The Connectivity Conundrum: Exploring the Effect of India's Rural Roads Programme on Localised Crime

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Version: 12 December 2025

Preliminary draft. Please do not circulate or cite.

Abstract

While improvements in road infrastructure spurs economic activity and structural transformation, less is known about its negative spillovers on crime. In this paper, we examine the impact of India's rural roads programme, Pradhan Mantri Gram Sadak Yojana (PMGSY), on localised crime at the district level. Using a two-way fixed effects estimation strategy, we examine the effects of PMGSY roads on crime across 546 Indian districts from 2000 to 2015. The findings indicate a decline in acquisitive crimes such as burglary and theft, aligning with the economic theory that improved economic conditions reduce criminal incentives. Additionally, we find that incidents of crimes against women, bodily harm, and economic crimes increase, suggesting that better connectivity may also enable criminal activity. We offer plausible mechanisms for our findings. This suggests that while policies targeting rural integration improve socioeconomic conditions, they may have unintended adverse impacts on local safety in the rural landscape.

Keywords: Infrastructure, Roads, Crime incidence, Rural development

JEL Codes: K42, O18, P25, P37, R42, R40

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1 Introduction

The provision of road infrastructure is a key driver of economic development and social welfare, paving access to labour markets, education, healthcare, and other public goods and services. In the case of developing economies, where rural areas are often either poorly connected or entirely disconnected from the urban cores, it can be crucial . Evidence confirms the central role that infrastructural investments play in improving livelihoods and fostering structural transformation (Moneke, 2020; Dappe and Lebrand, 2024).

At the outset of the 21st century, more than 300 million Indians[1] (40% of the rural population) lived more than 2 kilometers (km) from a paved all-weather road (AWR).[2] This amounts to one-third of the world's 1 billion rural dwellers living more than 2 km from a paved road (Asher and Novosad, 2020; Roberts et al., 2006). To address the issue of rural isolation, the Indian government announced Pradhan Mantri Gram Sadak Yojana (PMGSY) in 2000, with the aim of providing all weather connectivity to previously *isolated* rural habitations. The PMGSY focused on providing single-road connectivity to an eligible habitation's nearest market centre. Since its inception, it has been credited with improving economic opportunities, increasing non-farm employment, and enhancing access to education, healthcare, consumption quality and technological adoption in rural India (Asher and Novosad, 2020; Aggarwal, 2018; Shamdasani, 2021; Aggarwal, 2021; Datta, 2012; Sharma, 2016).

While PMGSY's role in economic development has been well studied, its impact on social outcomes- particularly crime- remains under explored. With that, we pose our research question: Did PMGSY affect localised crime? This paper aims to establish novel evidence and add to the emerging body of literature on the relationship between road infrastructure and localised crime.

The consensus on the impact of road infrastructure on crime is ambiguous. Classical economic theories of crime consider criminals as rational agents who divide their time between legal and illegal activities so as to maximise their expected utility. They theorise that improving economic opportunities should reduce crime by increasing the opportunity cost of engaging in criminal activities and decreasing the returns to criminal activity (Becker, 1968; Ehrlich, 1973; Gould et al., 2002). Improved road connectivity can also facilitate access to employment and education, providing legitimate sources of income and potentially lowering criminal behaviour (Montolio, 2018). On the other hand, studies suggest that the expan-

[1] This figure is derived from the Rural Access Index (RAI) developed by Roberts et al. (2006). The RAI is a measure of rural population dwelling within 2 kilometers of an AWR, and was 60% for India between 1994-2004.

[2] All-weather road refers to a road that is passable by vehicles in all weather conditions.

sion of road networks can also increase crime by improving mobility for offenders, increasing returns to criminal activity, and altering victimisation risks (Agnew, 2020; Calamunci and Lonsky, 2024; Freedman and Owens, 2016).

Therefore, while PMGSY was designed to foster economic integration, it may also have unintended consequences on crime incidences by altering patterns of social interaction, migration, and criminal incentives. We discuss potential mechanisms against the backdrop of our analysis in Section 6. Our initial hypothesis is that crimes of acquisitive nature (like theft, burglary, looting, etc.) should decrease as PMGSY improves material conditions for rural dwellers.

Big push infrastructural policies can suffer from an endogeneity problem in road allocation. In our case, this problem is solved by the population cutoff-based eligibility rule implicit in PMGSY implementation, ensuring that there is no selection into treatment. Like Aggarwal (2018), we employ a two-way fixed effects (TWFE) estimation strategy to exploit the variation in PMGSY 'treatment' intensity across districts from 2000 to 2015 to estimate the causal effect of rural roads on crime.

We use annual district-level measures of crime incidence derived from the National Crime Records Bureau of India (NCRB) for our dependent variables. The smallest geographical resolution at which crime statistics are published by the NCRB is the district, hence we have to aggregate our analysis to the district level. In the absence of village-level crime data, the analysis compares districts with high and low intensity of treatment rather than comparing treated and untreated villages. For our explanatory variable, we use the official PMGSY road completion data from Asher et al. (2021), aggregated to the district. Our main treatment variable is defined as the *percentage of total habitations in a district that receive a new road under PMGSY*; this intensity of treatment varies over districts and years. Additional control variables are taken from the Indian population censuses (General and Commissioner, 2011) and economic censuses (Central Statistics Organisation, 2013), and Asher et al. (2021).

Our results indicate that the impact of PMGSY varied across different categories of crime. We find that acquisitive crimes (likee burglary and theft) and crimes due to economic dissatisfaction (like riots) decrease- property crimes fall by 0.68% and public order crimes fall by 2.97% (relative to their baseline means) in response to a 1 percentage point (p.p.) increase in the share of habitations that receive a new road.

The observed decline in property crimes aligns with economic theories predicting that increased employment opportunities reduce incentives for acquisitive crime (Becker, 1968; Ehrlich, 1973). As PMGSY improves connectivity, individuals shift towards improved in-

come levels, reducing their reliance on theft and burglary (Asher and Novosad, 2020; Garg et al., 2024). A positive spillover effect of improved economic conditions might alleviate some dissatisfaction, hence reducing incidences of public order crimes such as riots. Though rural policing needs improvements and reform, greater mobility can enable law enforcement to respond more effectively, ultimately deterring crimes like burglary and dacoity.[3]

Our results indicate positive and significant increases in crimes against women, economic crimes, and crimes against the body (kidnapping and assault by causing grievous hurt). The increase in crimes against women and body suggests that new roads may facilitate the movement of offenders, increasing the risk of predatory crimes (Strand, 2012; O'Flaherty and Sethi, 2015).

One of the most striking findings of our analysis is the significant rise in domestic violence and intra-household gender-based violence, particularly cruelty by husbands and relatives), we observe a sizeable increase in domestic crime against women- increasing by 13.8% relative to its baseline mean. Men disproportionately reap the benefits of improved employment opportunities outside their village while women, especially in rural settings, face mobility restrictions and commuting frictions (Joshi, 2024; Mehta and Sai, 2021; Dappe et al., 2021). Our results align with the "exposure reduction" hypothesis, which suggests that when economic shocks lead to male-dominated employment gains, women are more likely to experience violence at home due to increased economic dependency and within-household time (Hsu and Henke, 2021; McCrary and Sanga, 2021).

Finally, we conduct a heterogeneity analysis to examine the role of institutional quality in moderating the relationship between road connectivity and crime. Using BIMAROU states[4] as a proxy for weak institutional presence, we find that economic crimes or crimes related to fraud and corruption, increase significantly in these states following PMGSY implementation. These results suggest that in areas with weaker institutional oversight, new infrastructure may also facilitate the expansion of criminal networks and corrupt practices. At the same time, we find that public order crimes (like riots) decline in these states, likely reflecting improved access to economic resources that mitigate social unrest.

These findings suggest that rural road connectivity may simultaneously enhance economic opportunities and expose rural populations to new risks of victimization.

Ultimately, our findings contribute to a growing literature on the relationship between infras-

[3]See this article on rural crime and policing in India.

[4]BIMAROU stands for the Indian states of Bihar, Madhya Pradesh, Rajasthan, Odisha, and Uttar Pradesh. They are historically characterized by weaker institutions and higher corruption.

tructural development and localised crime. Though PMGSY has set the ball rolling for rural economic development, our paper explores its unintended spillover effect on crime incidence. These results underscore the need for complementary policy interventions, such as improvements in rural policing, schemes to enhance gender-sensitive mobility, etc. to mitigate the negative spillover effects of rural road connectivity and balance economic growth with social stability in developing economies.

The rest of this paper is organised as follows. Section 2 discusses the background and context for this paper, along with a review of the related literature and our contribution to it. Section 3 goes on to describe the data while Section 4 lays out the identification used for our analysis. We present our results in Section 5 and discuss them in Section 6; Section 7 concludes.

2 Background & Context

Pradhan Mantri Gram Sadak Yojana (PMGSY)

As part of India's comprehensive strategy to address rural isolation by providing all-weather road (AWR) connectivity to unconnected habitations, the **Pradhan Mantri Gram Sadak Yojana** (PMGSY) was launched in 2000 as India's flagship rural road connectivity program. Prior to PMGSY, absent or inadequate road infrastructure precluded 40% of India's rural population from access to a paved AWR (Roberts et al., 2006; The World Bank Group, 2016).[5]

The program was fully funded by the central government at its inception, while implementation was carried out at the state level. The scheme was funded by a combination of diesel tax and federal funds along with World Bank and Asian Development Bank loans (Asher and Novosad, 2020; The World Bank Group, 2012). After 2015, funding was shifted to a 60:40 split (90:10 for north-eastern and Himalayan states) between the centre and state governments.

The objective was to connect all habitations[6] with a population of at least 500 as per India's 2001 population census to the nearest market centre or higher-order road (such as State and District Highways). This cut-off was reduced to 250 in special cases.[7] The scheme primarily

[5]Sesonal or *kuccha* roads comprise of mud tracks and unpaved roads found in place of paved roads in rural areas. They often become unmotorable in unfavourable weather conditions.

[6]Habitations are defined as a 'cluster of population, the location of which does not change over time'. Villages may include one or more habitations.

[7]For hilly, desert, tribal regions, the cut-off was eased to 250. Additional amendments were made for

focused on the provision of new single-road connectivity based on a population cut-off rule, although upgrades to existing roads were permitted upon completion of new road works within each district. All PMGSY roads are part of the Core Network- a network of existing and proposed rural roads that provide all weather 'farm-to-market' access for all eligible rural habitations.

The population rule was to be implemented by construction of priority lists at the district level, resulting in District Rural Roads Plan (DRRP) for districts with eligible habitations. Habitations with population of more than 1000 received immediate priority, followed by those with population of 500+, and finally population of at least 250. The scheme originally aimed to connect habitations in priority 1 (population of 1000+) by 2003, priority 2 by 2007, and priority 3 thereafter.

Exceptions to the cut-off allocation rule were allowed in certain cases- for example, villages that lay in the 'least cost' path of a PMGSY prioritised habitation would be connected, or neighbouring habitations may combine their population to meet the cut-off if they were located within 500 metres of each other. The most suitable threshold was adopted depending on the population composition of eligible habitations within a state/district.

PMGSY followed phased implementation with the staggered announcement of four verticals, each with a specific set of objectives. PMGSY-I announced in 2000 aimed to provide single AWR connectivity to eligible habitations based on the population cut-off rule. PMGSY-II was launched in 2013 and focused on upgradation of existing roads to improve the Core Network's efficiency while PMGSY-III (2019) aimed to enhance connectivity to Gramin Agricultural Markets (GrAMs), and educational and health facilities. The fourth vertical, Road Connectivity Project for Left Wing Extremism Areas (RCPLWEA) was launched in 2016, giving special attention to areas affected by extremism. [8]

At the end of 2014-15, almost 450,000 kilometres of road construction had been completed, connecting nearly 135,000 habitations under PMGSY-I and II. 84% of sanction roads and 78% of eligible habitations had received a road.[9] This paper is limited to the analysis of habitations connected under PMGSY by 2015. Furthermore, as we focus on new road connectivity, upgrade roads (built under PMGSY-II) are excluded from our analysis.

areas affected by left-wing extremism.

[8]Source: https://pib.gov.in/PressRelease

[9]Data and progress on the PMGSY can be accessed on the Online Management, Monitoring and Accounting System

Rural Roads & the Indian Context

Investment in 'last mile connectivity infrastructure' through the PMGSY has significantly influenced the economic landscape of India. Improved connectivity to the outside world enhances economic and social welfare (Jacoby, 2000; Fafchamps and Shilpi, 2009). Aligning with evidence from broader infrastructural development literature, primary effects are driven by an improvement in market access and reduction in transportation costs (Asher and Novosad, 2020; Aggarwal, 2018; Shamdasani, 2021; Datta, 2012; Sharma, 2016). Using a fuzzy regression discontinuity design to exploit the population cut-off rule, Asher and Novosad (2020) find that rural roads lead to a large reallocation of workers out of agriculture. A new road led to an estimated 9% decrease in the share of workers in agriculture as access to labour-market opportunities outside the village improved, with an equivalent increase in wage labour. They conclude that while rural roads improve factor mobility, they are alone insufficient to bring about structural transformation as remote areas continue to lack economic opportunities (confirming what Banerjee et al. (2020) find in the Chinese context).

Garg et al. (2024) find that though PMGSY promoted factor mobility out of agriculture, it had little to no impact on rural income or assets. The increase in non-farm employment led to labour-saving practices, particularly crop-burning, leading to an increase in agricultural fires and particulate emissions and a subsequent increase in infant mortality by 5.5%. Shamdasani (2021) has complementary findings for factor mobility, finding a significant increase in the commercialisation of agricultural produce (crop diversification) and adoption of improved technology. This finding is essential as agricultural diversification has been established as a pre-condition for local economic development (Bustos et al., 2016). Additionally, the The World Bank Group (2014) finds a change in cropping patterns from food grains to cash crops in Jharkhand and Himachal Pradesh upon receiving PMGSY roads.

Aggarwal (2018) also documents that a changes in market access leads to increased agricultural technology adoption. They also find that improvement in market integration leads to diversification of consumption goods and reduced prices for non-local goods. This also comes with labour market implications- younger children enjoyed enrolment gains while teenaged population showed an increase in drop-outs, favouring the connectivity-induced labour market opportunities over education (Aggarwal, 2018; Mukherjee, 2012).

Infrastructural development can improve human capital development, though these effects are inequitably distributed subject to regional heterogeneity in wages and labour market opportunities. Adukia et al. (2020) present a positive effect of PMGSY road construction

on educational outcomes, with a 7% increase in middle school enrolment and improved school performance. They highlight two main mechanisms- an 'opportunity cost' effect and a 'returns to education' effect. The evidence points to educational investment gains being concentrated in regions with a higher urban-rural skill premium gap, while regions with higher low-skill wages increased the opportunity cost of education, hence reducing enrolment.

Reduction in transportation barriers also have positive implications for health-seeking behaviour (Adhvaryu and Nyshadham, 2012). Evidence shows improved adoption of preventative healthcare and ante-natal care, and vaccination coverage in habitations connected by PMGSY (Banerjee and Sachdeva, 2015; Aggarwal, 2021). A complementary effect is documented by Bell and van Dillen (2014) in an impact evaluation of the scheme in Orissa- with AWR provision reducing the probability of falling sick by 4.5%.

Overall, the literature documents positive effects from the implementation of the scheme when it comes to factor mobility, market access, non-farm employment opportunities, and health and education access. However, there is no significant impact on rural income or asset holdings (Asher and Novosad, 2020; Garg et al., 2024), suggesting that rural roads alone cannot boost rural development. Though labour force participation for prime-aged women improved (Aggarwal, 2018), these gains are disproportionately enjoyed by males out-migrating for employment while women take up household and farm work (Dappe et al., 2021).

Increased non-farm employment and access to socioeconomic welfare facilities may drive local crime incidence down, as hypothesised by Becker (1968) in a pioneering economic theory of crime- a rational agent will engage in less crime if he spends more time employed. As individuals gain employment and the returns to criminal activity reduce, we should observe a reduction in overall crime – but mechanisms are seldom so straightforward. This paper explores the extent to which PMGSY roads might affect localised crime, and potential mechanisms to explain these effects across several crime types.

Contribution

This paper is motivated by the possibility of negative spillover effects and unintended consequences of the PMGSY, specifically, localised crime. The evidence for the effect of connectivity on localised crime and it's underlying mechanisms is mixed.

Using a staggered difference-in-differences strategy to study inter-county effects of the Interstate Highway System (IHS) on local crime in the United States, Calamunci and Lonsky (2024) find that the opening of a highway led to an estimated 8% rise in total crime. The

effect was driven by acquisitive crimes such as theft and burglary, which the authors attribute to highway-induced increase in employment and firm sizes inducing greater returns to criminal activities. They also find a small increase in violent crimes.

Across the pond in Ireland, Agnew (2020) finds that motorways lead to an estimated 10% rise in burglary rates. They argue that removal of transportation barriers increases criminals' mobility, and by providing them a 'least-cost' path, increases returns to criminal activities. According to Baires et al. (2020), the expansion of road networks enabled national gangs to penetrate new territories in El Salvador.

Similarly, Freedman and Owens (2016) find that improved economic conditions lead to an increase in appropriative criminal behaviour. Interestingly, they also find that an improvement in employment conditions that do not benefit the population equitably leads to an estimated 3.4% increase in intra-family assault. This is interesting, and in line with some of the results we find in our analysis.

The literature finds that improvements in local economic and labour market opportunities increase criminal opportunities and victimisation risk (Freedman and Owens, 2016; Cantor and Land, 1985). However, an extension of these mechanisms to the rural Indian setting is unclear- as PMGSY seems to improve market integration but fails to influence rural assets and income levels (as discussed in Asher and Novosad (2020) and Garg et al. (2024)).

Road infrastructure may increase predatory crime (including crimes against women and the human body) as it brings together persons previously unknown to one another (Strand, 2012) and boosts in-migration of working age (aged 15-34) persons with a disproportionately higher propensity to commit crime (O'Flaherty and Sethi, 2015). These channels can increase the risk of victimisation of previously 'underexposed' rural populations. On the other hand, road infrastructure can increase the opportunity cost of committing crime by improving employment opportunities (Gould et al., 2002) and educational prospects. In the Spanish context, Montolio (2018) finds that a decreased unemployment rate as a result of a nationwide infrastructure investment policy reduced crime and reoffending rates.

These effects vary by country and by case; crime is as spatially segregated as socioeconomic development. It makes for an interesting question against the backdrop of structural transformation and non-farm employment gains induced by the PMGSY.

- Could local crime be an unintended consequence of the PMGSY?
- If so, to what extent?

A closely related and relevant paper, Jain and Biswas (2021) study the relationship between

crime and rural roads using an instrumental variable strategy. They find that households in habitations connected by an AWR experience 5% less crime than households in habitations without AWR access with double the effect size when controlling for population composition and inequality. Key among their findings is that roads deter crime only in states with 'lower quality' of institutions. Their paper uses indicators for AWR from the Indian Human Development Survey (IHDS) as a proxy for PMGSY roads, and survey-based data on 'criminal activity faced by respondents' to construct their dependent variables or crime outcomes. The analysis is limited to crimes relating to burglary, female harassment, home invasions, and threats.

Our paper differs from Jain and Biswas (2021) in two distinct ways. First, we utilise official data on roads completed under the PMGSY to construct our independent variables. Second, we use nationally published district-level crime statistics to construct crime outcomes. Our analysis, unlike theirs, is aggregated to the district level. While their paper has an advantage in granularity of outcomes, we report estimates across varied crime types, allowing us to exploit variation in crime composition and add to the literature on how acquisitive and non-acquisitive crimes respond to infrastructural developments.

To the best of our knowledge, this paper is the first to conduct a district-level analysis of the programme's impact on local crime incidences of varying types and severity. We aim to add to an emerging literature on the relationship between infrastructural development and crime incidence, specifically in rural settings where the average Joe owns little to no property to be appropriated.

3 Data

Dependent Variables: National Crime Records Bureau

We obtain our primary outcomes from the National Crime Records Bureau (NCRB hereafter), established under the Ministry of Home Affairs as India's apex body for the collection and compilation of crime statistics. It operates through a hierarchical reporting structure – State Crime Records Bureaux (SCRBs) aggregate data from District Crime Records Bureaux (DCRBs), which NCRB collates to produce annual *Crime in India* reports.[10] NCRB's annual reports publish crime statistics under two main categories – Indian Penal Code (IPC) and Special and Local Laws (SLL) cognizable crimes. Our analysis is limited to the former.

[10]The latest edition is Crime in India 2022. The data & annual reports can be accessed at https://www.ncrb.gov.in/crime-in-india.html

The smallest geographical resolution of openly available crime data in India is the district-hence our analysis is at the district level.[11] We elaborate on this further in Section 4. Our cleaned dataset contains an unbalanced panel of 546 districts over 26 years (from 1990 to 2015) with 25 crime types or IPC heads, allowing further linkage to census and programme-exposure data.

To define our main outcome variables, we further categorise IPC heads into five umbrella variables – Crimes against Body, Crimes against Women, Crimes against Property, Crimes against Public Order, and Economic Crimes.[12] Table 1 presents summary statistics for the different categories of crime and all IPC heads.

There are two notable concerns with NCRB data. First, crime statistics are a function of reporting behaviour which is a function of inter alia literacy, trust in institutions, and access to police station. Poor reporting behaviour can bias the statistics to reflect lesser crime incidence than is occurring. Second, the NCRB employs the '**Principal Offence Rule**' for the classification of crime. The rule implies that in case of multiple offenses registered under a single First Information Report (FIR), the *most heinous crime* will be considered as a unit.[13] This increases the likelihood of underreporting of 'less severe' crime incidences. These possibilities are likely to generate downward bias. Hence, our estimates are likely a lower bound of the true effect of rural roads on crime.

Explanatory Variable: Rural Roads Programme Data

The data for PMGSY coverage comes from Asher et al. (2021) & their novel database, the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG). The SHRUG has shrid-level data for road completion date, sanction date, length completed under the scheme up to 2015.[14] It has additional data such as block name, road name (of newly built/upgraded) roads etc. Like Aggarwal (2018) this paper focuses on newly built roads, upgrade roads are excluded from our analysis. This paper uses the terms shrid, village, & habitation interchangeably.

We construct our treatment variables using shrid-level data on 'earliest completed new road' and 'length of earliest completed new road.' Aggregating the former, we create the variable 'comp_hab' describing the count of habitations connected by PMGSY per district per year.

[11] The data can be accessed on the Open Government Data (OGD) Platform.

[12] IPC heads are categorised according to broad IPC classification (link Indian penal code) and constructed to fit our analysis; see Hazra and Cui (2018) and Prakash et al. (2024).

[13] For example if the offenses of theft, rape, and murder are filed in a single report, the incidence will be counted as a murder case; see Jha (2024).

[14] The 'shrid' is shrug's unique identifier. It identifies villages that keep consistent boundaries.

The main assumption in the construction of our treatment variables is that each habitation, regardless of when it receives a PMGSY road, is treated only once. This is easily verified by PMGSY guidelines, as it proposes only single road connectivity.[15] Therefore we aggregate village-level PMGSY data to the district, allowing our treatment to be of varying intensity at the same geographical resolution as our outcomes. Figure 1 depicts how PMGSY coverage evolved with time within our panel.

Other Data

District shapefiles and additional data for control variables come from Asher et al. (2021), Central Statistics Organisation (2013) and General and Commissioner (2011). We use three waves of the Population Census (1990, 2001, and 2011) for basic demographic controls, and waves 3 through 6 of the Economic Census for district level non-farm employment. An important control is night-time lights (NL) data, as a proxy for district economic growth/prosperity and electrification. This approach is well established in the literature (Henderson et al., 2011; Chen and Nordhaus, 2011). NL data was recorded by the Defense Meteorological Satellite Programme (DMSP) up to 2013, and by the Visible and Infrared Imaging Suite (VIIRS) thereafter. We construct standardised NL data combining DMSP and VIIRS measures of average total NL recorded in a polygon (here, polygon coincides with district) to obtain annual observations from 1990-2015.[16] Table 1 presents the summary statistics for our control variables.

District Concordance

Owing to splitting and merging, Indian district have shifted boundaries over time. To ensure consistency, our sample is restricted to districts that can be mapped across the three Population Census waves using the common SHRUG identifier. After accounting for these disparities in district boundaries, we are left with a sample of 546 districts.[17]

4 Empirical Strategy

NCRB data lacks village-level granularity, since crime statistics are published at the district level. In the absence of outcome data below the district level, we are unable to exploit the PMGSY rule of allocating roads to villages based on the population cutoff in a regression

[15] Section 3.10 in PMGSY guidelines

[16] More information on DMSP-OLS and VIIRS annual measures of night-time luminosity can be found in the linked urls.

[17] India has a total of 640 districts as of the latest Population Census (2011).

discontinuity design as seen in Asher and Novosad (2020). Like Aggarwal (2018), we turn to a Two-Way Fixed Effects (TWFE) model to estimate the causal effect of rural roads on crime. Our identification is based on the comparison of districts with varying intensity of treatment and not on comparing treated villages with untreated villages.

Average Treatment Effect on the Treated (ATET)

Ideally, if village-level data for crime had been accessible, our estimating equation would be of the following form:

$$y_{vdt} = \alpha + \gamma_t + \delta_d + \beta \times D_{vt} + \eta' X_{vdt} + \epsilon_{vdt} \tag{1}$$

Where y_{vdt} is the incidence of the crime outcome y for village v in district d at time t. δ_d is a set of district fixed effects to control for time-invariant & district specific factors. γ_t is a set of year fixed effects to control for shocks common to all villages in a given year. X_{vdt} is a vector of village controls (including demographic and economic factors). D_{vt} is an indicator variable for whether a rural road is present in village v at time t, and ϵ_{vdt} reports the error term. Here, β captures the ATET of road connectivity for a village given by a two-way fixed effects model.

However, since our outcomes are at the district level, we adopt an approach similar to Aggarwal (2018) and aggregate the above equation to fit our case as given below:

$$y_{dt} = \alpha + \gamma_t + \delta_d + \beta \times (\frac{D_{dt}}{H_{dt}} \times 100) + \eta' X_{dt} + \epsilon_{dt} \tag{2}$$

Where y_{dt} is the incidence of the crime outcome y in district d at time t. Here, D_{dt} is the number of habitations or villages in district d that have received a road under the scheme by time t and H_{dt} is the total number of habitations in district d at time t.[18] β captures the ATET of road connectivity for a district given by the two-way fixed effects model.

δ_d is a set of district fixed effects to control for district specific time-invariant factors. γ_t is a set of year fixed effects to control for shocks common to all villages in a given year. X_{dt} is a vector of district-level controls. ϵ_{dt} reports the error term. Standard error terms in each regression are clustered at the district level.

[18] This equation uses the fraction of habitations connected (multiplied by 100) as the 'treatment intensity', and amounts to exploiting the variations in the percentage of villages that received a new road in each district-year.

In all regressions, controls include population, social group (scheduled caste or SC, scheduled tribe or ST), literacy, and non-farm employment measures. We also control for economic activity and electrification using NL. As we will discuss in Section 5, our estimates remain robust to the inclusion of these controls.[19]

We define our main explanatory variable below.

Completed Roads: For any district d at time t, this variable measures the percentage of total habitations (or villages) within district d that have been connected by a completed road as of year t. Formally, it corresponds to $\frac{D_{dt}}{H_{dt}} \times 100$ in Equation (2), where D_{dt} is the count of habitations that have received a completed road, and H_{dt} is the total number of habitations in district d. This variable is used as the primary independent variable in our TWFE estimation. Figure 2 shows the geographical distribution of 'Completed Roads', comparing the progress of PMGSY between 2005 and 2015.

Falsification Test

Districts with higher baseline road connectivity might be on different trajectories than those with low baseline road connectivity– ipso facto, if there are 'pre-trends' in the evolution of our crime outcomes, this can threaten the validity of our analysis.

To address this concern, we adopt a standard method from the literature of conducting a falsification test to check for any 'pre-trends'. In order to do so, we conduct regressions identical to our main specification (given by Equation 2) to check if roads completed in the 'post' period under PMGSY had an effect on the crime outcomes during a pre-programme period.

In this case, we use the treatment intensity of PMGSY from 2006-2015 as treatment for the 'placebo' or 'fake' pre-programme crime outcomes during 1994-1999 (since this is our placebo window of pre-period years). For this placebo window, the explanatory variable is 'Completed Roads', given by the percentage of habitations connected by PMGSY for each district. The explanatory variable is identical to that of our main specification (Equation 2).

If indeed districts with higher treatment intensity were on different trajectories as those with low treatment intensity before PMGSY implementation, the placebo test should return significant and non-zero coefficients. This would mean that there is a presence of 'pre-trends'

[19]It is possible that village-level observables are inadequately controlled since our identification strategy is not suited to doing so. We reconcile this with the evidence that Muralidharan and Prakash (2017) show; their coefficients remain identical for specifications with and without village-level covariate like public goods (Aggarwal, 2018).

and the validity of our empirical strategy would be questioned.

The results for this falsification test are reported in Table 2. The falsification test gives insignificant or small estimates, indicating that there were no 'pre-trends' before the implementation of PMGSY. We are able to successfully conduct this falsification test for four out of the five main outcome categories, as presented in Table 2. Only one outcome, crimes against public order, displays a positive significant estimate. However, this effect is small in magnitude and significance. We report the results for this category for completeness in Section 5, but caveat it with the presence of pre-trends.

5 Results

We estimate the impact of 'Completed Roads' on both, categorical crime outcomes and individual crime outcomes within each category using the estimation described by Equation 2. We seek to answer how each IPC category and type responds to PMGSY road allocation across districts. A 1 percentage point (p.p.) increase in Completed Roads (as defined in Section 4, is equivalent to a 1 p.p. increase in the 'percentage of habitations that receive a new road'. This translates to an extra 1% of however many habitations there are in the district having an additional PMGSY-connected village.

Effect on Categorical Crime Outcomes

Table 3 presents the effect of Completed Roads on five umbrella crime outcomes. Columns (1), (2), and (5) report positive significant estimates, implying that incidences of crimes against body, women, and economic crimes go up, while public order and property crimes fall as rural road connectivity improves.

Though estimates in Table 3 do not include controls, **our results remain robust to the inclusion of controls and are reported in Column (1) of Table 4 and Table 5**. The effect on each overall category is described below. A p.p. increase in the percentage of habitations that receive a new road is associated with an estimated increase of 5.33 incidents of crimes against the body, 5.52 incidents of crimes against women, and 1.38 incidents of economic crimes. These estimates correspond to 1.33%, 5.36%, 1.51% increases in crimes against body, women, and economic crimes relative to their baseline means. Though modest in magnitude, these estimates point to a small but positive increase in crime incidence due to new road connectivity.

Contrastingly, a p.p. increase in the percentage of habitations that receive a new road leads

to an estimated decrease of 5.10 incidents of property crimes- corresponding to a 0.68% decrease relative to its baseline mean. Crimes against public order also show an estimated decrease of 6.14 incidents (2.96% decrease relative to baseline mean).

We also analyse the effect of 'Connected Roads' on individual IPC heads to observe which crimes are driving the overall category effects.

Effect on Crimes against Women & Body

Table 4 reports the results for the effect of 'Completed Roads' on Crimes against body and women, along with the IPC heads that fall in these categories. Panel A describes results for crimes against body. Columns (5) and (6) show positive and significant estimates. A p.p. increase in the percentage of habitations that receive a new road leads to an estimated increase of 0.91 incidents of kidnapping and 3.55 incidents of hurt/grievous hurt. These estimates correspond to 2.33% and 1.60% increase in kidnapping and grievous hurt with respect to their baseline means.

Panel B describes the effect of PMGSY on crimes against women – with significant estimates for Columns (2) to (4). Notably, a p.p. increase in the percentage of habitations that receive a new road leads to an estimated increase of 'Cruelty by Husband and/or his Relatives' by 5.20 incidents or 13.80% relative to baseline mean (Panel B, Column 4). Rape and dowry deaths are estimated to increase by 0.38 and 0.11 incidents respectively. 'Insult to Women's Modesty' decreases by 2.50% relative to its baseline mean (Panel B, Column 5).

While incidents of crimes against women increase, it is interesting to observe that a large portion of this effect is driven by within-household violence against women (Panel B, Column 4). We chalk out potential mechanisms for this finding in Section 6.

Effect on Economic, Property, & Public Order Crimes

The effect of PMGSY on property, public order, and economic crimes are reported in Table 5 by panels A, B, and C respectively.

Panels A and B consistently show negative or null effects across each IPC head. A p.p. increase in the percentage of habitations that receive a new road leads to a 0.72% decrease in incidents of burglary and a 0.67% decrease in incidents of theft (relative to their baseline means). There is a significant negative effect for public order crimes – a p.p. increase in the percentage of habitations that receive a new road leads to a decrease of 6.14 incidents of public order crimes. This effect seems to come from a 3.14% decrease in incidents of riots

(relative to its baseline mean).

The effect of 'Completed Roads' within the economic crimes category is concentrated in 'cheating' – a p.p. increase in the percentage of habitations that receive a new road leads to an estimated 2.16% increase in cheating relative to baseline mean.

Heterogeneity Analysis

How do states with weak institutions fare?

The role of state-level institutions cannot be disentangled from criminal activity. A 'weak rule of law environment' is synonymous with weak institutions, and evidence suggests that such states foster criminal leaders and politicians, high rates of corruption, and poor socioeconomic development (Fisman et al., 2014; Prakash et al., 2019).

In the Indian context, 'BIMAROU' is an acronym for states with historically weaker institutions and poor economic, social, and demographic growth.[20] Using a heterogeneity analysis approach, Prakash et al. (2024) notably find that the effect of electing criminal politicians has a significant effect on the incidence of crime in BIMAROU states specifically. Adopting a similar approach, We use a BIMAROU sample (representative of weak institutions) to conduct a heterogeneity analysis to see how states with weak institutions fare.

Table 6 presents results comparing states with and without weak institutions; Panel A, reports BIMAROU crime outcomes. The BIMAROU estimates for crimes against women and economic crimes are positive and significant; A p.p. increase in the percentage of habitations that receive a new road (for districts in BIMAROU states) leads to an increase of 2.84 incidents of crimes against women (significant at the 1% level), and 2.07 incidents of economic crimes (significant at the 10% level). Additionally, a p.p. increase in the percentage of habitations that receive a new road leads to a decrease of 9.73 incidents of public order crimes.

In sharp contrast, the non-BIMAROU estimate for crimes against women though equivalent in significance, is larger in magnitude. A p.p. increase in the percentage of habitations that receive a new road (for districts in non-BIMAROU states) leads to 10% increase in incidents of crimes against women compared to a 2.50% increase for the BIMAROU sample (relative to baseline means). Crimes against body and property crimes also show significant

[20] Coined by the Indian demographer Ashish Bose, BIMARU was an acronym for the Indian states of Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh. This was subsequently updated to include Odisha, hence making the acronym BIMAROU.
See more in the op-ed: Why India's 'BIMARU' States Have Remained So.

estimates, with 3.21% increase and 0.69% decrease (relative to baseline means) in crime incidence respectively.

A key takeaway here is that the estimation for the BIMAROU sample shows a positive significant effect on incidence of economic crimes- a category under which crimes associated with anti-corruption laws are booked. An underlying mechanism might be the tendency of weak institutional environments hosting higher corruption and 'document' crime incidences (such as counterfeiting.)

Upon comparison, although the pre-intervention mean for most crime categories are greater in the BIMAROU sample (excluding property crimes), improving rural connectivity seems to have had a relatively smaller impact on incidents of crimes against body and women. Section 6 discusses potential reasons for this disparity.

The results are interesting and suggest that the effect of rural roads on crime incidence *may not always be worse for states with weaker institutions* .

6 Discussion & Potential Mechanisms

Our analysis a picture of rural road connectivity leading to an increase in non-acquisitive crimes or crimes against body and women, and economic crimes, and a decrease in public order crimes and acquisitive crimes like burglary and theft. General mechanisms on the impact of road infrastructure on local crime are ex-ante ambiguous, subject to context-specific heterogeneity in economic and demographic conditions. In this section, we propose potential mechanisms and channels through which rural road infrastructure could have induced the observed results in the Indian context.

Substituting Away from Acquisitive Crime

Consistent with our initial hypothesis in Section 1, our analysis finds that crimes of an acquisitive order, such as theft and burglary, decreased as PMGSY provided AWR connection to previously unconnected habitations. Panel A in Table 5 reports that a p.p. increase in the number of habitations that receive a new road under PMGSY leads to an estimated decrease of 5 incidents of property crimes (Column 1).

PMGSY had positive effects on rural economic conditions and structural transformation. Specifically, local economic development was quantified by improvements in factor mobility, non-farm employment opportunities, crop diversification and technology adoption in agricultural production (Asher and Novosad, 2020; Garg et al., 2024; Aggarwal, 2018; Shamdasani,

2021). Adukia et al. (2020) and Aggarwal (2018) find enrolment gains for middle-school and younger children, while suggesting that older children and prime-aged individuals drop out to take advantage of improved job prospects previously inaccessible by unconnected habitations.

Building on the base of Becker (1968) and Ehrlich (1973), rational individuals divide their time between legal and illegal activities to maximise their expected utility. A straightforward implication is that PMGSY-induced improvements in labour market opportunities can bias their propensity to commit crime downwards, more so for low-wage workers shifting from primary to secondary and tertiary sectors.

This potential mechanism explains the 'substitution effect' in favour of employed activities over criminal activity.

Population Dynamics

Evidence documents that improvements in road infrastructure can have unwanted effects. Finding that motorways increase local crime by 10%, Agnew (2020) states that road infrastructure may offer a 'least-cost path' to previously unconnected locations, thereby increasing criminals' mobility and returns to criminal activity. Complementarily, Strand (2012) finds that connectivity improvements can facilitate predatory crimes by bringing together individuals previously unknown to each other – a major deciding factor in the risk of victimisation.

This mechanism also ties into Becker (1968) idea of the 'incentivisation' of crime – access to a wider range of potential victims decreases the likelihood of being caught and convicted, and improves the gains from criminal activity. Moreover, factor mobility induced by road construction can lead to an influx of individuals with a higher propensity to commit crime, such as young men and individuals aged 15 to 34 (O'Flaherty and Sethi, 2015).

Working together, this combined mechanism can explain the observed increase in crimes against body like kidnapping, battery (grievous hurt under IPC).

Time Allocation Shocks

The benefits of road infrastructure are not equally distributed. Infrastructure improvements benefit different demographics disproportionately. Males enjoy a greater proportion of PMGSY induced mobility gains and women remain in farm-employment or shift to housework (Dappe et al., 2021). Aggarwal (2018) shows an improvement in employment for prime-aged women, however this effect is marginally small and weaker in magnitude than

for prime-aged men. Studying the impact of labour demand shocks on gender employment gaps, Joshi (2024) shows that men were able to travel across urban-rural boundaries for non-farm employment in expanding sectors, while women switched to locally available, usually agriculture, jobs or exited the labour force.

The evidence suggests that road infrastructure improvements induce men to seek non-farm employment outside their villages to a larger extent than their female counterparts (Asher and Novosad, 2020; Dasgupta et al., 2024; Herzog et al., 2024; Joshi, 2024). This may be due to a variety of barriers, inter alia commuting frictions (Joshi, 2024), gendered mobility restrictions induced by social norms (Mehta and Sai, 2021), and reallocation of women to within-household or farm work (Dappe et al., 2021).

An intra-habitation gender gap in incomes and employment is then plausible. Within households, this can perpetuate cycles of dependency as the man's income exceed that of the woman. Especially in the case of married women that drop out of the labour force as their husbands' earnings improve (Dappe et al., 2021), there can be within-household time allocation shocks.

Mobility restrictions and disproportionate employment gains for men combined with connectivity-induced returns to criminal activity and inflow of unfamiliar male workers, can increase women's risk of victimisation and explain the observed increase in crimes against women.

Lastly, the literature on domestic and intra-family violence against women during the COVID-19 pandemic reveal that a time-allocation shock leads to an increase in intimate partner violence and domestic abuse against women in international as well as Indian contexts(Maji et al., 2022; Hsu and Henke, 2021; Nigam, 2020; Kaukinen, 2020; McCrary and Sanga, 2021). These effects are consistent with the theory of 'exposure reduction', where victims are more likely to suffer violence when they spend more time in a 'risky household'. This acts as the primary potential mechanism for the observed 13.8% increase in incidents of 'Cruelty by Husband and/or his Relatives' (relative to baseline mean.)

Weaker Institutions

A heterogeneity analysis of BIMAROU states with historically weaker institutions reveals interesting insights. BIMAROU states have been established to have corrupt constituencies, and greater economic losses from the election of corrupt leaders (Prakash et al., 2019). Additionally, Prakash et al. (2024) find a positive relationship between the share of criminal accused leaders and crime incidence, with seriously accused leaders having pronounced effects on crimes against women.

Though PMGSY eligibility was determined exogenously due to the population cutoff-based eligibility rule, there was room for collusion when it came to contracting decisions for road building. Lehne et al. (2018) show an 83% increase in the share of contractors that shared a surname with the winning politician in a term after a close election, signalling that a degree of political influence and muscle may still have existed within districts.

Such persistence of corruption along with a 'weak rule of law' environment can explain the positive estimates for incidents of crimes against women and economic crimes in the BIMAROU sample. This mechanism is more credible when one notes that economic crimes are crimes committed under IPC's Prevention of Corruption Act and related sections (Hazra and Cui, 2018). Therefore, improving connectivity in states with weaker institutions might also improve 'muscle' mobility, and penetration of corruption, leading to an observed increase in economic crimes.

Lastly, we also observe a large and significant negative effect of PMGSY on public order crimes. As PMGSY-induced connectivity improves the rural population's material conditions via increased economic opportunities, positive external demand shocks, and access to diverse consumption baskets- public unrest quiets down and the incidence of crimes motivated by public dissatisfaction (such as riots) reduce (as observed in Panel B, Table 5).

7 Conclusion

This paper investigates the effect of India's federal rural roads programme, the PMGSY, on local crime incidence. While the literature extensively documents the economic benefits of road connectivity, its social implications, particularly in the form of crime spillovers, remain underexplored. Our findings underscore the complex interplay between infrastructure expansion, economic opportunities, and crime patterns, revealing both crime-reducing and crime-inducing effects.

The results indicate that improved rural connectivity reduces acquisitive crimes such as theft and burglary, aligning with classical economic theories that predict a decrease in crime as economic opportunities improve. We find significant increases in crimes against women, crimes against the body (including kidnapping and grievous hurt), and economic crimes. The increase in crimes against women, particularly domestic violence and cruelty by husbands and relatives, suggests that women– constrained by mobility frictions and social norms– face heightened vulnerability within rural households.

Furthermore, our results suggest that in regions with weaker governance, new roads can

inadvertently facilitate illicit activities, including fraud and corruption-related offenses. The variation in crime responses between states with strong versus weak institutions underscores the need to consider local governance capacity when implementing large-scale infrastructure projects.

This paper emphasizes the need for complementary policy interventions to mitigate negative spillovers of road connectivity. Rural policing, along with women's mobility and labour force participation must be improved. Institutional oversight in historically weaker states must be addressed to prevent new infrastructure from exacerbating corruption and economic crimes.

This paper has certain limitations. First, in the absence of village-level data on crime incidence, we conduct our analysis at the district level. A village level analysis would enable a more direct comparison of treatment effects across treatment and control groups. Second, we have not observed the long-run effect of PMGSY on crime outcomes. Lastly, we do not formally test the potential mechanisms provided in the paper. This paper provides valuable insight on how different crime types respond to improvements in road infrastructure. The persistent and dynamic effect of rural roads on crime along with potential mechanisms for different types of crime using well-calibrated models could be a direction for future research.

References

Adhvaryu, A. R. and A. Nyshadham (2012). Schooling, child labor, and the returns to healthcare in tanzania. *Journal of Human resources 47*(2), 364–396.

Adukia, A., S. Asher, and P. Novosad (2020). Educational investment responses to economic opportunity: evidence from indian road construction. *American Economic Journal: Applied Economics 12*(1), 348–376.

Aggarwal, S. (2018). Do rural roads create pathways out of poverty? evidence from india. *Journal of Development Economics 133*, 375–395.

Aggarwal, S. (2021). The long road to health: Healthcare utilization impacts of a road pavement policy in rural india. *Journal of Development Economics 151*, 102667.

Agnew, K. (2020). Crime highways: The effect of motorway expansion on burglary rates. *Journal of Regional Science 60*(5), 995–1024.

Asher, S., T. Lunt, R. Matsuura, and P. Novosad (2021). Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in india using the shrug open data platform. *The World Bank Economic Review 35*(4).

Asher, S. and P. Novosad (2020). Rural roads and local economic development. *American Economic Review 110*(3), 797–823.

Baires, W., L. Dinarte, and C. Schmidt-Padilla (2020). Unintended effects of roads: Labor, education and crime outcomes in el salvador. Mimeo.

Banerjee, A., E. Duflo, and N. Qian (2020). On the road: Access to transportation infrastructure and economic growth in china. *Journal of Development Economics 145*, 102442.

Banerjee, R. and A. Sachdeva (2015). Pathways to preventive health, evidence from india's rural road program. *USC-INET Research Paper* (15-19).

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of political economy 76*(2), 169–217.

Bell, C. and S. van Dillen (2014). How does india's rural roads program affect the grassroots? findings from a survey in upland orissa. *Land Economics 90*(2), 372–394.

Bustos, P., B. Caprettini, and J. Ponticelli (2016). Agricultural productivity and structural transformation: Evidence from brazil. *American Economic Review 106*(6), 1320–1365.

Calamunci, F. and J. Lonsky (2024). The road to crime: An unintended consequence of the interstate highway system. *The Economic Journal*, ueae068.

Cantor, D. and K. C. Land (1985). Unemployment and crime rates in the post-world war ii united states: A theoretical and empirical analysis. *American sociological review*, 317–332.

Central Statistics Organisation (2013). Economic census of india. Accessed via SHRUG https://www.devdatalab.org/shrug_download/, v2.1.pakora.

Chen, X. and W. D. Nordhaus (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences 108*(21), 8589–8594.

Dappe, M. H., M. M. Alam, and L. Andres (2021). *The Road to Opportunities in Rural India: The Economic and Social Impacts of PMGSY*. World Bank.

Dappe, M. H. and M. Lebrand (2024). Infrastructure and structural change in africa. *The World Bank Economic Review 38*(3), 483–513.

Dasgupta, A., A. Karandikar, and D. Raghav (2024). Road access, fertility, and child health in rural india. *Population and Development Review 50*(1), 117–147.

Datta, S. (2012). The impact of improved highways on indian firms. *Journal of Development Economics 99*(1), 46–57.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of political Economy 81*(3), 521–565.

Fafchamps, M. and F. Shilpi (2009). Isolation and subjective welfare: Evidence from south asia. *Economic Development and Cultural Change 57*(4), 641–683.

Fisman, R., F. Schulz, and V. Vig (2014). The private returns to public office. *Journal of Political Economy 122*(4), 806–862.

Freedman, M. and E. G. Owens (2016). Your friends and neighbors: Localized economic development and criminal activity. *Review of Economics and Statistics 98*(2), 233–253.

Garg, T., M. Jagnani, and H. K. Pullabhotla (2024). Rural roads, farm labor exits, and crop fires. *American Economic Journal: Economic Policy 16*(3), 420–450.

General and C. Commissioner (2011). Census of india. Accessed via SHRUG https://www.devdatalab.org/shrug_download/, v2.1.pakora.

Gould, E. D., B. A. Weinberg, and D. B. Mustard (2002). Crime rates and local labor market opportunities in the united states: 1979–1997. *Review of Economics and statistics 84*(1), 45–61.

Hazra, D. and Z. Cui (2018). Macroeconomic determinants of crime: Evidence from india. *Journal of Quantitative Economics 16*(Suppl 1), 187–198.

Henderson, J. V., A. Storeygard, and D. N. Weil (2011). A Bright Idea for Mesuring Economic Growth. *American Economic Review*.

Herzog, I., S. Liu, and Y. Yu (2024). National road upgrading and structural transformation: Evidence from ugandan households.

Hsu, L.-C. and A. Henke (2021). Covid-19, staying at home, and domestic violence. *Review of Economics of the Household 19*(1), 145–155.

Jacoby, H. G. (2000). Access to markets and the benefits of rural roads. *The economic journal 110*(465), 713–737.

Jain, R. and S. Biswas (2021). The road to safety-examining the nexus between road infrastructure and crime in rural india. *arXiv preprint arXiv:2112.07314*.

Jha, R. (2024). Crime in india: A critical review of data collection and analysis. *ORF Issue Brief No. 710*.

Joshi, S. (2024). Spatial shocks and gender employment gaps. Mimeo, University of Warwick.

Kaukinen, C. (2020). When stay-at-home orders leave victims unsafe at home: Exploring the risk and consequences of intimate partner violence during the covid-19 pandemic. *American journal of criminal justice 45*(4), 668–679.

Lehne, J., J. N. Shapiro, and O. V. Eynde (2018). Building connections: Political corruption and road construction in india. *Journal of Development Economics 131*, 62–78.

Maji, S., S. Bansod, and T. Singh (2022). Domestic violence during covid-19 pandemic: The case for indian women. *Journal of community & applied social psychology 32*(3), 374–381.

McCrary, J. and S. Sanga (2021). The impact of the coronavirus lockdown on domestic violence. *American Law and Economics Review 23*(1), 137–163.

Mehta, V. and H. Sai (2021). Freedom of movement: Studying women's mobility in north india. *Urbanisation 6*(1_suppl), S77–S114.

Moneke, N. (2020). Can big push infrastructure unlock development? evidence from ethiopia. *STEG Theme 3*, 14–15.

Montolio, D. (2018). The effects of local infrastructure investment on crime. *Labour Economics 52*, 210–230.

Mukherjee, M. (2012). Do better roads increase school enrollment? evidence from a unique road policy in india. *Evidence from a Unique Road Policy in India (August 28, 2012)*.

Muralidharan, K. and N. Prakash (2017). Cycling to school: Increasing secondary school enrollment for girls in india. *American Economic Journal: Applied Economics 9*(3), 321–350.

Nigam, S. (2020). Covid-19, lockdown and violence against women in homes. *SSRN Electronic Journal 10*.

O'Flaherty, B. and R. Sethi (2015). Urban crime. *Handbook of Regional and Urban Economics 5*, 1519–1621.

Prakash, N., M. Rockmore, and Y. Uppal (2019). Do criminally accused politicians affect economic outcomes? evidence from india. *Journal of Development Economics 141*, 102370.

Prakash, N., S. Sahoo, D. Saraswat, and R. Sindhi (2024). When criminality begets crime: The role of elected politicians in india. *The Journal of Law, Economics, and Organization*.

Roberts, P., S. Kc, and C. Rastogi (2006). Rural access index: a key development indicator.

Shamdasani, Y. (2021). Rural road infrastructure & agricultural production: Evidence from india. *Journal of Development Economics 152*, 102686.

Sharma, A. (2016). Urban proximity and spatial pattern of land use and development in rural india. *The Journal of Development Studies 52*(11), 1593–1611.

Strand, G. (2012). *Killer on the road: Violence and the American interstate*, Volume 2. University of Texas Press.

The World Bank Group (2012). India - rural roads project. Technical Report.

The World Bank Group (2014). Rural road development in India: an assessment of distribution of PMGSY project benefits in three states by gender and ascribed social groups. Technical Report.

The World Bank Group (2016). Measuring rural access: Using new technologies. Technical Report.

Tables & Figures

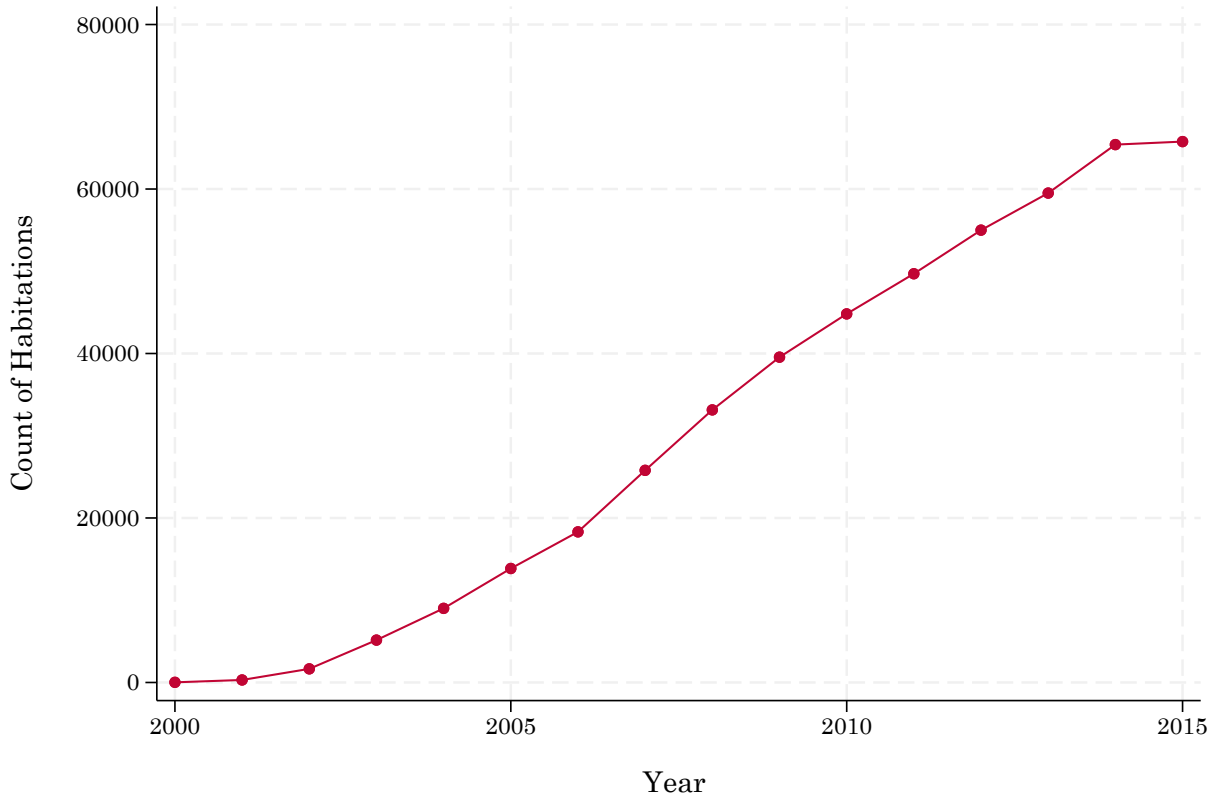

Figure 1: Total Count of Habitations Connected by PMGSY (2000 – 2015)

Notes: Figure 1 plots the number of habitations that receive a new road under PMGSY-I for the years 2000 - 2015. Each point corresponds to the number of villages with a newly built rural road for a given year. This plot is restricted to the 546 districts in our analysis panel. Upgrade roads built under PMGSY-II are excluded from our analysis.
Data used: Official Data for PMGSY derived from Asher et al. (2021).

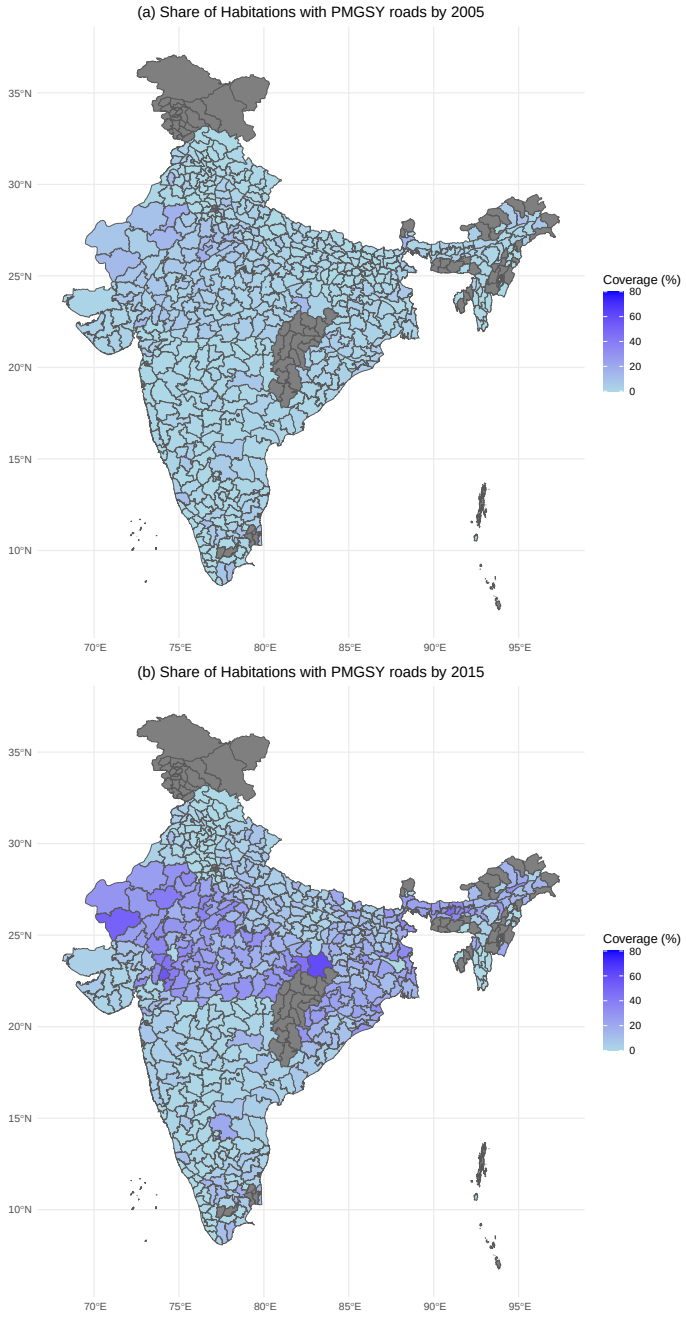

Figure 2: Geographical Distribution of Connected Habitations across Districts

Notes: Figure 2 plots the evolution of district-level percentage of habitations that receive a new rural road under PMGSY-I, comparing programme exposure in 2005 with that in 2015. District boundaries are consistent throughout the intervention period (2000 - 2015). This plot is restricted to the 546 districts in our analysis panel. Upgrade roads built under PMGSY-II are excluded from our analysis.
Data used: Official Data for PMGSY roads and district shapefiles from Asher et al. (2021).

Table 1: Summary Statistics

	Observations	Mean	Median	Std. Dev.
Panel A: Crime Categories				
Crimes against Body	4,616	400.104	217.000	477.717
Crimes against Women	4,616	103.099	41.000	148.318
Property Crimes	4,616	754.619	522.000	918.306
Public Order Crimes	4,616	207.415	126.000	305.152
Economic Crimes	4,616	91.413	53.000	147.152
Panel B: IPC Crime Heads				
Murder	4,616	73.328	55.000	66.499
Attempt to Murder	4,616	57.250	35.000	70.468
Culpable Homicide	4,616	8.032	3.000	13.706
Rape	4,616	25.007	18.000	22.344
Kidnapping	4,616	39.217	27.000	41.640
Dacoity	4,616	18.104	9.000	25.785
Preparation for Dacoity	4,616	2.114	0.000	6.010
Burglary	4,616	227.418	168.000	243.473
Theft	4,616	506.983	320.000	704.581
Riots	4,616	195.517	112.000	301.091
Criminal Breach of Trust	4,616	29.934	17.000	44.218
Cheating	4,616	56.657	29.000	91.847
Counterfeiting	4,616	4.821	1.000	46.599
Arson	4,616	11.898	0.000	27.362
Hurt or Grievous Hurt	4,616	222.276	0.000	431.311
Dowry Deaths	4,616	6.067	0.000	12.864
Sexual Harassment	4,616	28.729	0.000	50.481
Molestation/Assault on Women	4,616	5.607	0.000	24.024
Cruelty by Husband/Relatives	4,616	37.690	0.000	82.509
Panel C: Controls				
Night-time Light (in lumen)	5,460	15148.576	3102.473	23217.709
Literate Population	5,460	579519.830	457876.000	513848.465
Total population	5,460	1391754.546	1160529.000	985211.731
SC Population	5,460	233575.434	186984.500	217407.861
ST Population	5,460	107406.341	30783.500	173154.592
Non-farm Employment	5,460	58168.178	39618.000	66310.601

Note: This table depicts the pre-period summary statistics for the explanatory and control variables. Column (1) depicts the number of observations, column (2) depicts the mean, column (3) depicts the median value and column (4) depicts the standard deviation.

Data used: NCRB panel of district-level crime; district-level Population Census, Economic Census, Night-time lights data from SHRUG (Asher et al., 2021).

Table 2: Falsification Test: Effect of post-period 'Roads' on pre-period Crime

	(1)	(2)	(3)	(4)	(5)
	Body	Women	Property	Public Order	Economic Crimes
Completed Roads	-1.405	0.613	-1.593	1.643*	-0.335
	(2.082)	(0.603)	(2.304)	(0.981)	(0.280)
Constant	184.104***	-24.596***	938.172***	190.023***	89.942***
	(36.969)	(8.621)	(37.110)	(22.164)	(6.265)
Mean of Dependent Var.	400.104	103.099	754.619	207.415	91.413
Observations	4,613	4,613	4,613	4,613	4,613
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates from the falsification test described in Section 4. Column (1) is for crimes against body, column (2) for crimes against women, column (3) for property crimes, column (4) for public order crimes, and column (5) for economic crimes.

Robust standard errors clustered at the district level are reported in parentheses.

Regressions are of the form Equation 2.

Data used: Crime categories constructed from NCRB's district-level crime panel; district-level Rural Roads data from SHRUG (Asher et al., 2021).

Levels of significance: *p $<$ 0.1 , **p $<$ 0.05 , ***p $<$ 0.01.

Table 3: Effect of Completed Roads on Crime Categories

	(1)	(2)	(3)	(4)	(5)
	Body	Women	Property	Public Order	Economic Crimes
Completed Roads	6.686***	5.111***	-5.495***	-6.441***	1.289*
	(2.562)	(1.589)	(2.081)	(1.470)	(0.710)
Constant	506.197***	192.336***	659.061***	178.886***	113.407***
	(8.651)	(5.367)	(7.026)	(4.965)	(2.399)
Mean of Dependent Var.	400.104	103.099	754.619	207.415	91.413
Observations	13,194	13,194	13,194	13,194	13,194
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No

Note: This table depicts the effect of newly completed rural roads on IPC crime categories. Column (1) is for crimes against body, column (2) for crimes against women, column (3) for property crimes, column (4) for public order crimes, and column (5) for economic crimes. Mean of Dependent Var. reports the pre-intervention mean for each dependent variable. Robust standard errors clustered at the district level are reported in parentheses.

Regressions are of the form Equation 2.

Data used: Crime categories constructed from NCRB's district-level crime panel; district-level Rural Roads and control variable data from SHRUG (Asher et al., 2021).

Levels of significance: *p $<$ 0.1 , **p $<$ 0.05 , ***p $<$ 0.01.

Table 4: Effect of Completed Roads on Crimes against Body & Women

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Crimes Against Body	Overall	Murder	Att. Murder	Homicide	Kidnap	Hurt
Completed Roads	5.328*	0.079	0.824	-0.033	0.906***	3.553*
	(2.839)	(0.116)	(0.645)	(0.026)	(0.283)	(2.127)
Constant	546.393***	88.378***	107.892***	11.177***	-48.560**	387.507**
	(162.070)	(11.076)	(30.371)	(2.275)	(20.395)	(155.282)
Mean of Dependent Var.	400.104	73.328	57.250	8.032	39.217	222.276
Panel B: Crimes Against Women	Overall	Rape	Dow. Death	Cruelty	Insult	Assault
Completed Roads	5.517***	0.381**	0.109***	5.200***	-0.718***	0.544
	(1.525)	(0.158)	(0.032)	(1.158)	(0.122)	(0.348)
Constant	289.769***	24.067***	-12.044***	144.482**	15.671	117.593***
	(70.723)	(8.216)	(4.078)	(56.029)	(9.989)	(20.422)
Mean of Dependent Var.	103.099	25.007	6.067	37.690	28.729	5.607
Observations	13,194	13,194	13,194	13,194	13,194	13,194
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table depicts the effect of newly completed rural roads on the incidence of crime in two categories- Panel A reports estimates for crimes against body, and Panel B reports estimates for crimes against women. Column (1) describes the overall effect on each category for all panels. In panel A, column (3) is for the outcome attempted murder', (4) for culpable homicide, (5) for kidnapping & abduction, and (6) for grievous hurt to the body. In panel B, column (3) is for dowry deaths, column (4) for cruelty by husband and his relatives, (5) for insult to a woman's modesty (sexual harassment), and column (6) for assault against women (or molestation). Mean of Dependent Var. reports the pre-intervention mean for each dependent variable. Robust standard errors clustered at the district level are reported in parentheses.

Regressions are of the form Equation 2.

Data used: Crime categories and corresponding IPC heads from NCRB's district-level crime panel; district-level Rural Roads and control variable data from SHRUG (Asher et al., 2021).

Levels of significance: *p $<$ 0.1 , **p $<$ 0.05 , ***p $<$ 0.01.

Table 5: Effect of PMGSY on Property, Public Order, and Economic Crimes

	(1)	(2)	(3)	(4)	(5)
Panel A: Property Crimes	Overall	Dacoity	Prep. Dacoity	Burglary	Theft
Completed Roads	-5.102***	-0.069	0.000	-1.628***	-3.405**
	(1.924)	(0.055)	(0.051)	(0.567)	(1.519)
Constant	220.803	37.293***	-9.989	241.179***	-47.680
	(195.014)	(5.501)	(14.644)	(56.859)	(174.694)
Mean of Dependent Var.	754.619	18.104	2.114	227.418	506.983
Panel B: Public Order	Overall	Riots	Arson		
Completed Roads	-6.139***	-6.124***	-0.015		
	(1.342)	(1.293)	(0.149)		
Constant	182.637***	163.905***	18.732***		
	(50.032)	(47.604)	(6.795)		
Mean of Dependent Var.	207.415	195.517	11.898		
Panel C: Economic Crimes	Overall	Trust	Cheating	Counterfeiting	
Completed Roads	1.375**	0.110	1.225**	0.040	
	(0.666)	(0.172)	(0.601)	(0.069)	
Constant	4.450	38.253***	-62.546	28.744	
	(66.586)	(10.722)	(82.063)	(21.895)	
Mean of Dependent Var.	91.413	29.934	56.657	4.821	
Observations	13,194	13,194	13,194	13,194	
District FE	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	
Controls	Yes	Yes	Yes	Yes	

Note: This table depicts the effect of newly completed rural roads on the incidence of crime in three categories- Panel A reports estimates for Property Crimes, Panel B for Public Order Crimes, and Panel C for Economic Crimes. Column (1) describes the overall effect on each category for all panels. In panel A, column (3) is for the outcome 'Preparation & Assembly for Dacoity'. Mean of Dependent Var. reports the pre-intervention mean for each dependent variable. Robust standard errors clustered at the district level are reported in parentheses.

Regressions are of the form Equation 2.

Data used: Crime categories and corresponding IPC heads from NCRB's district-level crime panel; district-level Rural Roads and control variable data from SHRUG (Asher et al., 2021).

Levels of significance: *p < 0.1 , **p < 0.05 , ***p < 0.01.

Table 6: Heterogeneity Analysis for BIMAROU Sample

	(1)	(2)	(3)	(4)	(5)
Panel A: BIMAROU States	Body	Women	Property	Public Order	Economic Crimes
Completed Roads	-3.816	2.838***	-4.245	-9.729***	2.074*
	(2.684)	(0.892)	(3.443)	(2.283)	(1.121)
Constant	352.268	-10.368	168.431	270.494***	-65.805
	(278.134)	(76.566)	(303.120)	(92.641)	(112.151)
Mean of Dependent Var.	408.016	111.400	752.169	236.517	95.132
Observations	5,405	5,405	5,405	5,405	5,405
Panel B: Non-BIMAROU States					
Completed Roads	14.852***	10.092***	-5.141**	-1.312	0.115
	(5.593)	(3.118)	(2.557)	(1.140)	(0.929)
Constant	793.540***	334.792***	-28.324	117.886**	-29.041
	(184.468)	(101.447)	(295.333)	(54.370)	(92.813)
Mean of Dependent Var.	394.589	97.313	756.326	187.130	88.820
Observations	7,789	7,789	7,789	7,789	7,789
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Note: This table depicts the effect of newly completed rural roads on the incidence of crime for two samples- Panel A reports estimates for BIMAROU states, Panel B for non-BIMAROU states. BIMAROU is an abbreviation for the Indian states of Bihar, Madhya Pradesh, Rajasthan, Odisha, and Uttar Pradesh. For both panels, Column (1) is for crimes against body, column (2) for crimes against women, column (3) for property crimes, column (4) for public order crimes, and column (5) for economic crimes. Mean of Dependent Var. reports the pre-intervention mean for each dependent variable. Robust standard errors clustered at the district level are reported in parentheses.
Regressions are of the form Equation 2.
Data used: Crime categories are constructed from NCRB's district-level crime panel; district-level Rural Roads and control variable data from SHRUG (Asher et al., 2021).
Levels of significance: *p < 0.1 , **p < 0.05 , ***p < 0.01.