one would expect a coefficient of at most  $\beta^{25}=0.07$ , controlling for caste. This is not sufficient for unconditional coefficients that are of the same order of magnitude as those reported in Table 9, namely 0.33 for the period 1958-83 and 0.4 for the period 1983-2009. This contrasting outcome to the findings in Table 9 quite possibly point to the role played by networks and personal connections in a village like Palanpur; a dimension not captured in our model. Finally, only the unconditional coefficients in Table 21 are significant. In this version of the model intergenerational persistence of income differences therefore stems from long-term inequality between the castes.

Table 21: Alternative approach: Intergenerational income mobility

Regression	Autoregressive parameter ( <i>P</i> value)	
	1958–83	1983–2009
Child–parent (conditional on caste)	0.1798 (0.088)	0.1542 (0.026)
Child–parent (same age, conditional on caste)	0.0293 (0.413)	0.0717 (0.021)
Child–parent (unconditional)	0.4734 (0.104)	0.3284 (0.054)
Child–parent (same age, unconditional)	0.2010 (0.104)	0.1542 (0.069)

Source: Authors' calculations based on simulation and Palanpur survey data.

## 4 Concluding remarks

The village of Palanpur, located on the Gangetic plain of western Uttar Pradesh, is unremarkable in the sense that it does not obviously stand out in any special way from the many other villages located in this densely populated region of North India. We summarize in Section 2 key findings from a detailed study of economic development in Palanpur between 1957/8 and 2008/9 by Himanshu et al. (2018). Alongside steady growth in population, two important forces of change are studied by Himanshu et al. (2018). First, agricultural intensification linked to the expansion of irrigation, adoption of new seeds and fertilizers, and increased mechanization took hold early in the study period and continued in varying degrees throughout. Second, somewhere around the middle of the study period the village economy began diversifying out of agriculture and this process then accelerated over time. Himanshu et al. (2018) document trends in per capita income growth and poverty decline that resonate fairly closely with what has been observed at the all-India level. They show, however, that in Palanpur income inequality showed no clear trend until the 1980s whereupon it rose significantly. Seeing that the rise in inequality occurred alongside the increasing diversification of the village economy, the question arises as to the role of non-farm diversification in driving this change.

We pursue this question on the basis of a simulation model based on Palanpur characteristics. The simple model that we have constructed and calibrated on Palanpur data resonates with, and is able to track, the true Palanpur data rather well. What this indicates is that a village that resembles



Palanpur in certain basic ways—notably a breakdown of population into certain sub-groups that engage in agriculture and participate in the non-farm sector in ways that are broadly similar to what is observed in Palanpur—might expect to see living standards like poverty and inequality evolve in similar ways to that in Palanpur. It is obviously unreasonable to study a village like Palanpur closely and to then assert that the experiences and processes observed there will hold in many, or all, of India’s villages. What our modelling exercise shows, however, is that we need not insist on the exact duplication of all of Palanpur’s characteristics for a similar evolution of outcomes to become plausible elsewhere. This finding lends support to, and possibly helps to interpret, the finding by Mukhopadhyay and Garces (2018) that within-village inequality is rising in many parts of the country. It helps also to alert policy makers to possible distributional processes underway within villages that might not be easily discernible at the macro level.

A further insight from our model relates to our findings from the counterfactual simulations. Decomposition exercises, such as that described in Section 2, might have been interpreted to suggest that rising non-farm incomes have been responsible for the rise in observed inequality in Palanpur between 1983/4 and 2008/9. What our counterfactual simulations suggest, however, is that inequality and poverty might actually have been even higher in the absence of non-farm diversification. These findings are not contradictory once one realizes that the inequality decomposition reported in Section 2 is only an accounting exercise and needs to be interpreted carefully.

An important implication of this particular counterfactual analysis is that it points to the possibility that inequality increases in rural India might be expected to be larger in those villages that have failed to see significant non-farm diversification over time. The common perception in the literature is that non-farm income diversification is likely to be a force for rising inequality in rural areas. Instead, we suggest that if the diversification process resembles that observed in Palanpur, with the poorer segments also gaining access to the non-farm occupations, then the diversification process may actually be acting as an important driver of poverty reduction and a brake on further widening of inequality.

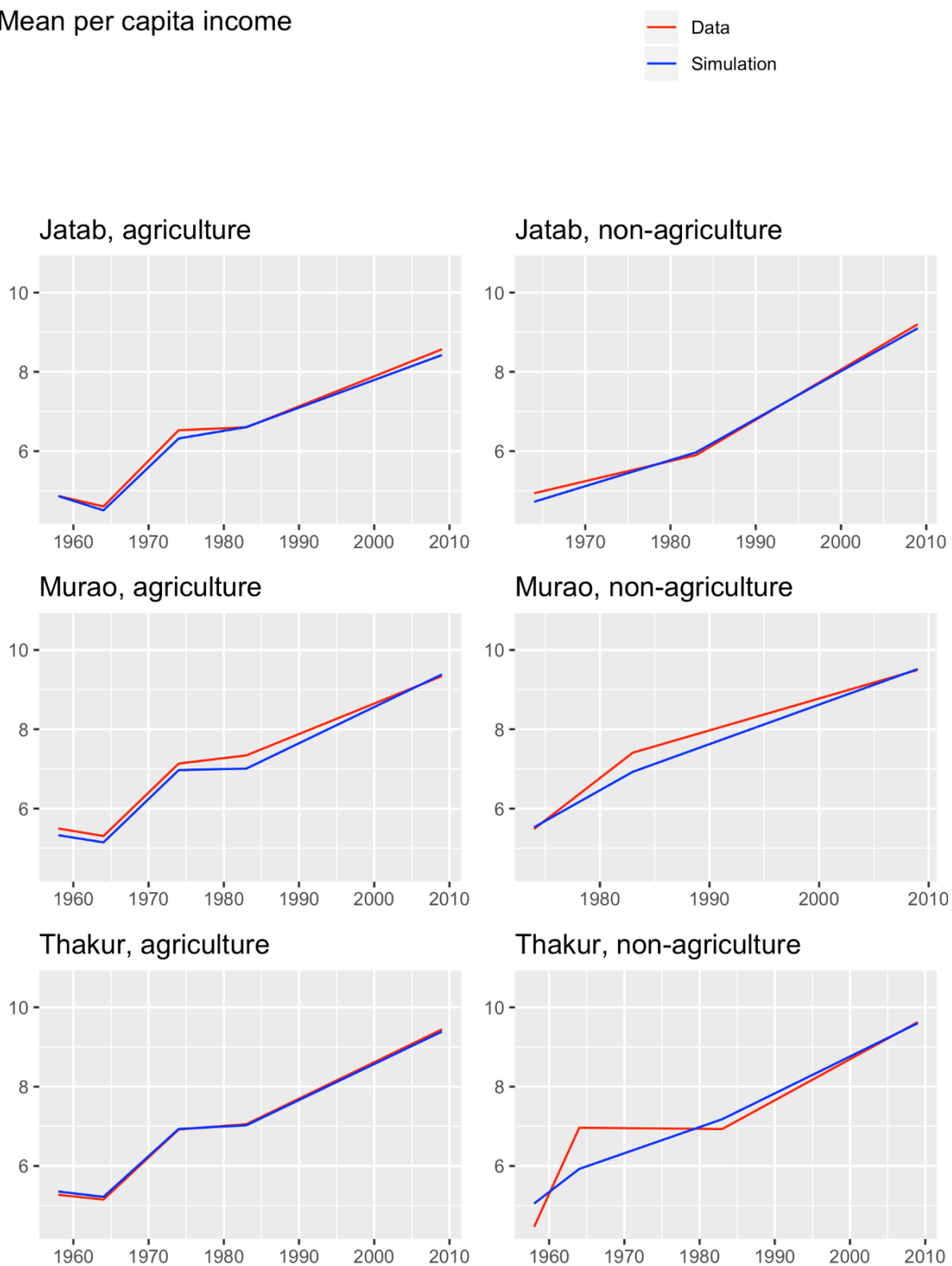
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## Appendix A: Match between data and baseline scenario

Figure A1: Mean log income by cast, occupation, and year

Mean per capita income

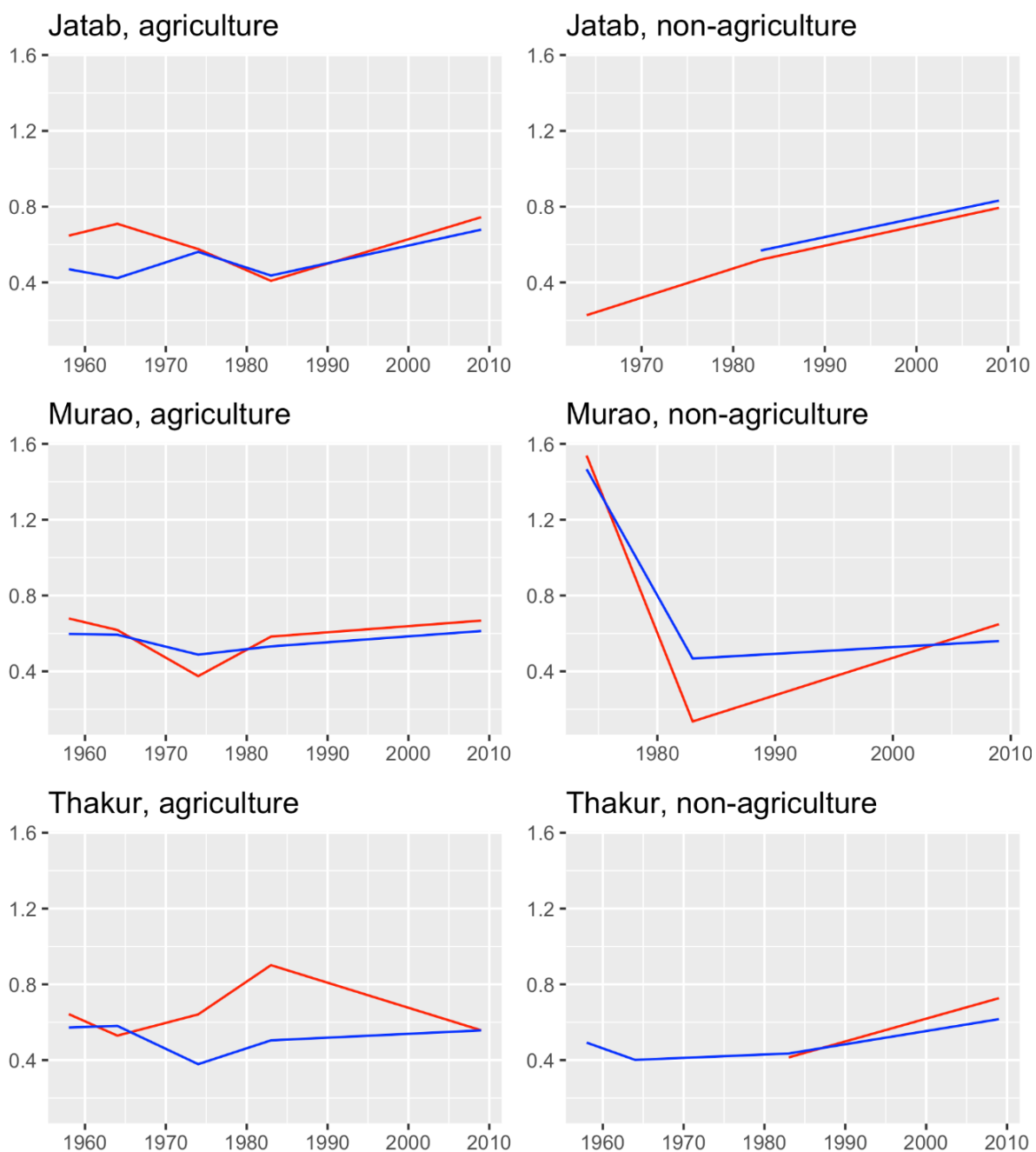


Source: Authors' calculations based on simulation and Palanpur survey data.

Figure A2: Mean standard deviations by caste, occupation, and year

# Std.dev of per capita income

— Data  
— Simulation



Source: Authors' calculations based on simulation and Palanpur survey data.