A Road for all Seasons: Market Access and Inter-temporal Arbitrage in Rural India*

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Abstract

While the effects of transportation infrastructure on spatial price dispersion through market integration are well-known, it is unclear if connectivity can also temper inter-temporal price volatility. We examine the impact of a large-scale rural road infrastructure program, which connected market towns to unconnected villages, on inter-temporal price volatility in agricultural markets in India. Leveraging the staggered roll-out of the program, we find that improved road connectivity significantly reduces the annual price dispersion of non-perishable crops, by allowing farmers to delay sales to later in the harvest cycle when prices are higher. The effects are strongest in regions with access to storage facilities and rural credit, underscoring the importance of complementarities in agricultural marketing infrastructure.

JEL Codes: O18, Q11, Q13, R40

Keywords: Rural Roads, Price Volatility, Inter-temporal Arbitrage, Agricultural Markets, PMGSY

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1 Introduction

Agricultural markets in developing countries are characterized by large intertemporal fluctuations in prices, driven by a sharp increase in supply at the beginning of the harvest cycle, followed by a substantial decline toward its end (Fafchamps et al. 2005; Gilbert et al. 2017; Cedrez et al. 2020). In India, as illustrated in Figure 1, the market arrivals of major crops decline by about 50% within five months of harvest and correspondingly, prices are nearly 15% higher than their harvest-time low, increasingly up to 20% just before the onset of the next harvest.[1] Moreover, these increases are even larger (of the order of 30% over the harvest year) when not including wheat and rice, the main staples, whose prices are strictly monitored by the government and held at somewhat stable levels through open market operations by public agencies.

Against this backdrop, it seems obvious that farmers should engage in inter-temporal arbitrage, but in practice, they rarely do, often selling right after harvest. The literature has documented several reasons behind this seemingly sub-optimal behavior, such as immediate liquidity needs coupled with financial market constraints (Barrett 2007; Giné and Yang 2009; Stephens and Barrett 2011; Albuquerque et al. 2024);[2] information frictions which hinder farmers' ability to obtain accurate, real-time data on prices (Overå 2006; Jensen 2007; Goyal 2010; Mittal et al. 2010; Aker 2011; Fabregas et al. 2025); poor physical infrastructure, especially storage (S. Aggarwal et al. 2018; Delavallade and Godlonton 2023); and price risk coupled with the risk of pest damage to stored grains (Barrett and Dorosh 1996; Park 2006;

[1](Cedrez et al. 2020) analyze price data for four staple crops (maize, sorghum, millet, and rice) across 160 markets in Africa. They find that food prices are lowest during the three months following the harvest and then gradually rise at an average rate of 2% per month leading up to the next harvest.

[2]In general, there is a much larger literature that examines financial constraints as a factor driving sub-optimal agricultural decisions; for example, Binswanger et al. (1993); Karlan et al. (2014); Casaburi and Willis (2018) highlight that imperfect financial markets lead to underinvestment by farmers in productive and risk-hedging technologies such as fertilizers and insurance; Fink et al. (2020) shows that alleviating credit constraints during the lean season improves food security and crop yields; Dillon (2021) finds that households with school-going children often sell grain early to pay fees when schools open early; (Channa et al. 2022) demonstrates that access to credit at harvest allows farmers to store more grain for sale during the lean season, while (Melkani et al. 2024) reveals that liquidity constraints at harvest prevent farmers from accessing profitable markets due to high fixed costs. Refer (de Janvry and Sadoulet 2020) for a full review.

Kadjo et al. 2018; Cardell and Michelson 2023).

In this paper, we examine another constraint that may explain this behavior - a lack of adequate rural transportation infrastructure, which makes it cost-prohibitive for farmers to make multiple trips to the market. Thus, if liquidity constraints necessitate that farmers must sell at least some part of their produce at harvest time, infrastructure constraints will necessitate that they must sell all of it at this time. In this situation, if rural roads reduce the transportation cost of reaching the market, they may dampen the sharp price crashes during harvest and moderate price spikes later, thereby reducing overall inter-temporal price volatility. This paper, thus, investigates the impact of new rural road connectivity on the inter-temporal price volatility of major non-perishable crops.

We study this question in the context of India, an economy with about 54% of the population dependent on agriculture (Chatterjee, Kapur, et al. 2017) and 14% of the total villages still lacking paved roads until 2011[3]. We leverage the National Rural Roads Construction Program, commonly known as the *Pradhan Mantri Gram Sadak Yojana* (PMGSY), which aims to link market centers with unconnected villages with a population of at least 500 via all-weather roads. Between the program's inception in 2000 and 2010, approximately 35% of the previously unconnected villages received newly paved roads. The program prioritized connectivity of villages based on the 2001 population thresholds of villages, enabling us to causally estimate the impact of improved connectivity on market prices and quantities. Ideally, we would examine the effect of new connectivity on agricultural commodity prices traded at the village level. However, the absence of high-frequency village-level price data precludes this analysis. We, therefore, investigate the impact of village connectivity on market prices, where the markets are situated at varying distance bandwidths from the villages. Given the implementation design of the program, we argue that the markets can also be considered as treated units, since road density around them increased as a result of new connections

[3] According to data from the PMGSY official website, approximately 48% of the total villages were classified as "connected" in 2001 i.e. these villages had access to an all-weather road leading to their nearest market centers.

to previously inaccessible villages. Thus, we construct a new connectivity measure at the market level, defined as the fraction of eligible villages connected to the market center within a specified distance bandwidth.

For our empirical analysis, we obtain data on the progress of road construction from the official program website, which provides geographic identifiers for villages, population details, and the year of new connectivity. We combine this data with weekly market price information for agricultural commodities published by the central government. This dataset includes weekly prices and quantity arrivals for various crops in primary markets across the country, along with their market profile information. Additionally, we utilize several other public data sources, as outlined in Section 3, to conduct our heterogeneity analyses.

We find that road construction, indeed, led to a large and significant reduction in the annual price volatility of the major non-perishable crops in the markets. Specifically, if all the villages within a 20 km radius bandwidth around a market center[4] get paved roads under the program i.e. the proportion of villages connected around a market under the program in this same bandwidth, the inter-temporal price volatility of the crops would decline by 0.07. On average, during the sample period, 14% of villages within the 20 km radius had road connectivity, resulting in an average reduction of 0.01 in the within-year standard deviation of prices every year. Our baseline value of this standard deviation of crop prices in 2004 is 0.09, thus, this corresponds to an approximate 11% reduction in the baseline level.

A potential concern here is that the observed effects could be confounded by other channels through which road infrastructure might impact our result. For instance, improved road connectivity could increase farmers' income-earning opportunities, leading to higher household consumption. This, in turn, may reduce the quantity of crops supplied to markets during the harvest period, thereby moderating the typical post-harvest price drop and potentially lowering price volatility. Alternatively, roads could also induce changes in farmers' cropping patterns, leading to higher production of cash or other crops, affecting both

[4]There are about 400 villages around a market center in this radii bandwidth as shown in Table A1.

level prices and subsequently annual dispersion. To address these concerns, we first draw on the evidence provided by (Asher and Novosad 2020) showing that rural road infrastructure caused no changes in the incomes of agricultural households. Furthermore, our dataset also does not indicate any significant changes in the total volume of agricultural commodity arrivals in the markets or any impact on the district level area under cultivation, production, or yield due to improved connectivity. This result aligns with the findings of (Shamdasani 2021), who also reports no evidence of cropping pattern changes among households growing cereal crops, suggesting that enhanced road connectivity did not directly affect production decisions.

This result remains robust across several empirical checks, including restricting the analysis to states where the program's rules were strictly adhered to, excluding states without the market acts, removing large markets that may bias the coefficient, and excluding heavily procured crops such as wheat and rice. Our findings also hold under the IV(2SLS) strategy, where we instrument actual connectivity with "ideal" connectivity—defined as the proportion of villages with populations above eligibility thresholds that received new road connections. Using this strategy, we exclude connections made solely due to being on the least-cost path between eligible households or for political or administrative reasons. In our original sample, we further test the robustness of our results by modifying the independent variable in several ways, including using population instead of the proportion connected, using the previous year's connectivity, and mapping each village only to its nearest market. In all cases, we observe similar effects on annual price volatility.

Having established the gains from reduced price dispersion from the low-cost transportation network, we now turn to examine its impact on market prices and the quantity of arrivals. Notably, we observe that the reduction in price volatility is driven by a 0.3% higher and statistically significant price in the harvest period[5], coupled with a 1.3% decrease in prices during the post-harvest period in an average year within 20 km around a market.

[5] This result is in-line with the (Burke et al. 2019) who also report higher post-harvest market prices (2.5%) resulting from increased storage facilitated by improved access to credit.

Investigating further, we find that in the average year, market quantity arrivals of non-perishable crops within the 20 km bandwidth decrease by 10% during the harvest period and increase by 16% in the post-harvest period. This finding is particularly remarkable as it underscores the critical role of last-mile connectivity in enabling farmers to better manage their produce. By improving access to markets, farmers are able to hold onto their crops longer, allowing them to sell at higher prices and, consequently, achieve greater economic gains. This intertemporal shift in market supply from the harvest to the post-harvest period leads to smaller price declines during harvest and reduced price increases afterward, thereby reducing inter-temporal price fluctuations.

Next, we explore potential mechanisms underlying our main finding on annual price volatility. Specifically, we present evidence that access to storage infrastructure plays a critical role. We find that price volatility decreases only for the villages with access to nearby storage facilities. This suggests that the presence of roads alone is insufficient for farmers to fully capitalize on intertemporal arbitrage opportunities. Accessibility to functional agricultural warehouses is also crucial as it enables farmers to store their produce and make multiple trips to the market to sell their crops when prices are more favorable. In the next heterogeneity analysis, we observe that the reductions in price volatility are primarily driven by less competitive markets, with no statistically significant effects in more competitive ones. The intuition behind this is that in markets where intermediaries wield greater monopsony power, improving farmers' direct access to markets can enhance their bargaining position and lead to fairer prices.

Although we provide suggestive evidence on the potential channels above, there might be other alternative channels that warrant examination. One potential confounder is differential access to mass media such as television, radio, and telephone. (Jensen 2007) shows that when farmers have access to real-time price data, they are better able to time their market visits to maximize returns. In this paper, however, we find no significant differences in the coefficients for districts with higher and lower exposure to mass media devices, suggesting that this channel is unlikely to be driving our results. Similarly, the coefficients do not differ significantly between markets located in districts with lower nightlight intensity—an indicator highly correlated with income and economic activity—and those with higher intensity. The underlying hypothesis is that farmers in wealthier districts are less likely to face credit constraints, enabling them to delay sales and take advantage of arbitrage opportunities. However, our analysis finds no evidence supporting this hypothesis. We construct an alternative measure of farmers' credit access using household-level borrowing data. Our analysis reveals that farmers in districts with higher credit access are more likely to benefit from reduced price volatility resulting from improved road connectivity compared to those in districts with lower credit access.

Improving access to markets, especially for the rural poor, is a core topic in poverty alleviation and economic development (Emran and Hou 2013). Taken together, our findings suggest that, while no single intervention is a panacea, enhancing market connectivity through paved roads significantly empowers farmers. By reducing the need for distress sales during harvest, farmers are able to hold onto their produce longer, leading to more economically meaningful gains in the latter half of the agricultural year.

Our paper makes three broad contributions. First, it adds to the extensive body of research on the impact of last-mile connectivity on various economic outcomes[6]. Studies on the PMGSY program specifically show that it has strengthened rural-urban trade (S. Aggarwal 2018), increased adoption of productive technologies like hybrid seeds and fertilizers (Shamdasani 2021; S. Aggarwal et al. 2024), improved educational attainment (Adukia et al. 2020), modest increases in labor participation (Asher and Novosad 2020), and enhanced access to medical care (S. Aggarwal 2021). This paper extends the literature on rural road connectivity

[6](Moser et al. 2009) highlights the importance of reducing transportation costs for enhancing market competitiveness and spatial integration in Africa. (Suri 2011; S. Aggarwal et al. 2024) demonstrate how poor transportation infrastructure hinders the adoption of agricultural technologies. (Casaburi et al. 2013) finds that improved road quality reduces transaction costs for both traders and farmers, leading to lower market crop prices. (Shrestha 2020) shows that better road connectivity increases the value of agricultural land , and (Kebede et al. 2020) reports higher allocation of land and increased prices of villages' comparative advantaged crops due to reduction in trade costs. Improved road access with timely agricultural extension services has also been shown to boost agricultural productivity (Gebresilasse 2023).

by examining its impact on market prices. Improved road access enhances farm-to-market connectivity, enabling farmers to make multiple trips, sell their produce more evenly across the agricultural year and avoid harvest-time supply gluts. This smoothening of supply eventually reduces inter-temporal price volatility, leading to overall welfare gains[7]. However, the benefits of inter-temporal arbitrage rely on access to adequate storage facilities. While prior studies highlight the importance of storage technologies (Omotilewa et al. 2018; S. Aggarwal et al. 2018; Basu and Wong 2015; Brander et al. 2021; Delavallade and Godlonton 2023), this paper demonstrates that transport and storage are complementary, working together to enable farmers to realize trade gains.

Second, we contribute to the literature on the impact of improved transportation infrastructure on price dispersion[8]. Higher transportation costs on bad roads can substantially increase the inter-regional price variation (Minten and Kyle 1999; Brenton et al. 2014). (Donaldson 2018) shows that railroads reduced the regional price differences of commodities significantly. (Allen and Atkin 2022) finds that increased market access and lower transportation costs from national highway expansion increased local price elasticity to yields outside home districts[9]. Although (Allen and Atkin 2022) is the most closely related to our work, we differ by focusing on the impact of last-mile connectivity between villages and market centers, while they examine the effects of national highways on inter-state agricultural trade. Much of the literature has focused on the spatial dispersion of prices. This paper highlights the role of rural roads in reducing inter-temporal dispersion[10]. Reduction in inter-temporal dispersion is beneficial to both end-consumers and producers and this paper highlights how improving the lower-budget transportation infrastructure[11] can potentially

[7](Bellemare et al. 2013) finds that households, in general, value inter-annual price stability and an average household is willing to give up about one-fifth of their income in-lieu of stable prices of staple consumables.

[8]Several studies have also shown the importance of improved communication infrastructure on price dispersion as well (Jensen 2007; Ejrnæs and Persson 2010; Steinwender 2018).

[9]In a similar vein, (Burgess and Donaldson 2010) finds that railroads attenuated the severity of famines and food scarcity.

[10]This paper comes closer to (Gao and Lei 2021) which studies the impact of enhanced telegraph infrastructure on local price volatility. However, this study focuses on improvements in last-mile road connectivity rather than communication infrastructure.

[11]As per the $2001-2002$ Indian Government budget, INR $2,500$ crores ($\approx$ USD 530 million in 2001) were

be welfare-enhancing.

Lastly, we contribute to the sparse literature on understanding the agricultural markets in India. (Chatterjee 2023) shows increased spatial competition leading to competitive pricing and reduced intermediary power. (Abhijit Banerji and Meenakshi 2004; Meenakshi and Banerji 2005) document buyer collusion in staple grain markets, suppressing prices, while (Mitra et al. 2018) highlights significant intermediary markups due to farmers' restricted market access. Relatedly, several studies examine the effects of distortionary economic policies on agricultural markets highlighting how such interventions can lead to supply gluts and lower producer prices (A. Narayanan and Tomar 2023), and decline in overall trade (N. Aggarwal and S. Narayanan 2023). This paper provides reduced-form evidence that improved market access dampens price fluctuations, especially in remote regions, resulting in welfare benefits for both producers and consumers.

The paper proceeds as follows: In Section 2, we discuss the context and the intervention, followed by description of data in the Section 3. Section 4 describes our empirical approach, and Section 5 presents the results. Section 6 concludes.

2 Institutional Background

Agricultural markets

In the mid-1960s, India introduced the "Agricultural Produce Market Regulation (APMR) Acts" to ensure transparency in market functioning and protect farmers from exploitation by money lenders and local dealers. These acts empowered the individual state governments to establish "Agricultural Produce Market Committees (APMCs)" assigned to a local market, commonly referred to as a *mandis*. A *mandi* —comprising *mandi* yards or sub-yards— serves as the primary market infrastructure for agricultural trade in most Indian states[12].

allocated to the PMGSY program, whereas INR $8,727$ crores ($\approx$ USD 1.85 billion in 2001) i.e. 3.5 times the budget of the PMGSY were allocated to the construction of the National Highways.

[12] The Indian Constitution divides policy subjects into three lists - Union, State, and Concurrent list to define the legislative powers between the Union and State Governments. The State list covers subjects

The regulation of agricultural markets through APMC Acts was designed to achieve several objectives, including controlling the number of marketplaces, regulating intermediaries, access to amenities such as godowns and warehouses, weighbridges etc, and promoting fair trade. The acts mandate that agricultural produce can only be sold by the farmers within designated market areas of their state and only through government-approved traders or commission agents or *arhatiyas*[13].

The advent of the Green Revolution in the late 1960s significantly increased agricultural production, necessitating an expansion of market infrastructure. Consequently, the number of regulated markets in India rose from 3,528 in 1976 to 7,566 in 2006, with approximately 82% of the current markets constructed by 1991. However, no new APMC markets have been built since 2006[14]. Figure 2 illustrates the distribution of agricultural markets across various districts in the country. In our raw data, there are a total of 2,589 *mandis* with approximately 96 and 5 *mandis* per state and district respectively across India[15].

Due to the mandate of the APMC act, *mandis* often serve as the primary link in the agricultural trading process. Essentially, three main agents operate in these markets - farmers, intermediaries, and buyers. After the harvest season, farmers transport their produce for sale to the nearest *mandi*, typically located 20–25 kilometers from a village[16]. However, they often lack access to reliable price information before arriving at the *mandi*, leaving them unable to decide when, where, or how much to sell. Price discovery occurs only at the *mandi*,

of regional and local importance such as agriculture. Only the State Legislatures can make laws in these subjects by addressing their unique needs. The three states - Jammu & Kashmir, Manipur, Kerala and Bihar (which withdrew in 2006) chose not to implement APMC acts in their respective states.

[13] These intermediaries are required to possess state-issued licenses which are typically renewed every 5 to 10 years (Chatterjee 2023).

[14] India also introduced the Model APMC Act in 2003 to address the inefficiencies in the existing state-level APMC laws and to encourage a more competitive agricultural marketing environment. However, it remained largely advisory with most states opting not to implement the changes.

[15] As shown in Figure 2, there is significant variation in the locations of these markets. In our raw data, approximately 60% of the markets are concentrated in six states - Andhra Pradesh, Maharashtra, Uttar Pradesh, Madhya Pradesh, Gujarat, and Punjab. In contrast, northeastern states like Sikkim and Mizoram each have only two APMC markets. This variation primarily arises from the fact that the establishment of *mandis* is a decision made by the individual state governments.

[16] This estimate is calculated from the average geodetic distance between a market and village in our dataset. This figure is also aligned with the (Goyal 2010), who notes that farmers typically travel about $30-40$ kilometers on average to reach a market.

by which time they have already incurred significant transportation costs, making it impractical to withhold their produce from sale. At the *mandi*, they engage with licensed market agents (*arhatiyas*), who assist in displaying the produce in heaps within the market yard. Buyers, including traders and processors, visually inspect the produce, assess its quality, and determine their bids. The produce is subsequently auctioned, with payments disbursed to farmers and *arhatiyas* based on the agreed prices. Despite the inherent challenges, the *mandi* system thus, serves the first most crucial link in the agricultural trade in the country and eventually determining the final retail prices paid by the end customers.

Intervention: Rural Roads Construction Program (PMGSY)

Rural road connectivity is identified to be critical for rural development by promoting access to important social and economic centers such as centers of activities for marketing of agricultural produce and inputs, servicing of agricultural implements, health, higher education, postal, banking services etc and thereby generating increased agricultural incomes and productive employment opportunities (Ferreira and Walton 2005). Launched in December 2000, the centrally sponsored scheme - Pradhan Mantri Gram Sadak Yojana (PMGSY) aimed to improve rural connectivity[17] in India by constructing all-weather roads[18] to previously unconnected villages to ensure better farm-to-market access. Before the launch of the program, it was estimated that about 316,302 out of its 605,794 villages and habitations (about 52%) were without any all-weather road access. The then-existing roads in these areas were often poor-quality dirt roads that cannot be regarded as "All-weather" roads. PMGSY sought to build durable, single-lane roads that would link remote villages to market centers, other villages, and main roads, supporting agricultural trade and local economies. The program is funded by the central government, with state governments handling imple-

[17] Rural Roads, as per the PMGSY guidelines, cover the categories which were earlier known as "Other District Roads" (ODRs) or "Village Roads" (VRs). Other District Roads are roads serving the rural areas of production and providing them with outlet to market centers, Block, taluka/ tehsil headquarters or other main roads. Village Roads are roads connecting villages and group of villages with each other or to the market centers and with the nearest road of higher category.

[18] An all-weather road is one which is negotiable during all weathers, with some permitted interruptions

mentation. Villages were prioritized for road construction based on their population and current connectivity. The first part of the program focused only on providing roads to the eligible unconnected households. The program also focused on upgrading existing roads; however, new construction was given much higher priority. A state could only upgrade roads once all new constructions were completed. Even if the condition of the road is bad, a habitation[19]/village, which was earlier provided an all-weather connectivity was not eligible.

The program followed a population size[20] cutoff for determining eligibility. The villages with a population of more than 1000 were prioritized to be connected first, followed by the villages with a population 500 and then 250 where eligible[21]. A village or habitation was considered connected if it was within 500 meters of an all-weather road in plains or 1.5 kilometers in hilly areas. This quasi-experimental implementation framework based on the exogenous variable - "village population in 2001" provides us a unique opportunity to causally estimate the impact of rural connectivity on our outcome variables. The empirical design underpinning this analysis is discussed in the Section 4 below.

3 Data

We combine data from various sources described in detail below:

3.1 Market Prices and Profile

The Directorate of Marketing and Inspection (DMI), a division of the Ministry of Agriculture & Farmers Welfare, Government of India, regularly publishes agriculture-related information on its publicly accessible website called Agmarknet. Established in 2000, the platform was designed to create a unified online agricultural market information system to enhance trans-

[19]The PMGSY guidelines defines habitation as a cluster of population, living in an area, the location of which does not change over time. In this paper, we use habitation and village interchangeably

[20]The population of the villages was based on the information from Census 2001.

[21]Villages with population below the threshold level could be connected if they lay in the least-cost path of connecting a prioritized village.

parency and provide support to farmers and other stakeholders in the sector. The website offers data on average weekly wholesale market prices—minimum, maximum, and modal prices—as well as quantity arrivals of various commodities sold in government-regulated Agricultural Produce Market Committees (APMCs) or *mandis*. The data is sparsely reported from 2001 to 2003 and begins to be reported regularly from 2004 onwards. Most importantly, the portal also provides geo-coordinates for these markets, facilitating precise geographical location identification and thus, enabling us to calculate their distance from nearby villages. Additionally, it provides valuable information on whether a market includes a storage facility (with or without cold storage[22]) for agricultural goods, which we utilize in our heterogeneity analysis.

In the raw data, we have prices and quantities reported for 269 different commodities, which we have further classified into 4 broad categories: non-perishables, comprising cereals and pulses; perishables, consisting of fruits and vegetables; cash crops, including oilseeds, spices, fiber crops, and beverages; and processed foods[23]. We excluded meat and other items, such as flowers, forest products, dry fruits, and miscellaneous goods. Since our analysis focuses on storable agricultural products, we restrict our sample to the major non-perishable crops[24], accounting for 71% of the total observations within the non-perishable group in the final dataset. Additionally, we include major perishable crops[25] for comparison purposes.

India has two main crop planting seasons: summer (or *Kharif*) and winter (or *Rabi*). However, the exact harvest time for crops varies across states due to changing climate and geography across states. To determine the harvest months, we use data on crop arrivals in the market. Specifically, we calculate the monthly percentage change in crop arrivals at the end of the sample period (2010) and identify the month with the largest increase as the harvest month, marking the start of the harvest quarter. The harvest quarter is then defined

[22] About 84% of the markets do not have cold storage.

[23] This category includes rice, beaten rice, semolina, and processed oils such as coconut oil, among others.

[24] These crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram.

[25] The major perishable crops are banana, okra, eggplant, cabbage, cauliflower, cucumber, green chilly, tomato, onion, and potato

as the harvest month and the two following months.

3.2 Rural roads construction

The official website of the National Rural Roads Construction Program provides detailed village-level data regarding the progress of this program's implementation. We extracted publicly available information, including the village names and associated geo-identifiers such as state, district, and block[26]. The dataset also includes the connectivity status of each village in 2001 i.e. prior to the program's launch, along with updates on whether the village has received new road connectivity[27], the names of the roads, and the year of connectivity. The raw dataset comprises connectivity information for a total of $605,794$ villages across India. The quasi-random implementation rules of this program were revised and altered after 2010. Consequently, for our final sample, we have restricted the data from 2001 to 2010. Villages that received road connectivity after 2010 are classified as "unconnected" in our analysis. In 2001, approximately 52% of villages lacked access to rural roads. By 2010, following the launch of the program, this percentage dropped to around 40%.

3.3 Shapefiles

We obtained publicly available shapefiles for the states, districts, sub districts/blocks, and villages of India, which enabled us to geographically locate the villages and map the markets to their corresponding states and districts for analysis. Using the village and the market shapefiles, we were able to identify villages located within specified distances from each market.

[26]The state, district and block names of the villages matched with those reported in Census 2011 dataset.

[27]We downloaded the data in November 2018 and thus, the connectivity status of villages was reported as of 2018.

3.4 Other datasets

SHRUG: We leveraged the crosswalk of state, district, and sub-district identifiers from (Asher et al. 2021) for mapping of geo-identifiers across the Census 2001 and Census 2011 datasets. Additionally, this website also provides nightlight intensity data for various geographic level during the sample period to proxy for economic activity (Henderson et al. 2011). We use the nightlight density in the year 2000 to stratify our sample into high- versus low-income regions.

Rainfall: We obtained high spatial resolution monthly gridded (0.25 X 0.25 degrees) data from the Indian Meteorological Department website during our sample period. We overlaid the rainfall data onto our district shapefiles to calculate average monthly rainfall in each district from $2004 - 2010$.

Economic Census: We employed data from the Economic Census directories, which offer a comprehensive list of rural and urban firms categorized by their National Industrial Classification (NIC) code and geographic location, identified through zip codes. Our analysis focused specifically on firms classified under the storage of agricultural products, with or without refrigeration. This dataset enables the identification of villages with access to storage facilities within a specified distance.

DLHS: The District Level Household Survey (DLHS-2) conducted during 2002–2004 provides data on household access to Information and Communication Technology (ICT) tools such as radio, TV, or telephone. We calculated the proportion of households in each district with access to these devices and identified districts with below- and above-median access. This heterogeneity analysis examines how road accessibility interacts with ICT penetration to influence market prices.

AIDIS: The All India Debt and Investment Survey (AIDIS) conducted by the National Sample Survey Organization (NSSO) $59th$ round in 2003 provides information on the loans and borrowings made by a household during a calendar year. We calculated the proportion of households in each district that obtained credit from any source and categorized the sample into districts with below- and above-national median borrowing levels.

ICRISAT: We use farm harvest price[28] data for 15 major crops[29] obtained from the ICRISAT Village Dynamics in South Asia (VDSA) Macro-Meso Database for the period 2004–2010. This dataset covers 311 districts across 19 Indian states. The VDSA compiles these prices from the Directorate of Economics and Statistics, Government of India, which reports farm harvest prices over a six- to eight-week window corresponding to the peak harvesting and marketing season every year.

4 Empirical Strategy

We exploit the quasi-random assignment of road connectivity based on village population size under the PMGSY program. As mentioned earlier, villages were prioritized for road construction in a tiered manner, with those having a population of $1,000$ or more being connected first, followed by villages with populations between 500 and $1,000$, and finally, those with populations ranging from 250 to 500. This population-based prioritization provides a natural source of variation in road access, allowing us to examine the causal effects of road connectivity on various outcomes, while mitigating potential biases from other factors influencing road placement.

As the program progressively connected previously isolated villages to nearby market centers, the density of roads surrounding these centers increased over time. Our empirical strategy exploits this variation by constructing "connectivity rings" of varying radii of 10, 20, 30, and 50 kilometers[30](km) around each market. Next, within each ring, we calculate the proportion of villages that received road connectivity—a measure for *road density* around each market center—over the sample period from 2004 to 2010[31]. This approach allows

[28] These represent the average wholesale prices at which producers sell their crops to traders at the village level during the marketing season.

[29] These include coarse rice, coarse paddy, wheat, sorghum, pearl millet, maize, finger millet, barley, chickpea, pigeon pea (arhar), groundnut, sesamum, mustard, linseed, and cotton. We average the prices of rice and paddy to account for the missing values.

[30] One kilometer equals 0.62 miles approximately.

[31] In Figure A1, we diagrammatically illustrate the construction of rural road connectivity metrics. For

us to track the annual progression of road construction and assess the impact of increasing connectivity on villages located at varying distances from the market. We denote this variable as PC^{vill}_{mdt}, representing the proportion of villages connected around the market m in district d in year t.

Having constructed these rings, we then turn to an empirical design for testing the impact on the first and second-order moments of crop market prices and quantities with a unit increase in rural road connectivity. Our main estimation equation is:

$$Y_{cmdt} = \beta_0 + \beta_1 PC^{vill}_{mdt} + \beta_3 X_{dt} + \gamma_d + \gamma_t + \gamma_c + \gamma_m + \epsilon_{cmdt} \tag{1}$$

In the above specification, Y_{cmdt} denotes the various outcomes of interest, such as annual standard dispersion, average prices, and average quantities of crop c in market m of district d in year t. X_{dt} denotes the amount of rainfall in district d in year t, $gamma_d$,γ_t,γ_c, and γ_m denote the district, year, crop, and market fixed effects respectively. Our key coefficient of interest is β_1, which measures the change in the outcome variable as the proportion of connected villages increases from 0 to 1 around a market within a specific connectivity ring. We estimate equation 1 for several connectivity rings of bandwidth, ranging from 10 through 50.

Threat to identification: We conduct several validity checks for our research design. First, we need to confirm that the program's population cut-offs were adhered to before evaluating its causal impact. (S. Aggarwal 2018) plots the likelihood of road construction for villages based on their 2001 population, as illustrated in Figure A2. The plot demonstrates that larger villages (i.e., those with populations exceeding $1,000$) had a higher probability of receiving

simplicity, we focus on a single market, referred to as Market A, surrounded by 15 villages. Panel A shows the connectivity within a 20 kilometer radius of Market A across three years. In 2004, only 2 of the 5 villages had road access to the market, resulting in a connectivity proportion of $2/5 = 0.4$. By 2006, no additional villages gained road access, keeping the proportion as 0.4. The total number of villages with rural road access increased to 3 around the same market by 2010 in the same 20 kilometer radius, thus increasing the proportional connectivity in 2010 to 0.6. Panel B adds one more connectivity ring with a 30 kilometers radius around the same market A. For each year, we calculate the proportion of villages with road connectivity within each of these whole rings for analyzing the spatial distributional impact of the connectivity over time.

road connectivity than smaller villages. The sharp, discontinuous jumps in probability at the program's population threshold further support that the implementation rules were largely followed with minimal deviations.

Next, we conduct a second validity check to ensure that the prevailing crop prices in the *mandis* are not correlated with the population of the surrounding villages. A significant relationship between these variables would imply that the village population influences market-level prices, making it difficult to isolate the causal effect of connectivity based solely on the village population. For this analysis, we calculate the average price of a crop c in the market m in month t in 2004 for all the major non-perishables in our data. We then compute the total population of villages within 10, 20, 30, and 50 km radii around each market in the same state. Our estimating equation is:

$$Y_{cmt2004} = \beta_0 + \beta_1 Pop_m^{vill} + \beta_1 X_{d2004} + \gamma_c + \gamma_t + \epsilon_{cmt2004} \tag{2}$$

In the above specification, $Y_{cmt2004}$ denotes the average price of a crop c in the market m in month t in 2004. Pop_m^{vill} denotes the total population of the villages around market m in the same state for various radius bandwidths, X_{d2004} denotes the amount of rainfall in district d in year 2004, γ_c and γ_t denote the crop and month fixed effects respectively. The results in Table A2 show that the coefficients are statistically insignificant for all the bandwidths, providing no evidence of a correlation between village population and market prices.

5 Results

5.1 Main results

Annual dispersion of prices of Non-Perishables: Our first result of the main coefficient of interest (β_1) from the equation 1 is reported in Figure 3. The figure shows how a unit increase in the road connectivity affects the annual standard dispersion[32] (SD) of prices of non-perishables. The figure presents this effect while varying the radii of the connectivity bandwidths viz a viz $10, 20, 30$ & 50 km. We find that the annual SD of the crop prices decreased by -0.05 for every unit increase in connectivity in the 10 km ring. Since the average geodetic distance between a market and the village is about 20 km, henceforth, our preferred bandwidth is the 20 km connectivity ring. In this connectivity ring, we find that the magnitude of our main coefficient further drops to -0.07 with an additional one unit increase in rural road connectivity[33]. The baseline annual standard deviation of the crop prices for non-perishables in 2004 is 0.09, and the average connectivity around a market within 20 km radius bandwidth in our sample period is 14%. Thus, this constitutes a 11% annual decline in the baseline SD of the prices of non-perishables in the 20 km bandwidth[34,35]. We find a monotonic decline in the magnitude of the coefficient as we increase the radius, but the effect is mainly driven by the 10 km connectivity ring[36].

One potential concern is that the introduction of new road connections may influence farmers' production decisions, potentially leading to the same outcomes observed in the Figure A3. To address this issue, we examine the effect of new rural road connections on

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[32]The annual standard deviation of a crop c in market m is calculated as $\sqrt{\frac{\sum_{t=1}^{12}(p_{cmt}-\overline{p_{cm}})^2}{11}}$ where p_{cmt} denotes the price of a crop c in a market m in month t of a year and $\overline{p_{cm}}$ denotes the average price of the crop c in the market m in the whole year.

[33]We also run the same analysis for the top 10 perishables in our data - banana, okra, eggplant, cabbage, cauliflower, cucumber, green chili, tomato, onion and potato. We find no effect of increased connectivity on their annual SD of prices. The results are reported in the Figure A3. The results are not surprising as perishables require cold storage facilities for preservation, and thus, even with improved road connectivity, it is challenging to store them for an extended period for spoilage risks. Thus, we focus only on the non-perishables for the remaining analysis.

[34]We also estimated the coefficients using the event-study Difference-in-Difference (DiD) approach with multiple groups and periods as proposed by (De Chaisemartin and d'Haultfoeuille 2024). The findings in Figure A7 for all bandwidths indicate a negative decline, though not statistically significant, across all time periods following the treatment.

[35]In Figure A8, we also conducted a year-on-year decomposition on the annual price volatility for the major non-perishables for the 20 km connectivity bandwidth. The estimates are calculated using the equation: $Y_{cmdt} = \beta_0 + \beta_1 PC_{mdt}^{vill} + \beta_2 t_i + \beta_3 PC_{mdt}^{vill} * t_i + \beta_3 X_{dt} + \gamma_d + \gamma_c + \gamma_m + \epsilon_{cmdt}$, where Y_{cmdt} denotes the annual standard deviation in the prices and t_i is a categorical variable which takes the value 0 for 2004, 1 for 2005 ... and 6 for 2010. We notice a consistent decline since 2004 with the largest decline in the years 2009 and 2010.

[36]We performed the test of equality of the coefficients across different connectivity rings and found that the null hypothesis could not be rejected at the 5% confidence level.

the overall quantity of market arrivals. As illustrated in Figure A4, our analysis reveals no evidence of a change in the quantity of arrivals during the sample period. We also find no significant changes in the area under cultivation or in the production levels of crops with improvements in district-level connectivity during our sample period (Table A6). This result is aligned with the findings of (Shamdasani 2021), who also reports no significant effect of the same program on the cropping patterns of the farmers.

These results demonstrate that increased farm-to-market access via rural roads helps reduce the annual volatility of crop prices, thereby generating significant consumer welfare effects. We hypothesize that rural roads help reduce price volatility by stabilizing price levels throughout the year. Specifically, improved connectivity may prevent the sharp price drops typically observed during the harvest season and mitigate the steep price increases in the months leading up to the next harvest. We now proceed to test this hypothesis in our next analysis.

Average Prices of Non-Perishables: For this analysis, we divided the agricultural year into two halves: the first six months within the harvest cycle (referred to as the harvest period) and the subsequent six months leading up to the next harvest cycle (referred to as the post-harvest period). The rationale behind is that different states have slightly different harvest periods owing to the agro-geo climatic conditions. Analyzing the year in two halves also facilitates a more straightforward interpretation of the coefficients[37]. In Figure 4, we present the results from our estimating equation 1 on the log of average (level) prices. Our findings indicate that average prices increase during the harvest period and decline in the post-harvest period[38]. Specifically, if the connectivity around a market increases by 100 percentage points in the 20 km radius bandwidth, the market prices are approximately 2% higher during the harvest period, while prices in the post-harvest period are about 9% lower. When scaling the coefficients by the average connectivity within this bandwidth during a

[37]Look at the percentage increase in prices within six months of the harvest cycle.

[38]In addition to crop, market, district, and year fixed effects, our specifications on level prices also include quarter fixed effects.

typical year, the estimated effects translate to roughly 0.3% higher prices during the harvest period and 1.3% lower prices in the subsequent period. This observed price increase during the harvest period, rather than a sudden crash, along with a decline in post-harvest prices, instead of a steep rise, results in a lower annual standard deviation of crop prices, as shown in Figure 3. Similar to the annual standard deviation result, we notice that the coefficients for different connectivity rings are relatively consistent, with the primary effects concentrated within the 10 km connectivity ring.

Given that only approximately 27% of farmers report selling their major non-perishable crops in these markets[39], an important question arises: who benefits from the new connectivity? Due to the paucity in our datasets, we are unable to provide this answer by various farmer profiles. However, to address this gap, we turn to the ICRISAT dataset, which provides farm harvest prices at the district level for each harvest and market season. Following the methodology in (S. Aggarwal 2018; S. Aggarwal 2021), we aggregate our connectivity measure at the district level. The results, presented in the **??**, indicate that farm harvest prices increase by about 9% when district-level connectivity rises from 0 to 1. Since these are farm-level harvest prices, this result suggests that the benefits from the enhanced connectivity extend not only to farmers who sell their crops in the *mandis* but also to those who choose to sell outside these regulated markets.

We hypothesize that improved market accessibility enables farmers to store nonperishable produce for longer periods, allowing them to exploit arbitrage opportunities later in the harvest cycle. This likely results in reduced market supply immediately after harvest and an increase in supply in subsequent months. We now turn to test this hypothesis in our next result.

Average Quantities of Non-Perishables: To examine whether there is a shift in the timing of produce sales from the harvest to the post-harvest periods, we analyzed the two

[39] This estimate is based on the 2013 Situation Assessment Survey. It also finds that 26% of small farmers and 38% of large farmers reported selling their crops in the *mandis*. Large farmers are defined as those owning land above the 90^{th} percentile, i.e., more than 5 hectares.

semi-annual time windows as defined in the previous section. In Figure 5, we present the results from our estimating equation 1 on the quantity (arrivals) in the market[40]. The findings indicate a decline in quantities sold during the harvest period and a modest increase in market arrivals in the post-harvest period. In our preferred bandwidth of 20 km and scaling the raw coefficients with the average connectivity around the market center in the same bandwidth, we find that market arrivals drop by 11% during the harvest period and subsequently increase by about 16% during the non-harvest period. This shift in quantities sold in the market from the harvest to the post-harvest period validates our hypothesis that farmers are increasingly storing their produce instead of selling it immediately after harvest. Farmers aim to take advantage of higher expected prices during the post-harvest period by delaying sales to the latter half of the year.

5.2 Heterogeneity

Our results thus far demonstrate that improved road connectivity of villages reduces annual crop price volatility, thereby generating overall consumer welfare benefits. This reduction in price volatility is primarily driven by farmers shifting the timing of their sales from the harvest period to the post-harvest period. Having established that rural roads reduce inter-temporal price volatility, in this section, we examine the underlying mechanisms. We investigate the potential mechanisms underlying these results, such as access to storage facilities, credit access by institutional agencies, exposure to mass media, and local competition.

Agricultural storage: Rural roads enable farmers to exploit arbitrage opportunities only if they have access to storage facilities. Farmers with storage can hold their produce and make multiple market trips to sell at higher prices, particularly when connectivity improves. To test this hypothesis, we identify villages with access to agricultural storage facilities within a 20 km radius using data from the market directory and the Economic Census. We then construct separate measures of road connectivity for villages with and without storage

[40] In addition to crop, market, district, and year fixed effects, our specifications on level quantities also include quarter fixed effects.

access. Thus, for each year, we calculate the proportion of connected villages with storage access and the proportion without storage access within a given radius bandwidth around each market center. Our main results on the annual standard deviation of log prices are presented in Figure 6. We find that the effects are primarily driven by villages with access to agricultural storage facilities. In our preferred 20-kilometer bandwidth, the coefficient for villages without storage access is close to zero. However, with 100 percentage point increase in the connectivity of the villages with storage access, the annual SD of log prices of non-perishables decline by 0.09[41]. We further examine the impact of improved connectivity on log prices and quantities by storage access in figures A5 and A6. Similar to our main result on annual price volatility, we observe significant effects of enhanced connectivity only for villages with storage access, while villages without such access show no discernible impact within the 20-kilometer radius.

Mass media exposure: Another potential concern is the confounding role of mass media in influencing farmers' decisions, which could bias our estimates. Even with poor road connectivity, farmers may receive real-time price information through alternative channels such as radio, television, or landline telephones. Such information could influence their decisions to conduct a sale of their produce on days offering more favorable prices. This access to price information may, in turn, affect market arrivals and price variability during harvest periods similar to the effects of improved road connectivity.

To examine this potential confounding factor, we utilize the data from the DLHS-2 on household ownership of radios, televisions, and landline telephones[42]. We split our sample of districts based on the national medians of per capita ownership of these mass media devices to test whether our main results are driven by differential access to information rather than physical connectivity. We present our findings in Figure 7. We find that the coefficients are

[41] The average connectivity of villages with storage access within a 20 km radius of a market center is approximately 13%. This magnitude closely aligns with our main result on the standard deviation, suggesting that the entire observed effect may be primarily driven by villages with storage access.

[42] This round of the survey does not include information on mobile phone ownership, likely due to its limited adoption during that period.

not statistically different in the districts with below-median and the above-median access to mass media. Thus we conclude that the observed decline in the annual standard deviation of prices is not driven by differential access to information.

Credit access and local GDP: We also examine the differential impact of access to credit on our main results. Farmers are typically the most cash-constrained at the beginning of the harvest season, as they face immediate liquidity needs for household expenses and agricultural inputs. This financial pressure often forces farmers to sell their produce quickly, rather than holding it back for higher prices later in the season. However, if farmers have access to credit, either formally through financial institutions or informally, they can potentially delay the sale of their produce, waiting for more favorable market prices. Credit access thus enables them to manage their short-term cash flow needs without having to sell prematurely, allowing them to maximize their earnings by waiting for higher prices. We use the borrowings data from the All India Debt and Investment Survey (AIDIS), which records household-level information on outstanding cash loans from both institutional and non-institutional sources. In this dataset, approximately 54% of the surveyed households reported borrowing money in the past year. Among those who borrowed, only about 40% accessed credit through formal credit agencies, and the rest borrowed from informal sources. We thus compute the proportion of households with any form of credit access until 2003, i.e., before the beginning of our sample period. Based on this, districts are classified as having below- or above-median credit access per capita. The results of this analysis are presented in panel a of the Figure 8. We find that districts with above-median credit access exhibit a significant reduction in the annual standard deviation of prices, while below-median access districts show no effect for our preferred bandwidth of 20 km[43]. This pattern suggests that access to both credit and improved transportation infrastructure may enable farmers to better exploit intertemporal arbitrage opportunities by allowing them to delay their production sales.

In a similar vein, we also investigate whether the level of local economic activity, proxied

[43] Although the coefficients are not statistically different.

by night-time lights intensity, differentially impacts the effect of improved connectivity on the annual price volatility of non-perishable crops. Farmers in economically more active regions may be less cash-constrained, potentially dampening the effects we observe. However, as shown in panel b of the Figure 8, we find no significant difference in the estimated coefficients between districts with below- and above-median levels of economic activity.

Competition measures: Next, we examine whether local market competition influences the effects of improved road connectivity on our main outcomes. (Chatterjee 2023) shows that greater competition among intermediaries in agricultural markets leads to more favorable prices for farmers. Thus, we construct a market access measure for each market m that sells major non-perishable crops, similar to the measure in (Donaldson and Hornbeck 2016; Chatterjee 2023):

$$ma_m = \sum_{j \in M \setminus \{m\}} \left\{ \frac{1}{\text{distance}_{mj}} \right\} \cdot \mathbf{1}\{\text{state}_m = \text{state}_j\}$$

This measure captures how close a market is to other markets within the same state, which serves as a proxy for spatial competition. Our results, shown in Figure 9, indicate that the decline in price volatility is driven mainly by markets with below-median market access. In markets with above-median access, we do not find any significant effect. This suggests that road improvements have the strongest impact in remote areas where farmers have fewer selling options. In contrast, markets that are already well-connected likely benefit from existing competition, which helps in price stabilization.

5.3 Robustness

We next conduct several robustness checks on our estimates across a range of alternative samples, specifications, and identification strategies to validate our main findings. First, given that APMC Acts fall under the purview of state legislation, several states—namely

Kerala, Manipur, Jammu & Kashmir, and Bihar[44]—either did not implement or subsequently repealed these regulations. To account for this, we calculate our main result on annual price volatility, excluding these states. In the second exercise, following (Asher and Novosad 2020), we restrict our analysis to the states - Chhattisgarh, Gujarat, Madhya Pradesh, Maharashtra, Orissa, and Rajasthan - that closely adhered to the program's population-based eligibility criteria. The results are presented in panels a and b of the Figure 10, respectively. Consistent with the magnitude of our main result on standard deviation, we observe a decline of approximately 0.07 in states with APMC acts and a decline of 0.08 in states with stricter implementation of the program rules.

Another potential concern in our analysis could be that our estimates may be influenced by the volume of commodities traded at a given *mandi*. Larger markets, which handle higher transaction volumes, could exhibit different patterns of price volatility as compared to the smaller ones. To address this, first we identified large markets in our sample[45] and then excluded them to re-estimate the coefficients on annual price volatility. As shown in panel a of Figure 11, we find a decline of about 0.07 in the annual standard deviation of major non-perishables after excluding the large markets. This again further supports the robustness of our main result.

Additionally, we conduct another robustness test by excluding wheat and rice from our analysis. These crops are heavily procured by the government at the Minimum Support Price (MSP) during the harvest season. Given that a substantial proportion of their production is acquired by the government at a predetermined price (S. Aggarwal et al. 2023), price fluctuations in these commodities should be minimal. Consequently, we remove these crops from the analysis on price volatility to eliminate distortions arising from the government-

[44] Bihar repealed its APMC Act in 2006. As our sample period begins in 2004, and data coverage is limited in the early years, we exclude Bihar entirely as well in our robustness analysis.

[45] We define large markets as those where total commodity arrivals in 2010 exceeded the 99^{th} percentile. We selected 2010 as it had the highest number of recorded observations. Out of $2,428$ unique markets, 22 were classified as large. These markets are spread all across the country in the states of Karnataka, Andhra Pradesh, Punjab, Haryana, Madhya Pradesh, Rajasthan, Gujarat, Maharashtra, Uttar Pradesh, and West Bengal.

imposed price controls. We present the result in panel b of Figure 11. In an average year, we find that the standard deviation decreases by about 14% of its baseline level for the major non-perishables, excluding wheat and rice. This is slightly higher than the estimated 11% decline from baseline prices in our main result but still closely aligned in both magnitude and direction.

In our baseline design, a village may be associated with multiple markets if it lies within the specified radial bandwidth around each market center. For instance, consider a village v located 20 km from market A and 25 km from market B. In this case, village v contributes to the calculation of the proportion of connected villages around market A within the $(0, 20]$ km bandwidth, and also to that around market B within the $(0, 30]$ km bandwidth. As a robustness check, we reassign each village to a single market based on its distance to its nearest market. Thus, we construct a one-to-one mapping in which each village is linked exclusively to its nearest market. Using the same Equation (1) on this modified dataset, we estimated our key result on the annual standard deviation of log prices in panel a of Figure 12. Using this $1:1$ mapping of villages to their nearest market, the average annual proportion of connectivity for a market in its 20 km radius bandwidth is 13%. Thus, on average, a one-unit increase in market connectivity within a 20 km radius leads to a reduction of 0.0065 in the annual price volatility of crops, representing a decline of approximately 7% from baseline levels.

In another exercise, since the connected villages can vary in terms of their population, we modified our independent variable to be based on the population of the connected villages instead of the proportion of the connected villages around a market center. Thus, our new estimating equation is:

$$Y_{cmdt} = \beta_0 + \beta_1 PopC^{vill}_{mdt} + \beta_3 X_{dt} + \gamma_d + \gamma_t + \gamma_c + \gamma_m + \epsilon_{cmdt} \tag{3}$$

where $PopC_{mdt}^{vill}$ denotes the proportion of population connected in villages around a market m in district d in year t. Our main result on the annual standard deviation of the log prices based on the Equation (3) is shown in panel b of Figure 12. Our raw estimates show a decline of 0.06 in the annual SD of prices when the proportion of connectivity of the villages around the market center in the 20 km bandwidth goes to 100 percentage. The average annual proportion of connectivity for a market in its 20 km radius bandwidth based on this population measure is 18%. Thus, on average, a one-unit increase in market connectivity within a 20 km radius leads to a reduction of 0.01 in the annual price volatility of crops, representing a decline of approximately 11% from baseline levels. This aligns with our approach of using the proportion of villages connected rather than their respective populations. This makes sense, as in the program's early years, connectivity was prioritized for eligible households based on population thresholds. As a result, the new measure—the proportion of the population connected—becomes a linear function of our original measure, the proportion of villages connected.

Returning to our main specification, we implement a robustness check by using the proportion of connectivity from the previous year instead of the current year. One potential concern is that updates on road construction may not be immediately reflected in real time and could only be accounted for at the end of the year. Consequently, the connectivity from the previous year may have a more significant impact on market-level prices in the current year than the contemporaneous measure. To address this, we modify our estimation equation as follows:

$$Y_{cmdt} = \beta_0 + \beta_1 PC_{mdt-1}^{vill} + \beta_3 X_{dt} + \gamma_d + \gamma_t + \gamma_c + \gamma_m + \epsilon_{cmdt} \tag{4}$$

In the above equation, PC_{mdt-1}^{vill} denotes the proportion of villages that received new roads around market m in district d in the year $t-1$. The results from the above estimation are shown in the Figure 13. On average, a one-unit increase in the proportion of village connectivity within a 20 km radius around a market in the previous year results in a reduction of approximately 0.006[46] in the annual standard deviation of non-perishables, corresponding to a 7% decline from baseline levels. This result, again, is closely aligned with our main result using the proportion of village connectivity in the current year.

Alternate empirical strategy: As a final robustness check, we re-estimate our main results on annual price volatility using an instrumental variables (IV) strategy to address potential endogeneity in village connectivity. The program was designed to prioritize road construction for villages with populations exceeding $1,000$ first, followed by those with populations greater than 500. However, in practice, villages with populations below these thresholds may have also received connectivity, either due to their geographical reasons i.e. being located between two threshold villages or for other political and administrative reasons.

To account for these endogenous factors, we instrument actual connectivity with an exogenous measure of "ideal" connectivity. We define "ideal" connectivity as the proportion of villages with populations exceeding either $1,000$ or 500 that received connectivity within a given radius around a market center. Therefore, our first-stage regression is:

$$PC_{mdt}^{vill} = \alpha_0 + \alpha_1 TPC_{mdt}^{vill} + \gamma_d + \gamma_t + \gamma_m + \epsilon_{mdt} \tag{5}$$

where TPC_{mdt}^{vill} is our instrument variable denoting the proportion of villages with a population above the threshold that got connected around a market m in district d in year t.

Our second-stage regression then becomes:

[46]The raw coefficient is 0.05 and the average connectivity in a year during our sample period is 12%

$$Y_{cmdt} = \beta_0 + \beta_1 \widehat{PC}^{vill}_{mdt} + \beta_3 X_{dt} + \gamma_d + \gamma_t + \gamma_c + \gamma_m + \epsilon_{cmdt} \tag{6}$$

Using the "ideal" connectivity as an instrument for villages with populations of either 1,000 or 500, our raw coefficient estimates indicate a decline of approximately 0.07 in the annual standard deviation of crop yields when all eligible villages within a 20 km radius of the market center are connected by paved roads. On average, the connectivity rate within a year around a market center in the 20 km radius is 11% when using a population threshold of 500 and 9% when using a threshold of 1,000. These estimates correspond to an average reduction of approximately 9% and 7% from the baseline levels, respectively. Therefore, using this alternative estimation strategy yields results that are consistent with our main findings.[47].

6 Discussion

In this paper, we provide evidence on how improvements in local rural infrastructure can significantly reduce the inter-temporal volatility of agricultural commodity prices, particularly for non-perishable crops. By enabling farmers to better time their sales across the agricultural year, improved last-mile connectivity helps mitigate the sharp price declines typically seen during harvest and dampens the price surges that follow in the latter period. Importantly, we find that these effects are most pronounced in areas with access to storage infrastructure and household credit, highlighting that transportation alone is not sufficient; it is the interaction with complementary market-enabling conditions—such as storage and financial liquidity—that drives welfare gains. These findings carry important policy relevance:

[47] Following the approach used by (Clots-Figueras 2012), we implement an instrumental variables (IV) strategy to address potential endogeneity. Specifically, we instrument the proportion of villages connected around a market center within a given radius bandwidth using the proportion of villages with populations just above the policy threshold within the same market center and radius bandwidth. Our results, as shown in the Figure A9, remain consistent with our main finding.

strategic, low-cost investments in rural infrastructure not only improve trade efficiency and reduce market distortions but also strengthen the bargaining power and income stability of the producers. Furthermore, reduced price volatility benefits consumers as well by ensuring more stable food prices year-round. Taken together, improvements in local infrastructure have the potential to generate sustained, long-term welfare gains for both producers and consumers.

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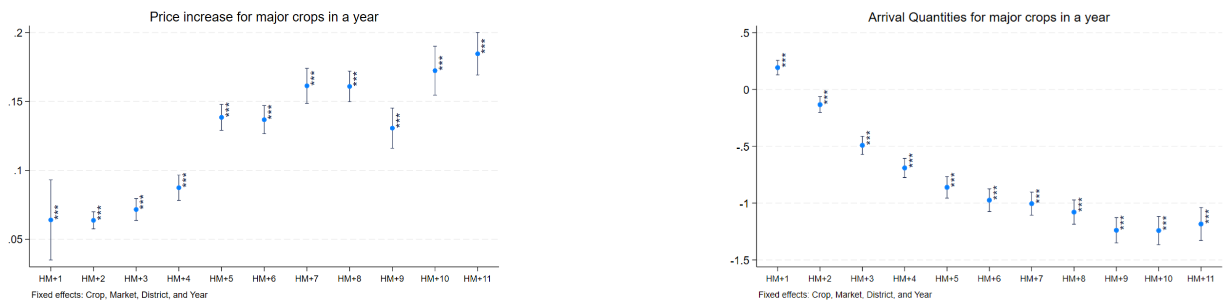
Figures

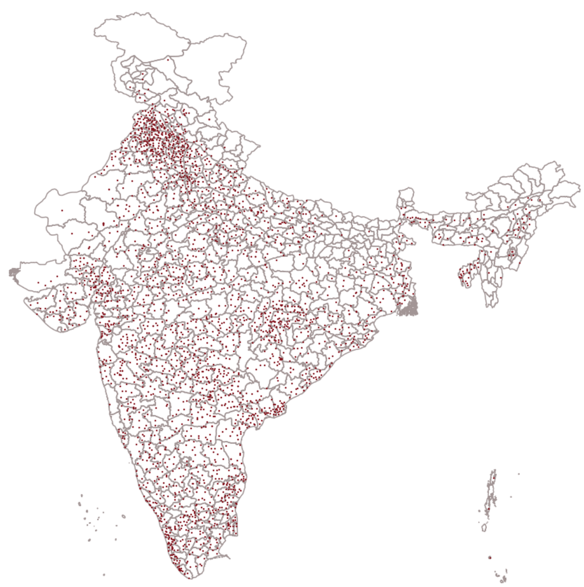
Figure 1: Market price and quantity fluctuations in a typical agricultural year



(a) (b)

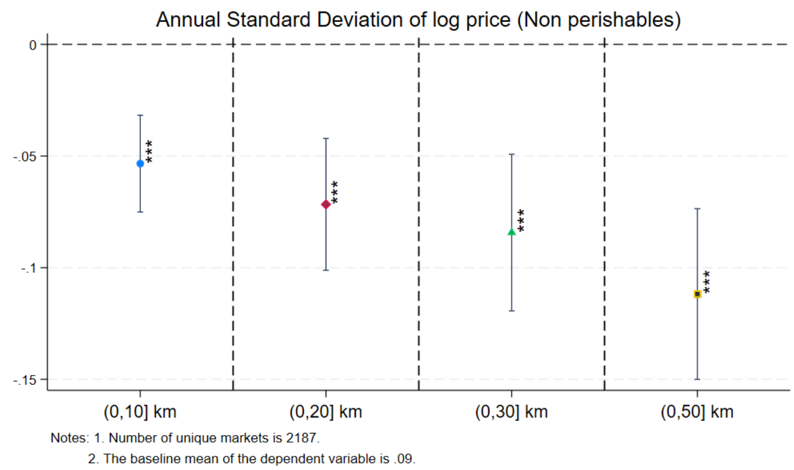
Notes: This figure reports the price increase and the quantity decrease from the harvest quarter for the major non-perishable crops in India. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2: APMC market locations in India



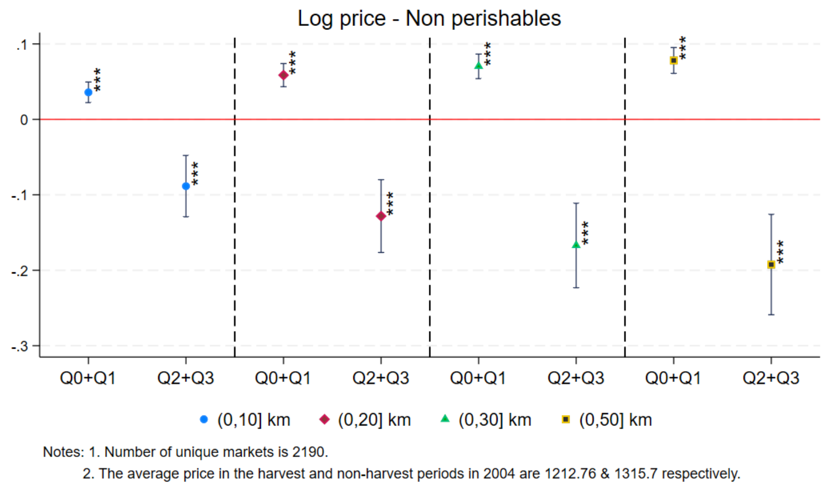
Notes: The figure above shows the location of the government-regulated agricultural APMC markets or *mandis* across all districts in India.

Figure 3: Impact of rural roads connectivity on annual dispersion of log prices of major non-perishables



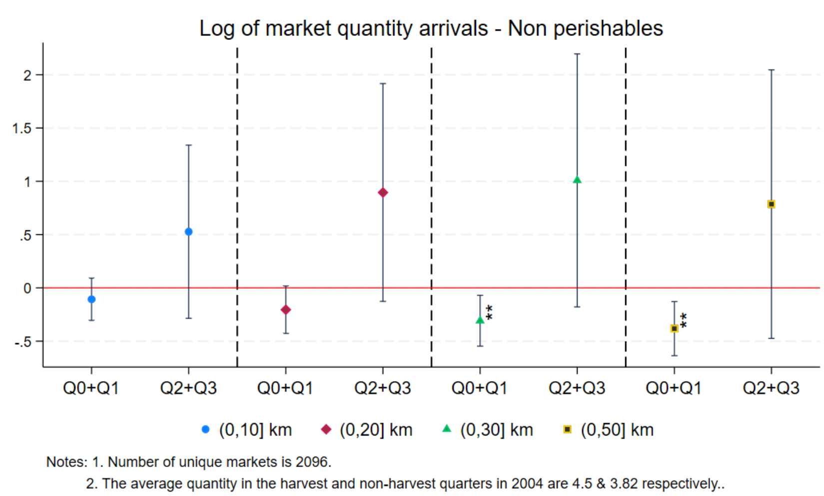
Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity* are reported in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4: Impact of rural roads connectivity on prices of major non-perishables



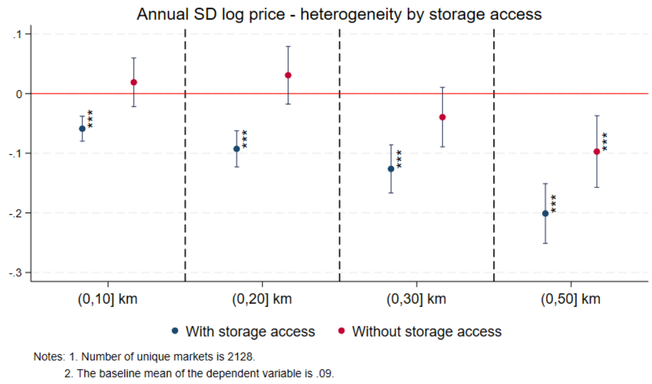
Notes: This figure reports the estimates on the log of average monthly prices of major non-perishable crops across various distance bandwidths using the Equation (1). The harvest period is defined as the first six months following the start of the harvest season, while the post-harvest period corresponds to the latter half of the year. Our dependent variable is the log of the average monthly price of a crop c in market m of district d in year t. The coefficients of our variable of interest- *Proportion of village connectivity* are reported in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. The baseline prices are reported in (INR/Quintal). Controls include district-level rainfall and crop, market, district, quarter, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5: Impact of rural roads connectivity on quantity arrivals of major non-perishables



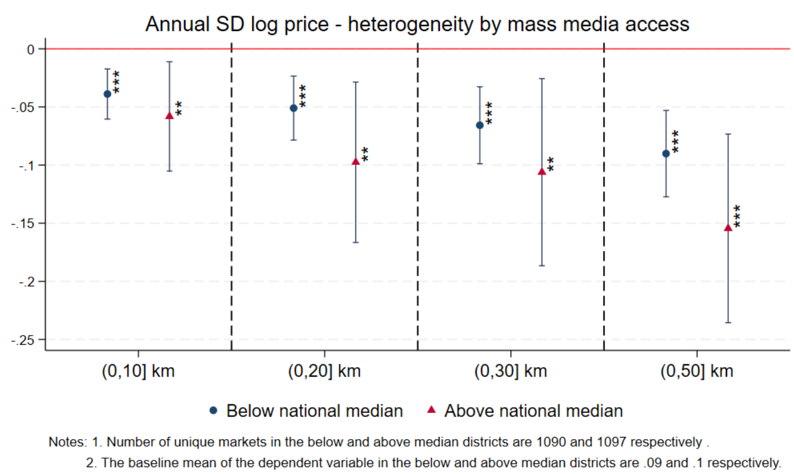
Notes: This figure reports the estimates on the log of average monthly quantities of major non-perishable crops across various distance bandwidths using the Equation (1). The harvest period is defined as the first six months following the start of the harvest season, while the post-harvest period corresponds to the latter half of the year. Our dependent variable is the log of the average monthly quantity arrivals of a crop c in market m of district d in year t. The coefficients of our variable of interest- *Proportion of village connectivity* are reported in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, quarter, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 6: Impact of rural roads connectivity on annual standard deviation of log prices of major non-perishables by storage access



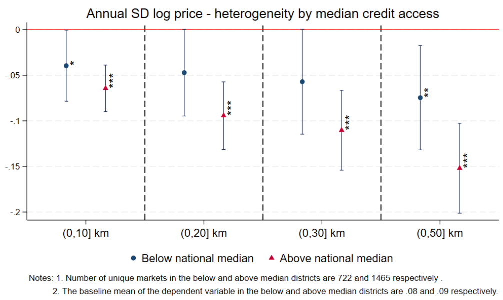
Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity*, for villages with and without storage access within 20 km are presented in the figure above across different distance bandwidths. It is defined as the proportion of villages (with or without storage access within 20 km) that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 7: Impact of rural roads connectivity on annual standard deviation of log prices of major non-perishables by mass media access

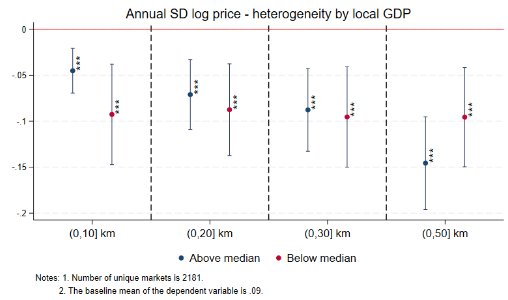


Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. We split the districts by the median per capita ownership of mass media devices such as radio, television, and telephones. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity* presented in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 8: Impact of rural roads connectivity on annual standard deviation of log prices of major non-perishables by credit access and local GDP



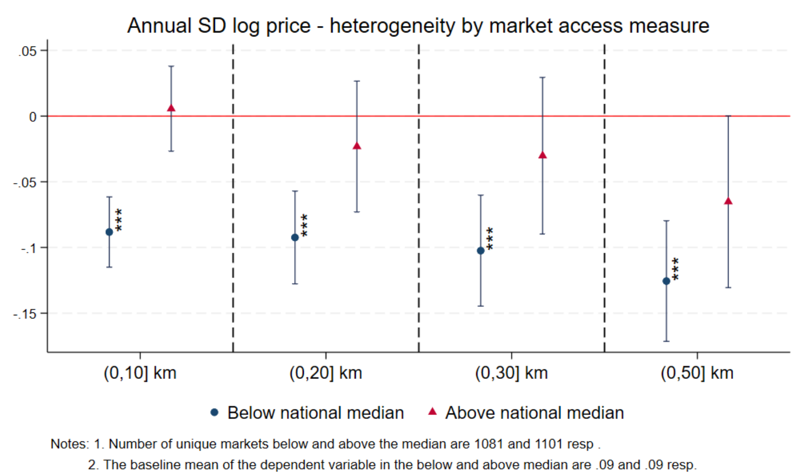
(a)



(b)

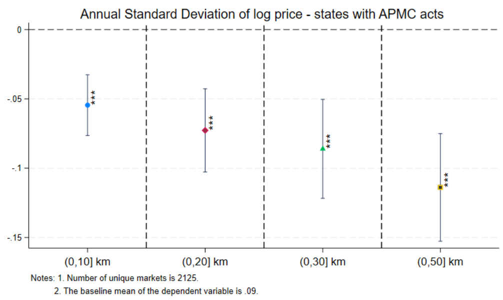
Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. In Panel a, we split the districts by the national median per capita borrowings from both formal and informal sources. In Panel b, we split the districts by the national median levels of nightlight intensity, which serves as a proxy for local income. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity* presented in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 9: Impact of rural roads connectivity on annual standard deviation of log prices of major non-perishables by local competition

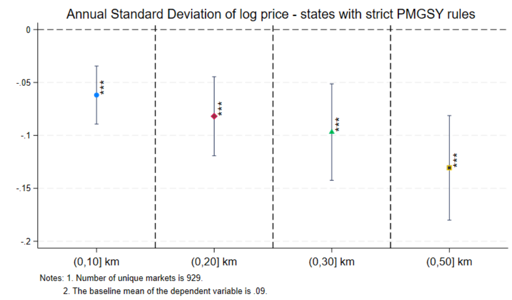


Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. We divide the markets based on the median market access measure, calculated as the inverse distance-weighted sum of nearby markets within the same state. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity* presented in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 10: Robustness checks on annual price volatility restricting to certain states



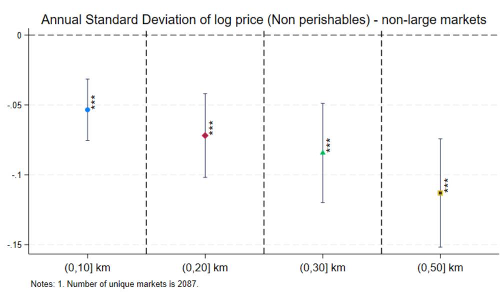
(a)



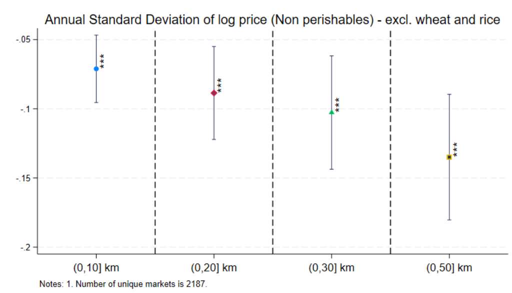
(b)

Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. In panel a, we drop the states - *Jammu & Kashmir, Kerala, Bihar, and Manipur* which did not implement the APMC Acts. In panel b, we restrict our analysis to the states - *Chhattisgarh, Gujarat, Madhya Pradesh, Maharashtra, Orissa, and Rajasthan* that closely followed the program's rule-based construction. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity* presented in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 11: Robustness checks on annual price volatility for non-large markets and excluding wheat and rice



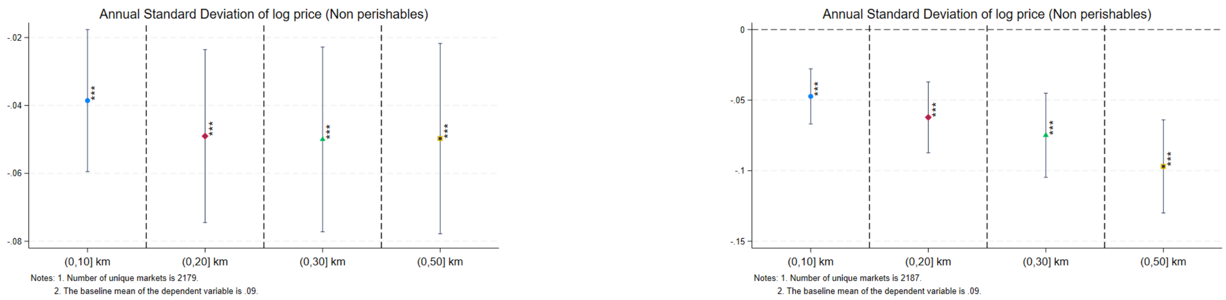
(a)



(b)

Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. In panel a, we drop the large markets - whose total commodity arrivals in 2010 exceeded the 99^{th} percentile from the sample. In panel b, we drop rice and wheat from our analysis as they are procured heavily by the government. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity* presented in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 12: Robustness checks on annual price volatility using nearest market mapping and population-based connectivity measure

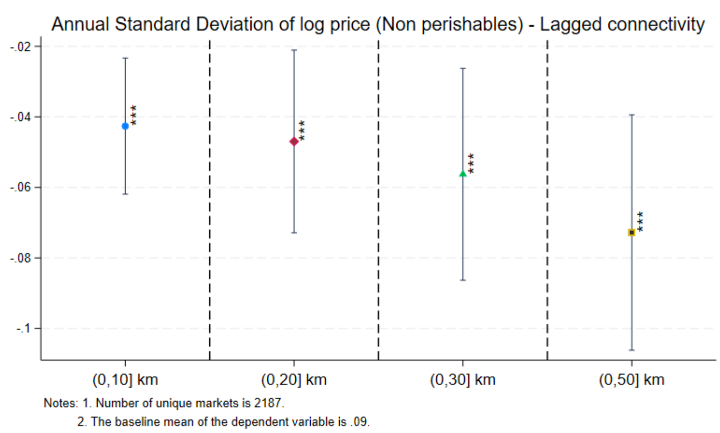


(a)

(b)

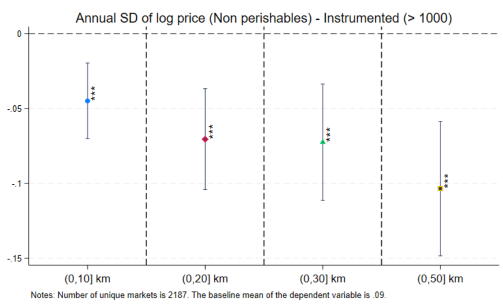
Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths. These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. In Panel a, each village is mapped to its nearest market, creating a unique one-to-one village-market correspondence. The estimates are calculated using Equation (1). The coefficients of our variable of interest - *Proportion of village connectivity* presented in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. In panel b, we return back to our original sample and recalculate our estimates using Equation (3). The coefficients of our variable of interest - *Proportion of population connectivity* presented in the figure above across different distance bandwidths. It is defined as the proportion of population in villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 13: Robustness checks on annual price volatility using lagged connectivity measure

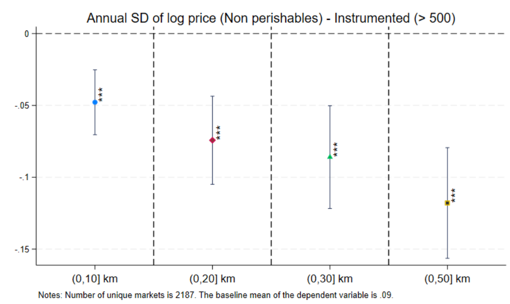


Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (4). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity last year* are reported in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year $t-1$. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 14: Robustness checks on annual price volatility using instrumental variable (2SLS) strategy



(a)



(b)

Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (6). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. We instrument the actual connectivity with the "ideal" connectivity that is defined as the proportion of villages with populations exceeding either $1,00$ (panel a) or 500 (panel b) that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Table A1: Summary Statistics

Market Data	Mean	Median	Std Dev
# markets in a state	190.54	184	86.19
# markets in a district	8.61	7	5.29
# months reported by each market in a year	9.53	11	2.92
# major non-perishables reported in each market in a year	5.85	6	2.96
# major perishables reported in each market in a year	6.70	7	2.73
# villages less than 20 km from a market	400.04	326	272.47
Distance between a village and its nearest market (kms)	18.45	16.70	10.29
Distance between a village and its second nearest market (kms)	27.15	26.35	10.25
Distance between two closest markets (kms)	15.77	21.89	13.28
PMGSY Data			
% villages connected around a market within 20 kms in 2004	6.85	4.97	6.59
% villages connected around a market within 20 kms in 2010	18.02	15.38	12.75

Table A2: Correlation between baseline prices and population around markets

	Prices in 2004 (INR/Kg)			
	(1)	(2)	(3)	(4)
Total population in (0,10) kms	-0.00			
	(0.00)			
Total population in (0,20) kms		-0.00		
		(0.00)		
Total population in (0,30) kms			0.00	
			(0.00)	
Total population in (0,50) kms				0.00
				(0.00)
Observations	16322	16453	16453	16527

Notes: The table above presents the correlation between the average monthly prices of major non-perishable crops in 2004 and the total population of villages located within different radius bandwidths around a market in the same state. The controls include crop, month, and district fixed effects. Standard errors, clustered at the market level, are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Average prices of major non-perishables during harvest and non-harvest periods in 2004

Crop	**Harvest Prices**		**Non-Harvest Prices**	
	Level (INR/Quintal)	Log	Level (INR/Quintal)	Log
Barley	552.60	6.31	598.44	6.38
Sorghum	607.30	6.35	613.75	6.37
Maize	504.31	6.21	542.82	6.29
Paddy	603.42	6.38	843.51	6.37
Pearl Millet	525.34	6.25	510.24	6.21
Finger Millet	500.18	6.20	519.40	6.24
Wheat	728.91	6.58	1,224.227	6.65
Cotton	2,229.95	7.68	2,273.94	7.72
Groundnut	1,797.55	7.47	1,852.69	7.50
Linseed	1,869.91	7.53	1,809.12	7.49
Mustard	1,742.35	7.46	1,781.01	7.48
Sesame	3,081.34	8.01	3,302.78	8.07
Arhar	1,796.67	7.46	2,258.66	7.51
Bengal gram	1,518.56	7.31	1,583.29	7.35
Black gram	1,485.2	7.28	1,472.51	7.26

Notes: This table reports the average monthly prices in levels (INR/Quintal) and log of the average prices for major non-perishable crops in the harvest and non-harvest periods separately.

Table A4: Effect of rural roads connectivity on various measures of inter-temporal price dispersions of major non-perishables

	Measures of dispersion			
	SD	CV	Mean Dev	Mean Dev (log)
	(1)	(2)	(3)	(4)
Proportion of connected villages in (0,20) kms	-0.07***	-0.06***	-245.85*	-0.03***
	(0.02)	(0.02)	(137.08)	(0.01)
Baseline Mean	.09	.09	145.62	.04
Observations	39540	39540	44808	44808

Notes: This table reports the estimates on the various measures of price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. Our dependent variables are the annual standard deviation (column 1), coefficient of variation (column 2), mean deviation of prices (column 3), and mean deviation of log prices (column 4) of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of connected villages in (0,20) km* are reported in the table above. It is defined as the proportion of villages that received new road connections around a market m of district d in year t within the (0,20) km radius bandwidth. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Effect of rural roads connectivity on farm harvest prices of major non-perishable crops

	Farm Harvest Prices (INR/quintal)	
	Level(prices)	Log(prices)
	(1)	(2)
Proportion of village connectivity in district	145.52	0.09*
	(135.77)	(0.05)
Baseline Mean	1170.85	6.89
Baseline SD	693.77	.59
Observations	14444	14444

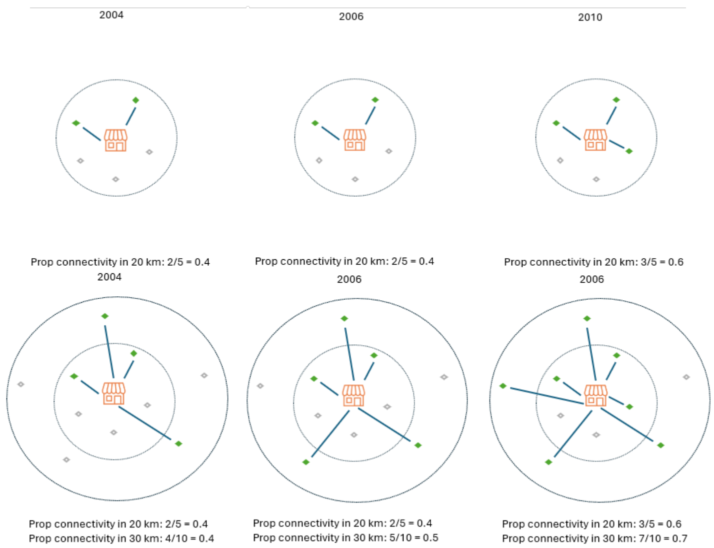
Notes: The sample period for this analysis is from 2003 − 2010. The major non-perishable crops are rice/paddy, wheat, sorghum, pearl millet, maize, finger millet, barley, chickpea, pigeon pea, groundnut, sesamum, rapeseed/mustard, linseed, and cotton. The controls include rain and crop, year, state, and district fixed effects. Standard errors, clustered at the district level, are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effect of rural roads connectivity on district-level area under cultivation, production, and yield of major non-perishables

	Log (area)	Log (production)	Log (yield)
	(1)	(2)	(3)
Proportion of village connectivity in district	-1.31	-1.05	0.18
	(1.01)	(1.01)	(0.16)
Post=1	-0.20**	-0.10	0.09***
	(0.08)	(0.08)	(0.02)
Post=1 × Proportion of village connectivity in district	0.66	0.71	-0.09
	(0.77)	(0.76)	(0.13)
Baseline Mean	6.64	6.62	.77
Baseline SD	3.66	3.83	.64
Observations	11422	11422	9848

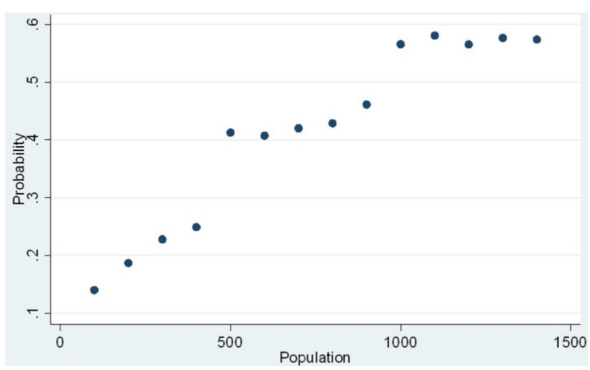
Notes: The data on the area under cultivation, production, and yield of various crops at the district level was obtained from the official website of the Directorate of Economics and Statistics. Area under cultivation, production, and yield are reported in hectares, tonnes, and tonnes/hectare, respectively. The variable *post* takes the value 1 for 2010 and 0 for 2004. The major non-perishable crops are rice/paddy, wheat, sorghum, pearl millet, maize, finger millet, barley, gram, groundnut, sesamum, rapeseed/mustard, linseed, and cotton. The controls include rain and crop, year, state, and district fixed effects. Standard errors, clustered at the district level, are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Diagrammatic illustration of connectivity rings around a market over years



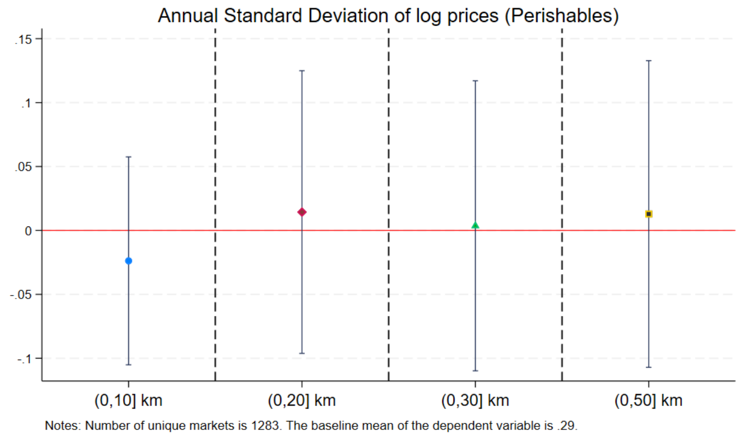
Notes: The figure illustrates our empirical strategy, showing radius-based connectivity bands around market center A. The top panel presents a 20 km connectivity ring encompassing 5 villages. As more villages received roads under PMGSY, the share of connected villages within this ring rose from 0.4 in 2004 to 0.6 in 2010. The bottom panel adds one more ring with a 30 km bandwidth. Connectivity proportions within each ring increase over time as more villages receive the rural roads under the program.

Figure A2: Road Construction Probability by 2010



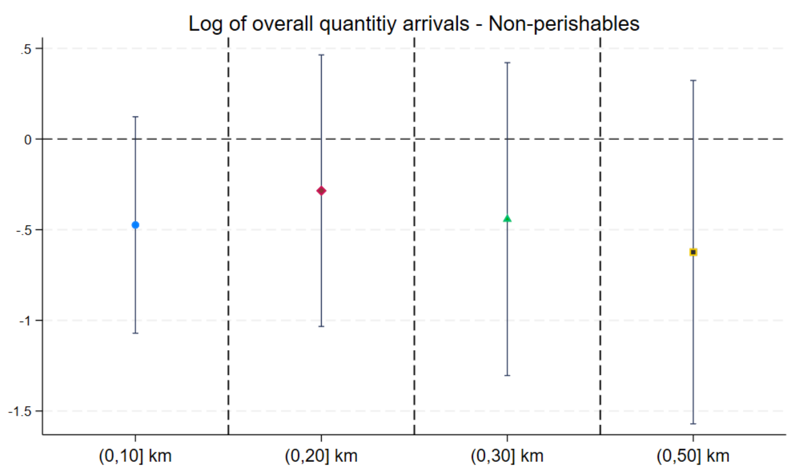
Source: Do rural roads create pathways out of poverty? Evidence from India (S. Aggarwal 2018)

Figure A3: Impact of rural roads connectivity on annual dispersion of log prices of major perishables



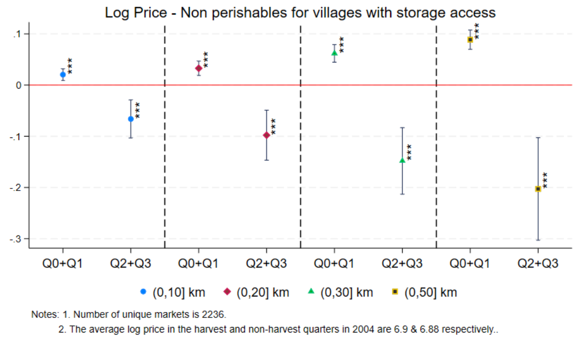
Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (1). The major perishable crops are banana, okra, eggplant, cabbage, cauliflower, cucumber, green chilly, tomato, onion, and potato. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. The coefficients of our variable of interest- *Proportion of village connectivity* are reported in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A4: Impact of rural roads connectivity on the overall quantity arrivals of major non-perishables

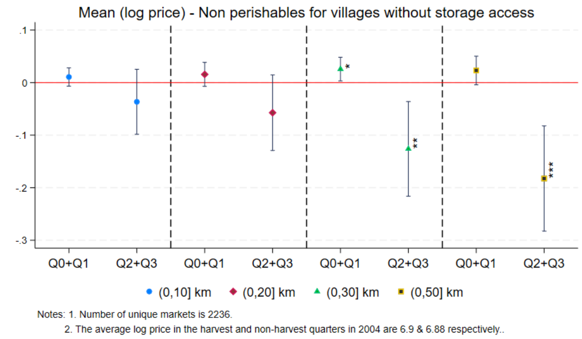


Notes: This figure reports the estimates on the overall quantity arrivals of major non-perishable crops across various distance bandwidths using the Equation (1). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. Our dependent variable is the total quantity arrivals of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity* presented in the figure above across different distance bandwidths. It is defined as the proportion of villages that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A5: Impact of rural roads connectivity on log prices of major non-perishables by storage access



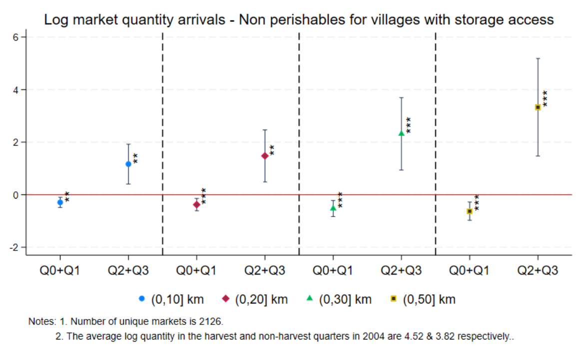
(a)



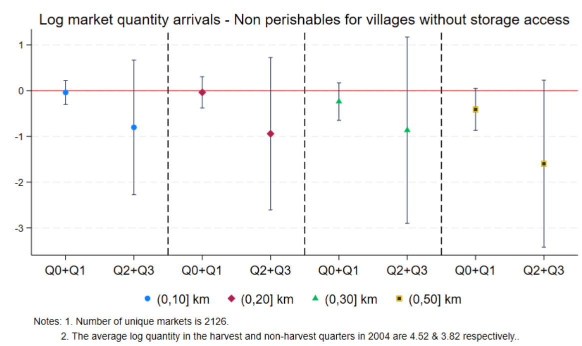
(b)

Notes: This figure reports the estimates on the log of average monthly prices of major non-perishable crops across various distance bandwidths using the Equation (1). The harvest period is defined as the first six months following the start of the harvest season, while the post-harvest period corresponds to the latter half of the year. Our dependent variable is the log of the average monthly price of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity*, for villages with and without storage access within 20 km are presented in the figure above across different distance bandwidths. It is defined as the proportion of villages (with or without storage access within 20 km) that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, quarter, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A6: Impact of rural roads connectivity on log quantities of major non-perishables by storage access



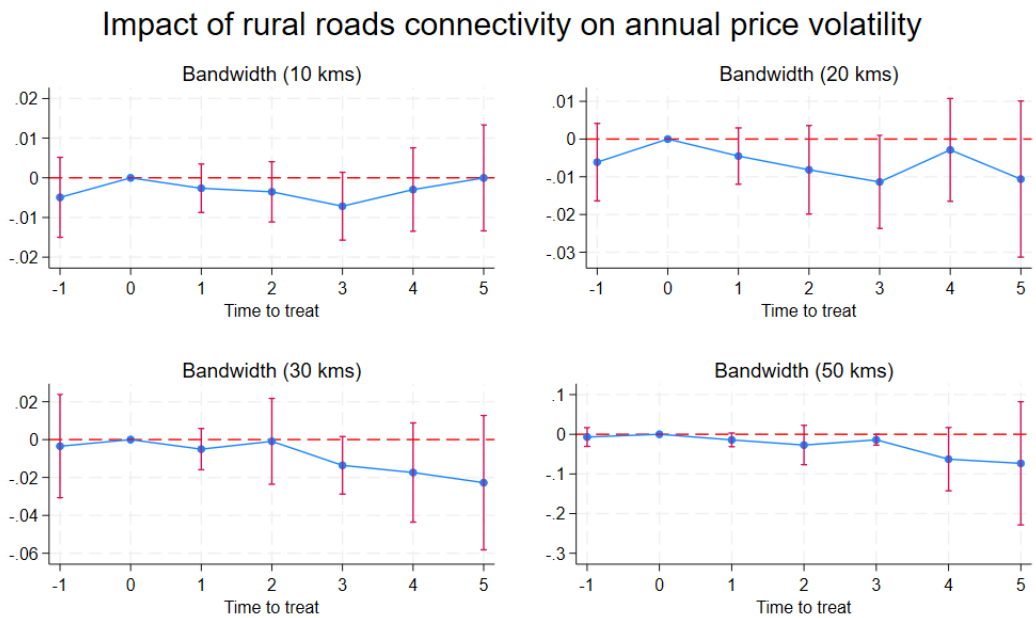
(a)



(b)

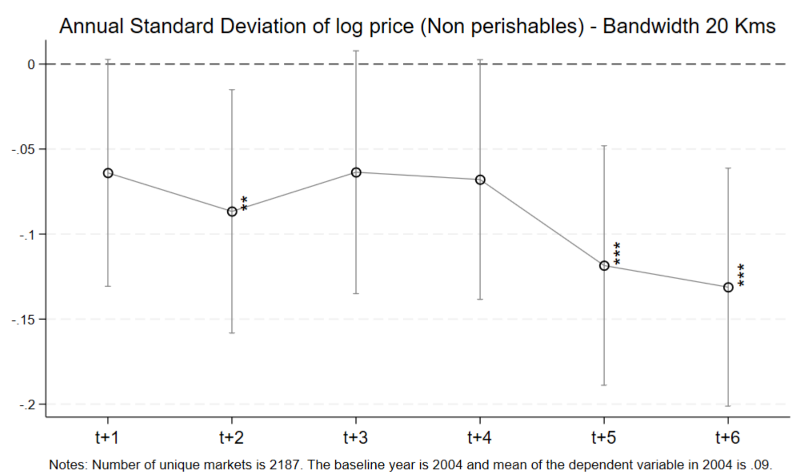
Notes: This figure reports the estimates on the log of average monthly quantities of major non-perishable crops across various distance bandwidths using the Equation (1). The harvest period is defined as the first six months following the start of the harvest season, while the post-harvest period corresponds to the latter half of the year. Our dependent variable is the log of the average monthly quantity arrivals of a crop c in market m of district d in year t. The coefficients of our variable of interest - *Proportion of village connectivity*, for villages with and without storage access within 20 km are presented in the figure above across different distance bandwidths. It is defined as the proportion of villages (with or without storage access within 20 km) that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, quarter, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A7: Impact of rural roads connectivity on annual dispersion of prices of major non-perishables - Event study DiD



Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A8: Impact of rural roads connectivity on annual dispersion of prices of major non-perishables using year-on-year decomposition

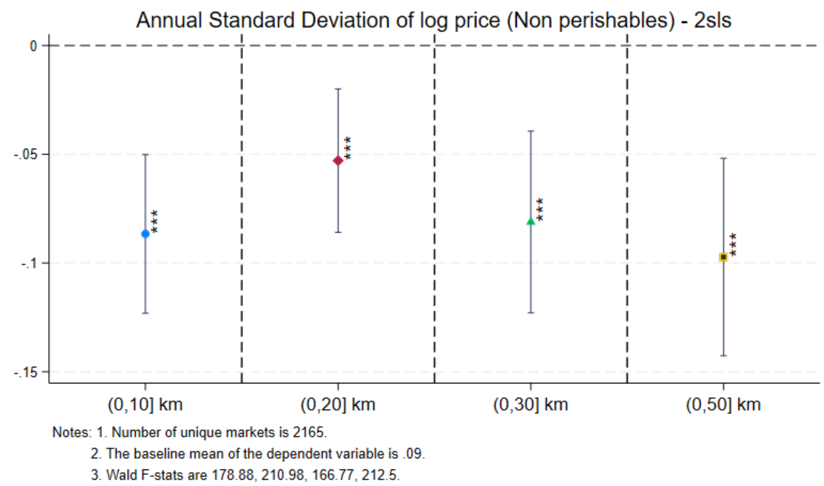


Notes: Includes crop, market, district, and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Alternate empirical strategy As shown in Figure 14, our main finding on annual price volatility remains consistent when we use "ideal" connectivity as an instrument for actual connectivity. However, one potential concern is that villages just above the population threshold might differ significantly from those located farther from the threshold.

To address this issue and further validate our results, we conduct an additional robustness check following the methodology used in (Clots-Figueras 2012). In this approach, we instrument the proportion of connected villages around a market center within a specified radius by using the proportion of villages with populations just above the policy threshold within the same market center and radius. Following (Asher and Novosad 2020), we use their population cut-off value of 84. Therefore, we restrict our analysis to villages with populations within the intervals $(500, 584]$ or $(1000, 1084]$. We then estimate our results using equations similar to Equation (5) and Equation (6), as presented below. We note a significant decline of 0.05 in the annual standard deviation of crops when the proportion of village connectivity goes to 100% in the 20 km bandwidth around a market center. In an average year, the proportion of connectivity for villages just above the threshold remains 14% during our sample period. This translates to an average decline of about 0.007 in annual standard deviation or about 8% from the baseline levels. This finding is consistent with both our main result and the instrumental variable strategy discussed in Section 5.

Figure A9: Impact of rural roads connectivity on annual dispersion of prices of major non-perishables using instrumental variables strategy



Notes: This figure reports the estimates on the annual price volatility of major non-perishable crops across various distance bandwidths using the Equation (6). These major non-perishable crops include barley, sorghum, maize, paddy, finger millet, wheat, cotton, groundnut, linseed, mustard, sesame, arhar/tur, bengal gram, and black gram. Our dependent variable is the annual standard deviation of a crop c in market m of district d in year t. We instrument the actual connectivity with the proportion of villages with populations within the intervals $(500, 584]$ or $(1000, 1084]$ that received new road connections around a market m of district d in year t. Controls include district-level rainfall and crop, market, district, and year-fixed effects. Standard errors are clustered at the market level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.