Rural Roads and Intermediated Trade: Regression Discontinuity Evidence from Sierra Leone*

Lorenzo Casaburi, Rachel Glennerster and Tavneet Suri†

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Abstract

Using a road-level regression discontinuity design in Sierra Leone, we study the impacts of improvements in rural road infrastructure on crop prices in rural markets. We show that the improved roads reduced market prices of local crops. These price effects are stronger in markets that are further from major urban centers and in less productive areas. In addition, these price effects are reversed in areas with better cell phone penetration. We show that our empirical findings are consistent with a search cost framework à la Mortensen, but inconsistent with other models, such as Bertrand competition, bilateral bargaining, Cournot oligopsony.

Keywords: Rural roads, agricultural product markets, prices, market structure, search

JEL Classication: O18, Q11, D40

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†Casaburi is at the Department of Economics at Harvard University. Email: lcasaburi@gmail.com. Glennerster is at the Abdul Latif Jameel Poverty Action Lab at the Massachusetts Institute of Technology. Email: rglenner@mit.edu. Suri is at the MIT Sloan School of Management. Email: tavneet@mit.edu. Casaburi is the corresponding author.

1 Introduction

Over the last two decades, governments and donors in Sub-Saharan Africa have devoted considerable resources to rural road construction and rehabilitation, of which a large share was used to upgrade feeder roads that link up small localities with each other or to larger roads.[1] The rationale behind these investments is that good feeder roads, while expensive, are central to the integration of markets, primarily because they reduce transport costs and hence improve the access of farmers to markets for their crops. The existing body of research on the impact of rural feeder roads is plagued by identification problems, and does not always provide compelling causal evidence on the impact of infrastructure improvement (van de Walle (2009)).

In this paper, we look at the impacts of a rural road construction program. In particular, the program improves the quality of small rural roads. This lowers transport costs, both for traders who come to rural markets to purchase agricultural produce, but also for farmers who bring their crops to these same markets. This implies that the improvement in road quality will have both demand effects (via changing transport costs for traders) as well as supply effects (via changing transport costs for farmers). We estimate the impacts of the improvements in road quality on prices. Since these effects are driven by changes on both the demand side as well as the supply side, we use theory to help interpret our results. In particular, we consider models of alternative market structures, and derive the predictions each of these have for the effects of changes in transport costs on equilibrium market prices. As we highlight, different models of market structure have different predictions for these price effects as well for the specific heterogeneity we should find in these price effects, with respect to farmer productivity, distance to the city and cell phone access.

Agricultural markets throughout Sub-Saharan Africa are characterized by high levels of fragmentation and poor transport infrastructure, with intermediaries playing a central role (Fafchamps et al. (2004)). The literature on the impact of rural roads, for the most part, has not explicitly dealt with the role of the underlying market structure in shaping the response to these infrastructure investments. Different models of trader competition and intermediation generate different predictions about the price response to an improvement in rural road quality and how this response varies with market characteristics. The empirical analysis of these price responses can therefore provide a test for competing theoretical frameworks of the market structure in agricultural trade. Understanding which of these theoretical frameworks best explains the nature of competition amongst these agricultural intermediaries can shed light on the impact of other supply chain interventions, such as subsidies to different agents of the value

[1]Since 2000, major feeder roads rehabilitation programs have been implemented in Cameroon, the DRC, Ghana, Mozambique, Sierra Leone, and South Sudan, among other countries in Sub-Saharan Africa. Carruthers et al. (2010) document that it would cost about 2% of African GDP every year for ten years to reach some reasonable targets on improved transportation.

chain or export promotion policies.

In this paper, we therefore make two broad contributions. First, we provide empirical evidence on the impact of rural road rehabilitation on transport costs and rural market prices. We focus on a specific program in Sierra Leone where the road selection algorithm allows us to use a Regression Discontinuity Design (RDD), and we use novel data collection strategies to measure changes in prices and transport costs. Sierra Leone is an economy with low population density where feeder roads could potentially have large impacts. Rural markets in the economy are not well integrated, and farmers and traders both travel long distances to engage in trade. Transaction costs are extremely high but transport costs are only a part of these transaction costs. These characteristics are common to many rural African economies (Fafchamps and Hill (2008), Fafchamps et al (2004)) and other developing countries (World Bank, 2009). As feeder roads are commonly advocated as a key policy intervention in these contexts, our first objective is to understand their impact. Well identified measures of feeder road impacts are particularly important given the high costs of effectively connecting such dispersed populations.

As a second contribution, we use our empirical results to test between alternative models of competition in agricultural markets. We focus on Bertrand oligopsony, bilateral bargaining, Cournot oligopsony (with and without endogenous entry), and a basic Mortensen (2003) search model. For each of these frameworks, we derive the equilibrium price in rural markets and provide comparative statics on the price effects of a change in rural road transport costs. We then show how this price effect varies by market characteristics, such as the distance to the main urban centers and the agricultural productivity in the surrounding areas. To the extent that the four classes of models deliver different predictions on these comparative statics, we can use our empirical results to test between these models. It is an open question as to what the relevant model of market structure for traders in agriculture is in developing economies. As we describe below, market structure is important to understanding what policies are most effective at improving market access and, more broadly, welfare for farmers in Sub Saharan Africa.

Our empirical analysis focuses on a feeder road rehabilitation program in Sierra Leone that was financed by the European Union (EU) and implemented in four districts that cover 27% of the country's area and 30% of its population.[2] Sierra Leone's infrastructure is extremely poor: in 2002, at the end of a decade-long civil war, only 8% of the country's 11,300 km of roads were paved. Agriculture is the country's largest employer, with 64% of households farming, of which 87% produce rice, the main staple. The infrastructure network is generally described as inadequate to support well-integrated agricultural markets.[3]

The project targeted local dirt feeder roads - it rehabilitated existing roads but did not build any new roads. The roads rehabilitated measured 20 km on average, and linked local markets

[2] Sierra Leone National Census (2004).

[3] See the Agricultural Household Tracking Survey (AHTS) Report (2011) and Pushak and Foster (2011).

to villages or to a more important road. They did not connect major cities in different parts of the country together. To structure the use of its funds, the EU created a priority ranking for each of 47 eligible roads based on an index of quantitative economic data. The highest-ranked roads were chosen in order until at least (or as close to) a total of 150 km of roads had been assigned to each district. A total of 31 roads were ultimately selected to be renovated. This method of fund allocation allows us to use a road-level RDD to study the impacts of the feeder road improvements.

Our empirical results can be summarized as follows. First, the rehabilitation program did improve road quality on the selected roads. Using data on transport fares and GIS video stream data, we show that transport costs fell significantly. Second, from trader surveys and monthly price surveys, we find that an improvement in rural road quality leads to a reduction in the prices of rice and cassava (the two main staples produced domestically) in rural markets along the rehabilitated roads.[4] These price reductions are larger for cassava than rice, since households sell cassava more regularly, there is less seasonality in the sales of cassava and it is bulkier to transport. Third, we find that this price reduction is stronger in markets that are farther away from main urban centers and is weaker in markets that are located in more productive areas.

Which of the standard classes of models best explains these findings? We look across a set of simple models which assume the city is a small open economy, traders are homogeneous and their transport costs are linear. In these models, rural roads can potentially affect transport costs for both buyers traveling from urban areas (primarily traders) and sellers (farmers) since both travel to rural marketplaces. In our analysis, we refer to the impact of the rural road rehabilitation on urban traders as the "demand effect", and the effect on producers as the "supply effect", with the former driving up prices in rural markets, and the latter driving them down. The relative importance of these two effects varies across the theoretical frameworks we present. In particular, both the Bertrand framework and the Cournot model with endogenous entry predict that reduced transport costs should be associated unambiguously with *increases* in prices in rural markets (i.e. the demand effect always dominates). However, this is inconsistent with our empirical findings - we find that improvements in road quality that reduce transport costs on average *reduce* prices. On the other hand, the remaining frameworks (bilateral bargaining, Cournot with an exogenous number of traders, and the search frictions framework) predict a role for both demand and supply effects.

Second, the models have different predictions regarding the heterogeneity in the price effect of reduced rural transports costs along two dimensions: (i) the distance between the rural markets and major urban areas, and (ii) farmer productivity. Again, these differences arise because the models predict different roles for the demand and supply effects of the roads. Both

[4]Rural markets in our sample are medium-sized marketplaces in which several crops are traded (rice, cassava, palm oil in particular). In Section 3 we describe our sampling strategy for markets and traders within markets.

the bilateral bargaining model[5] and the Cournot oligopsony case with an exogenous number of traders predict that market characteristics have no impacts on these price effects, which is inconsistent with our results. On the other hand, a basic Mortensen search framework predicts that the interactions of the price effect with distance and productivity are non-zero because the magnitude of both the demand and the supply effect varies with these two market characteristics. Specifically, for the markets that are further away, or the markets in areas with lower productivity, the relevance of search costs in determining equilibrium prices is higher. In turn, this implies that the negative price effects of the improved roads should be stronger for these sets of markets. Overall, our empirical results are consistent only with a search framework and inconsistent with other models.

Third, we provide further evidence on search costs using data on cell phone penetration. In a search framework, we would expect strong complemetarities between investments in the transportation network and investments in commincations networks, such as cell phone networks. Indeed, we find that our price effects are muted in areas where there is better cell phone penetration, which is what one would expect in the presence of search costs. In particular, we expect that cell phone penetration lowers search frictions. Therefore, the prices responses in areas with higher cell phone penetration will be closer to the Bertrand case, i.e. less negative or even positive. We find evidence of this, consistent with the findings in Allen (2012), Aker (2010) and Jensen (2007).

These results have important policy-implications. First, the impact of improved road infrastructure varies by the characteristics of the road's location. Features such as productivity and linkages between urban consumers and traders can affect not just the magnitude of rural market price responses, but also their sign. This implies that the benefits of improvements in infrastructure are heterogeneous, which is important for policy makers when deciding where to make such improvements. As in Suri (2011), where the returns to agricultural technologies are heterogeneous and some of this heterogeneity arises from differences in access to the rural road infrastructure network, returns to different road projects will vary sharply with underlying farmer heterogeneity. Second, the finding that agricultural intermediary markets in this setting are best characterized by a framework that includes search frictions has implications for other policies designed to influence agents in the agricultural value chain. These policies include price subsidies, agricultural export promotion interventions, credit-provision policies targeting traders, and more major road projects. Third, the empirical evidence in support of the presence of search frictions suggests a possible complementarity between hard infrastructure projects and other interventions aimed at reducing search costs, such as the introduction of marketing

[5]The bilateral bargaining model represents the case where a given producer is locked into a relationship with one particular trader. It can also be interpreted as a model with search costs approaching infinity, so that producers have no outside option, outside of the existing relationship.

boards or the extension of mobile phone coverage in rural areas (mobile phone penetration rates are only 36% in Sierra Leone (World Development Indicators, 2012)).

This paper's findings are consistent with recent empirical evidence on search frictions (see, for example, Jensen (2007), Aker (2010) and Goyal (2010)). While these studies focus on the price impact of a reduction in information frictions, we show that the response to improved transport infrastructure also depends on the presence of search frictions. In addition, our work draws from three other strands of literature. First, a small but influential set of papers has used rigorous identification strategies to shed light on the impact of large transport infrastructure improvements (examples include Michaels (2008), Donaldson (2012), Datta (2012), Faber (2012) and Banerjee, Duflo and Qian (2012)). We look at rural roads and not highways - van de Walle (2009) provides a good review of the literature on rural roads.[6] Second, a recent growing literature uses micro-data to estimate the degree of price pass-through internationally and domestically.[7] Third, our theory focus is motivated by the recent emphasis on trade intermediation (for example, Bardhan, Mookherjee, and Tsumagari (2012), Antràs and Costinot (2011)). In particular, we rely heavily on Chau, Goto and Kanbur (2009) in our theoretical setup and in the way we model search frictions.

The rest of the paper is structured as follows. In Section 2, we outline the theoretical frameworks and derive comparative statics of interest. Section 3 describes some background on Sierra Leone, the EU road rehabilitation program and data sources. Section 4 outlines the empirical strategy and tests the validity of RDD for our setting. Section 5 presents results of the empirical analysis, including a comparison of our results with the theoretical predictions of different models of competition and results from a number of robustness checks. Section 6 concludes.

2 Theoretical Frameworks

In this section, we present four different theories of trade intermediation between agricultural producers and traders. Traders play a central role in the rural economies of Sub-Saharan African by channeling product between crop-producing areas in the countryside and the consumers living in urban areas (Fafchamps et al. (2004)). We focus on rural markets where traders purchase and sell different crops. Traders are mostly small scale, traveling from one market to another before transporting crops to the capital city. We describe these traders in detail below.

We focus on four broad classes of theoretical models, representing different market structures: Bertrand competition, bilateral Nash bargaining, Cournot oligopsony (both with and without endogenous entry) and search frictions à la Mortensen (2003). The Bertrand case and

[6]Examples include Jacoby and Minten (2008), Dorosh et al. (2010), Gibson and Rozelle (2003), Ali (2011), Khandker, Bakht and Koolwal (2009), Khandker and Koolwal (2011), and Mu and van de Walle (2007).

[7]See, for example, Broda and Weinstein (2008), Burstein and Jaimovich (2009), Gopinath et al. (2011), Borraz et al (2012) and Atkin and Donaldson (2012).

the search frictions case, as well as the theoretical setup, are based on Chau, Goto and Kanbur (2009). We adapt their framework in three directions to fit our research questions. First, we explicitly model the role of rural roads in linking producers and traders to rural market places. Second, we introduce a productivity parameter that varies across villages. Third, we model two additional cases: a specific case of bilateral bargaining between traders and producers and the case of Cournot competition (with and without endogenous entry).

The primary goal is to derive key comparative statics to be tested in our empirical framework. We focus specifically on the price effects of an improvement in rural road infrastructure, and on the heterogeneity in this effect across market characteristics.

2.1 Setup

We model the transactions that occur between traders and rural agricultural producers in rural markets to which both types of agents travel.[8] We make two important simplifying assumptions here. The first is that traders are homogeneous - this seems to be a reasonable interpretation of our data. For example, 97% of traders are male, 88% are from two main ethnic groups, 65% have no education, 86% are married, 96% report that they started trading on their own, 62% own a mobile phone, 96% own a radio and only 19 traders of local rice own their own mode of transport (motorbike, car or truck - unfortunately the survey did not distinguish between these). The second assumption we make is that utility is linear: both farmers and traders maximize their (expected) profits.

Around each market, there is an exogenous number of producers, N, who produce σ units of a certain crop. This implies we are modeling just the short term effects of the roads (our data is also short term). The opportunity cost of each unit (for instance the utility from consuming each unit) is c. In order to reach the local market, rural producers use rural roads to travel distance α. The unit transport cost on the rural road, τ, is therefore the inverse of a measure of road quality. When road quality improves, the unit transport cost on the road decreases.

City traders travel to the local market to purchase the crop which they can then sell in the urban areas at an exogenous price p^*. The exogeneity of the city price p^* is based on the intuition that the city receives the crop from many different markets across the country. Each market is thus a small open economy and changes in the transport costs between a given village and the surrounding urban areas are assumed not to affect the city price or prices in other rural markets. In order to reach the market, the traders bear two types of transport costs: first, a "major road" transport cost, x, and second, a rural road cost $\beta\tau$, where β is the distance traders travel on the rural road. The "net city price" is thus $p^* - x - \beta\tau$. Throughout, we assume this form of linear

[8] Throughout, we use the term producers to refer to either farmers or "aggregators", where aggregators refer to larger farmers who aggregate product from other farmers in a village to bring it to the market to sell. The theoretical models we present below all hold whether it is farmers themselves that come to the market or aggregators.

transport costs as well as a separation between the major road and the rural road transport costs for the trader. The linearity seems a natural assumption for the transport costs since the main form of transport for traders is renting motorbikes, which price a fare per distance travelled. The market for transport along these roads (major and rural) is reasonably competitive. Very few traders actually own a mode of transport - in our trader data only 19 traders owned any form of transport. There is therefore little scope for a (discrete) investment that simultaneously affects transport costs on both the main road and the rural road. In addition, the improvement in the rural roads due to the EU program causes a reduction in transport costs but not a big enough reduction to allow traders to invest in their own mode of transport.

We denote the (endogenous) sale price in the rural market by p. In addition to city traders, we assume that farmers can sell to local consumers (non-farming rural households) at cost-recovery price $p^0 = c + \alpha\tau$. Throughout the paper, we assume there are gains from trade, that is: $p^* - x - \beta\tau > c + \alpha\tau$. The assumption that there is an exogenous number of producers and that there are gains to trade implies that there is no extensive margin effect of changes in τ on traders or producers entering the market.

Below, we discuss equilibrium prices under four alternative market structures. For each of these, we are interested in three comparative statics:

1. The equilibrium price change in response to a change in rural road transport costs: $\frac{\partial p}{\partial \tau}$
2. Heterogeneity in this price response by the distance travelled on the major road, x: $\frac{\partial^2 p}{\partial \tau \partial x}$
3. Heterogeneity in this price response by market-level productivity, σ: $\frac{\partial^2 p}{\partial \tau \partial \sigma}$

2.2 Bertrand Oligopsony

Bertrand competition is characterized by free entry of city traders into each village and perfect information. This implies that all the producers are matched to city traders and that competition drives up the equilibrium price, p^B, to equalize the net city price:

$$p^B = p^* - x - \beta\tau \tag{1}$$

It is easy to see that producers appropriate all the gains from trade. Looking at the predictions of the Bertrand model with regards to the three comparative statics of interest, we obtain:

1. $\frac{\partial p^B}{\partial \tau} = -\beta < 0$: rural road transport costs enter the equilibrium price only via their effect on traders' transport costs.
2. $\frac{\partial^2 p^B}{\partial \tau \partial x} = 0$: as the trader cost function is separable between the rural road and the major road costs, the price response to rural road costs is unaffected by major road transport costs.

3. $\frac{\partial^2 p^B}{\partial\tau\partial\sigma}$ = 0: productivity, or any other supply characteristic, does not affect the equilibrium price, and hence does not affect the price response to a reduction in rural transport costs.

2.3 Bilateral Bargaining with Lock In

We now present a simple model of prices under a specific model of bilateral bargaining in which each producer can only trade with one specific trader, with an outside option limited to the cost-recovery price $c+\alpha\tau$. In this scenario, the transactions equilibrium price, p^N, is assumed to be the generalized Nash-Bargaining solution:

$$\begin{aligned} p^N &= \arg\max_p\{[\sigma(p^* - x - \beta\tau - p)]^\gamma * [\sigma(p - c - \alpha\tau)]^{1-\gamma}\} \\ &= \gamma(c + \alpha\tau) + (1-\gamma)(p^* - x - \beta\tau), \end{aligned} \tag{2}$$

where $\sigma(p^* - x - \beta\tau - p)$ is the trader's surplus, $\sigma(p - c - \alpha\tau)$ is the producer's surplus, and γ is the bargaining weight for the trader. The Bertrand outcome is a special case of the Nash Bargaining solution for $\gamma = 0$. In addition, the bilateral bargaining setup implies that, in the presence of a positive surplus from trade, all the producers are matched to traders. The model delivers the following predictions with regards to our three key comparative statics:

1. $\frac{\partial p^N}{\partial\tau} = \gamma\alpha - (1-\gamma)\beta \gtrless 0$: with positive α and β, rural road transport costs now enter prices through their effect both on producers' and on traders' costs. The former drives down prices (what we term the supply effect), while the latter raises prices (what we term the demand effect).
2. $\frac{\partial^2 p^N}{\partial\tau\partial x}$ = 0, as in the Bertrand case.
3. $\frac{\partial^2 p^N}{\partial\tau\partial\sigma}$ = 0: the amount transacted, σ, does not affect how the price responds to a change in τ, even though σ does enter the equilibrium price.

2.4 Cournot Oligopsony

The third framework we present is one of Cournot competition. Here, we introduce an additional assumption to generate an upward sloping supply curve. We assume that the parameter α (the distance travelled by the producer on the rural feeder road) is a random variable uniformly distributed over $[\alpha^* - z, \alpha^* + z]$. Producers sell in the market only if the equilibrium price p is larger than their reservation price: $p > c + \alpha\tau$. This extensive margin on selling generates an upward sloping supply curve as only a share $F(\frac{p-c}{\tau}) = \frac{(p-c)/\tau - (\alpha^* - z)}{2z}$ of producers enters the market, where $F(\cdot)$ is the cdf of the uniform distribution.[9]

[9] We also studied the case where farmers are heterogeneous in the opportunity cost, c, instead of being heterogeneous in the parameter α. Since all the comparative statics for this case collapse to the Bertrand case, we do not report it here.

We study two versions of the Cournot model. First, we look at the case with an exogenous number of traders operating in the market, M. Second, we endogenize the number of entrants using a free entry condition, where we assume entrants have a fixed cost of entry K.

We focus on symmetric equilibria. With an exogenous number of traders, each trader chooses his optimal quantity given other traders' quantities which enter the profit functions through the (inverse) supply curve. After imposing symmetry, the equilibrium price, p^C is

$$p^C = \frac{c + \tau(\alpha^* - z) + M(p^* - x - \beta\tau)}{1 + M} \tag{3}$$

The Cournot model with exogenous entry delivers the following results with regards to our comparative statics of interest:

1. $\frac{\partial p^C}{\partial \tau} = \frac{\alpha^* - z - M\beta}{1+M} \gtrless 0$: both the supply and the demand effect of a change in τ enter the derivative of price with respect to transport costs.

2. $\frac{\partial^2 p^C}{\partial \tau \partial x}$ = 0: while x shifts the net city price, it does not interact with τ in determining the equilibrium price.

3. $\frac{\partial^2 p^C}{\partial \tau \partial \sigma}$ = 0: σ does not enter the solution for the equilibrium price, p^C.

We now extend the basic Cournot model above to allow for endogenous trader entry. By equating individual profits with the cost of entry, we find the equilibrium number of traders operating in the economy and then derive the corresponding equilibrium price, p^{CE}:

$$p^{CE} = p^* - x - \beta\tau - \sqrt{\frac{2\tau K}{Nz\sigma}}, \tag{4}$$

The comparative statics of interest are now:

1. $\frac{\partial p^{CE}}{\partial \tau} = -\beta - \sqrt{\frac{K}{2\tau N z \sigma}} < 0$: τ affects p^{CE} through its impact on both demand and supply. The demand effect operates though β, as before. However, the reduction in aggregate supply generates a more than proportional reduction in the number of traders entering the economy. As a result, the price reduction in response to an increase in τ is stronger than in the benchmark Bertrand case. Intuitively, an increase in τ has two effects. First, it reduces the "net city price", $p^* - x - \beta\tau$. All else equal, this leads traders to reduce p. Second, it reduces the elasticity of supply, $Q = \frac{\sigma N(p-c)}{\tau}$. All else equal, this induces traders to *increase* the mark down, thereby contributing further to a decrease in price.

2. $\frac{\partial^2 p^{CE}}{\partial \tau \partial x} = 0$: terms that only enter the net city price do not interact with transport costs in determining the equilibrium price.

3. $\frac{\partial^2 p^{CE}}{\partial \tau \partial \sigma} = \frac{\sqrt{K}}{2\sigma\sqrt{2rNz\sigma}} > 0$: by increasing aggregate supply, σ reduces the role of fixed costs in determining the equilibrium price. An economy with a higher productivity will be closer to the perfectly competitive case relative to one with a lower σ. Thus, an increase in σ implies a smaller in absolute value (i.e. closer to $-\beta$) price response to an increase in τ since the impact of τ on the elasticity of supply is lower.

Summarizing these results, the Cournot model with exogenous entry cannot be distinguished from the bilateral bargaining model based solely on the sign of the comparative statics. On the other hand, the version with endogenous entry delivers a unique set of predictions relative to the previous models.

2.5 Search Frictions

We now introduce search frictions in the model economy. Empirically, we think search costs may arise from two potential mechanisms. A first mechanism for search costs is that these markets are difficult to reach. Farmers and traders often travel on motorbikes to these markets and although transport is available, the timing is uncertain. This generates some search frictions as farmers and traders may not end up in a given rural market at the same time. There may therefore be waiting costs and uncertainty about what will be available in the market by the time the trader arrives. This is the type of search cost considered in Fafchamps and Hill (2008).

Second, farmers develop relationships with traders over time. There is a lot of evidence for such contracts both in Sierra Leone (see Casaburi and Reed (2012) for an example) as well as in other developing countries (see Deb and Suri (2012)). These relationships operate as search frictions in the sense that there are switching costs for farmers to shift across traders and this can generate market power for the traders. This is one explanation given by Fafchamps and Minten (2011) as to why a price information intervention did not have impacts on prices in India. These relational contracts may exist to enforce quality standards (see Bardhan, Mookherjee and Tsumagari (2012)) or due to the existence of trade credit as in the case of Casaburi and Reed (2012). The existence of such relationships between farmers and traders would generate search frictions of the sort we model here.

To construct our model, we closely follow Chau, Goto, and Kanbur (2009) and we refer readers to their paper for detailed derivations of the results. Their paper is in turn based on the static search framework derived by Mortensen (2003), which provides the key results. We choose a static framework to facilitate the introduction of search frictions in the setup above.

The interactions between traders and producers now occur in three stages. In the first stage, traders decide whether to enter a certain market. If they enter, they incur an entry cost, K, which includes bargaining time, travel fixed costs, waiting time and uncertainty. In the second stage, traders who entered the market choose a price offer. Due to the search frictions, only one random producer receives the offer. In the third stage, producers take up the best offer among those received. For a large enough market, the distribution of offers received by each producer follows a Poisson with mean $\lambda \equiv M/N$, where M is the endogenous number of traders entering the market:

$$Pr(z;\lambda) = e^{-\lambda}\frac{\lambda^z}{z!} \tag{5}$$

Thus, the cumulative distribution of the highest price offer received by each producer, or equivalently, from the trader's perspective, the probability of outbidding the second-best offer is:

$$H(p) = \sum_{z=0}^{\infty} Pr(z;\lambda)F(p)^z = \exp(1 - F(p)) \tag{6}$$

where $F(p)$ is the endogenous cdf of price offers made by the traders.

The trader's expected profit maximization implies that no symmetric pure strategy equilibrium exists. Rather, traders follow a mixed strategy where prices are in the support $[p_l, p_h]$, given by:

$$[c + \alpha\tau, (1 - e^{-\lambda})(p^* - x - \beta\tau) + e^{-\lambda}(c + \alpha\tau)] \tag{7}$$

and are drawn according to distribution:

$$F(p) = \frac{1}{\lambda}\ln\left(\frac{p^* - x - \beta\tau - c - \alpha\tau}{p^* - x - \beta\tau - p}\right) \tag{8}$$

Each price in the support leads to an equal expected profit. The free entry condition can therefore be written as $E[\pi(p_l)] = K$, which allows us to solve for the equilibrium ratio of traders to producers, λ:

$$\lambda^* = \ln\left(\frac{p^* - x - \beta\tau - c - \alpha\tau}{K/\sigma}\right) \tag{9}$$

We substitute λ^* into the optimal trader's price offer distribution, $F(p)$, in (8) and solve for both the expected price for farmers conditional on receiving at least one offer from traders and for the unconditional expected price, p^S. The latter can be written as:

$$p^S = p^* - x - \beta\tau - \frac{K}{\sigma}\left[1 + \ln(p^* - x - \beta\tau - c - \alpha\tau) - \ln\left(\frac{K}{\sigma}\right)\right] \tag{10}$$

We focus on the comparative statics from this expected unconditional price equilibrium. The model delivers the following predictions with respect to our three comparative statics:

1. $\frac{\partial p^S}{\partial \tau} = -\beta\left(1 - \frac{(K/\sigma)}{p^* - x - \beta r - c - \alpha\tau}\right) + \frac{(K/\sigma)\alpha}{p^* - x - \beta\tau - c - \alpha\tau} \gtrless 0$, where the first term represents the demand effect, and the second the supply effect, of a change in transport costs. The magnitude of the demand effect is lower in absolute value than the demand effect in the Bertrand

case: traders' market power induced by search frictions implies an imperfect pass-through of traders' cost shocks.

2. $\frac{\partial^2 p^S}{\partial\tau\partial x} = \frac{K(\alpha+\beta)}{\sigma(p^*-x-\beta\tau-c-\alpha\tau)^2} > 0$: in locations that are farther away for the city, a lower net price induces lower entry, more monopsony power and stronger deviations from the Bertrand benchmark. Thus, if x is higher, the (negative) price effect of a higher transport cost for traders is weaker and the (positive) price effect of a higher transport cost for producers is stronger.

3. $\frac{\partial^2 p^S}{\partial\tau\partial\sigma} = -\frac{K(\alpha+\beta)}{\sigma^2(p^*-x-\beta\tau-c-\alpha\tau)} < 0$: intuitively, an increase in σ lowers the "real" entry cost K/σ, bringing the economy closer to the benchmark competitive Bertrand case. A higher σ therefore moves the equilibrium both toward a stronger (negative) demand effect and toward a weaker (positive) supply effect of an increase in τ.

2.6 Summary of Theoretical Results

Table 1 summarizes the results from the models presented in this section. With regard to our comparative statics of interest, the models can be differentiated easily in two ways. First, some models predict that a decrease in τ will unambiguously lead to higher equilibrium prices, while others predict an ambiguous effect. This is due to the fact that a change in τ can induce either a demand effect alone, or both a demand and a supply effect. Second, the Cournot model with exogenous entry and the search friction frameworks are the only models predicting that the magnitude of the price response will depend on the market-specific features, x and σ. In section 5, we compare these predictions to our empirical results. In addition, we will test whether these price effects vary by cell phone penetration, something we may expect in a world with search frictions.

3 Background and Data Sources

3.1 The EU Rural Feeder Roads Rehabilitation program

3.1.1 Background and Implementation

The EU feeder roads rehabilitation program was designed to contribute to the reconstruction of Sierra Leone's infrastructure in the aftermath of a destructive civil war (1991-2002). The EU's program was implemented between 2009 to 2011 at a total cost of EUR 9.5 million (USD 13 million) - approximately EUR 16,000 per kilometer of rehabilitated road. The program targeted four districts in three different provinces: Kambia and Port Loko (Northern Province), Kenema (Eastern Province) and Pujehun (Southern Province). The roads in the rehabilitation program primarily connected small towns and markets to one another or to a major road, rather than linking big cities and regions to one another. Because these feeder roads do not dramatically alter access to population centers, they are unlikely to modify migration patterns in the areas surrounding the rehabilitated roads. The roads are also unlikely to affect agricultural technology adoption because improved technologies such as fertilizer and improved seeds are rarely available even in urban centers, as reflected in extremely low baseline rates of technology adoption.[10] Rehabilitation work began in mid-2009 and ended by early 2011 for all the roads. In the final construction progress report, dated August 2011, 25 of the 31 roads selected for rehabilitation were described as fully rehabilitated and 6 roads as partially rehabilitated.[11]

3.1.2 Program Design

The rehabilitation program was designed in a way that allows for a road-level Regression Discontinuity Design (RDD) analysis. In 2003, field investigations with local stakeholders led to the identification of a base list of 47 rural roads eligible for rehabilitation, totaling about 800 km. The task of prioritizing 600 kilometers of roads for rehabilitation from amongst this larger sample was given to an external consultant, Edward Davies & Associates (EDA). EDA (2004) provides extensive details of the prioritization process that was used to decide which of these roads would be rehabilitated. The roads were ranked according to a score, which was a weighted average of five components:

i) **Economic Production per kilometer**, defined on the basis of survey measures of the volume of crops produced, income from economic activities and mode of transportation;

ii) **Population per kilometer** within the area of influence of each road;

iii) **Road Assessment**, a 1 to 5 score measuring the pre-existing condition of the selected roads, based on seven parameters (culverts, bridges, drainage, pavement surface, vertical alignment, horizontal alignment, and riding quality);

iv) **Social Value**, a 1 to 5 score, based on the number of schools, health centers, wells and toilets in the catchment area of the road;

v) **Length**.

[10] Roughly 5% of farmers use fertilizer nationally (AHTS (2011)) and much of this use is centered around the capital Freetown and the national agricultural research station. In separate work, Suri (2011) found that deficient infrastructure and differential access to good infrastructure were among the reasons explaining low technology adoption rates in Kenya. In our context, the small size of the roads considered makes it reasonable to assume that the supply of agricultural technology from the main urban centers to the countryside did not dramatically increase as a result of the program.

[11] The average completion rate for the six roads partially rehabilitated was 64%. This percentage does not reflect the fraction of the total length of the road that had been rehabilitated. Instead, it illustrates what fraction of the planned improvements were completed on the road i.e. the average completion across all specifications of the work - in many cases, improvements were implemented along the entire length of the road, but not all the planned improvements were fully completed.

The data on these components was compiled by EDA. Each component of the score was normalized by its district-level maximum value. The final weighted sum of each of the five components had weights of 0.4, 0.2, 0.2, 0.1 and 0.1 for components (i) to (v) above, respectively.[12] The decision rule was that, in each district, roads would be rehabilitated starting with the highest-priority one (based on the score), following in order of decreasing score until as close to 150 km of road as possible was allocated to be rehabilitated in each district. Since the roads could not be split to get exactly 150 km, this means that in some districts slightly over 150 km of road was rehabilitated, and in some districts just under 150 km was rehabilitated. Following this rule, 30 roads out of the eligible 47 should have been selected across the four districts. Figure 1 presents maps of the priority roads in the initial list across the four districts, as well as the connections between these roads and the major roads in the country.

After collecting data from the EU, EDA, and the Sierra Leone Roads Authority (SLRA) to verify that the RDD had been followed, we found evidence of two potential manipulations that occurred around the cutoff. In the district of Kenema, the final list of roads rehabilitated covered 184 km, while selecting one less road would have brought the total rehabilitated in this district to 153 km, closer to the approximate desired cutoff of 150 km. One additional road was therefore rehabilitated although it was not supposed to be. We treat this as a fuzzy RDD where the additional treated road is allocated to the control group. In Kambia District, two roads had the same score and were ranked exactly at the cutoff point. Only one of the two roads was rehabilitated to reach the appropriate total, but no rules were established for how roads should be selected in the case of a tie. In this case, we drop the two roads from our baseline specifications, though we check the robustness of our results to their inclusion. We discuss the implications of these issues for our identification strategy in more detail in Section 4 below.

3.2 Data

This section provides an overview of the data used in our empirical framework, ordered chronologically by collection date.

3.2.1 Baseline Roads Data (2003-2004)

To construct the scoring index, EDA collected data around all 47 eligible roads before any rehabilitation began. We use this data to check for baseline differences between the roads above and below the cutoff in our RDD framework. We include all five components of the score, as well as a number of road characteristics, such as the number of bridges, palmlog bridges[13] and

[12] Appendix 1 provides the exact formula used to compute the score.

[13] A palmlog bridge is a makeshift bridge made from logs of palm trees. Regular cars are usually unable to cross such bridges, but four-wheel drive vehicles and motorbikes often can, although at times with considerable risk. During the rainy season, palmlog bridges get flooded, making the wood rot and sometimes causing the entire bridge

culverts,[14] data for which was provided by the EU. Table 2 shows summary statistics on the baseline condition of the roads considered for rehabilitation. The average length of the roads was 21 km. In this table we also report the average rescaled score, which is the value of the index created by the EU, rescaled so that zero is the selection cutoff score between the first road below and the first road above in each district.

3.2.2 National Population Census (2004)

To test our RDD assumptions, we use data from the last population census conducted in Sierra Leone, which was completed in 2004. From the census data, our variables of interest are the fraction of households involved in crop farming, the fraction of individuals over ten years old involved in crop farming, the literacy rate and the years of education completed by household heads.

3.2.3 Agricultural Households Tracking Survey (2010)

To identify areas of high productivity or high surplus for different crops, we use measures of agricultural production at the road level, computed from the Agricultural Households Tracking Survey (AHTS). The AHTS was a nationally representative agricultural survey conducted in March-April 2010 with a sample of 8,803 farming households. Since the AHTS was potentially administered concurrently with the implementation of the EU program, we do not use it as baseline data. Instead we only use the household-level data to compute measures of local production around the markets for rice and cassava. We also use measures of the fractions of households selling rice and cassava as well as household cell phone ownership. We compute chiefdom-level averages, as discussed in more detail below.

3.2.4 Endline Roads Data (2011)

We designed novel GIS data collection strategies to verify whether the roads had indeed been rehabilitated, and to collect objective measures of transport costs. First, we drove a sport utility vehicle with a geo-referenced camera secured to the hood along each road. This exercise was completed for 46 out of the 47 eligible roads in November 2011.[15] The camera recorded the GPS position and speed of the vehicle every second, as well as collected a continuous stream

to collapse.

[14] A culvert is a pipe or a drain that lets water flow below a road. Culverts are much smaller than bridges and are often used to create crossings over small waterways or as a way to improve drainage in locations where rainy seasons are extremely intense (as they are in Sierra Leone).

[15] One road was missed as part of this exercise because it could not be located. The road is 2.6 km long and was not selected for rehabilitation. Example videos are posted at `http://www.mit.edu/~tavneet/research.html`.

of video along all roads. In the analysis presented below, we use average speed on the roads traveled as one of our outcomes of interest.

In another effort to gather evidence of the impact of the roads on transport, we collected data on transport fares along all 47 roads. We negotiated with motorbike taxi riders (locally known as *okadas*) for a route fare on every road,[16] and travelled with the *okada* on a random subset of these roads. *Okadas* are the most commonly available type of public transportation in rural Sierra Leone, for both people and goods, and unlike buses they can travel on most roads all year round. These data give us a measure of actual transport costs and freight rates on the sample of roads in the study.

We show summary statistics on these transport variables in Table 2. The average speed on the roads was about 21 km per hour and the motorbike fare was an average of 16,000 Leones per road ($3.72). Since the roads are of different lengths we report the fare per km travelled, which is about 900 Leones ($0.21) per km.

3.2.5 Trader Surveys (2011-2012)

To understand the effects of these road improvements on prices, we use data from two waves of a nationwide survey targeting rice traders in rural markets. The first wave, conducted in February/March 2011, targeted all the markets located within five kilometers of the 35 roads that were closest to the rehabilitation threshold in each of the four districts. In addition, random sampling of the remaining markets located in the rest of the country led to a sample of 54 markets located within 11 kilometers of the 47 roads. The second wave, conducted in January/February 2012, included the universe of markets (82) located within 11 kilometers of any of the 47 roads, including the 54 markets sampled for the first wave.[17] Within each market, we first listed all traders of local rice, then randomly sampled two traders to participate in the survey (or surveyed the unique trader when only one trader was present).

Table 2 shows summary statistics from these trader surveys. Sale prices from traders' most recent sales transactions are presented for local rice, but not for cassava, which was not covered by this particular survey. We report prices in cups, as this is the standard unit across all our price data.[18] The trader surveys were conducted during the harvest season (February/March), a period when local rice is plentiful and the price of local rice is lower than its annual average.

The GPS coordinates of the markets are used to compute as-the-crow-flies distances between

[16] This exercise was designed so that the surveyor bargaining with the taxi was the residual claimant.

[17] The threshold of 11km was defined before the second wave of the survey to maximize the number of markets surveyed under tight survey budget constraints. Within our sampling frame of markets, 54 were located within 5 kilometers of the nearest road, 78 were located within 10 kilometers, and 86 within 11 kilometers. Out of the 86 markets visited, 4 had no rice trader at the time of the survey, leading to the final number of 82 markets.

[18] There are roughly four cups of local rice per kilogram. Two varieties of local rice are sold by traders - parboiled and milled. These varieties are nearly identical to each other. We averaged these prices to obtain one local rice price.

rural markets and larger towns or urban centers in Sierra Leone. We define a large town to be either one of the six largest towns in the country based on the 2004 census (these towns were Freetown, Bo, Kenema, Makeni, Koidu, Waterloo and Lunsar, with a median population across these towns of 81,000 individuals) or any district headquarter town across all the 13 districts in the country. This gives us a total of 14 unique large towns, however, when looking at the closest large town for all our markets, we only cover a subset of nine of those towns.

3.2.6 High Frequency Price Surveys (2011-2012)

Finally, between May 2011 and July 2012, we targeted the markets included in the trader survey sample to collect monthly price data via phone surveys. We think of the prices collected as the average price in the market for that month. The respondents were individuals identified as focal points for the markets during the data collection of the trader surveys. The number of markets for which we sought monthly pricing data increased after the tenth wave of calls to include the 28 additional markets targeted by the second wave of the trader survey. We focus on two main crops in our analysis of the high frequency data: local rice and a common type of processed cassava known locally as *gari*.[19] Table 2 shows summary statistics on the prices of these two crops, again reported in cups. The price of a cup of gari is about 340 Leones ($0.08) and that of a cup of rice about 1,000 Leones ($0.23).

Note that for both the trader surveys and the high frequency price surveys we do not have variance in price within markets. Although the search model certainly has implications for the higher moments of the price distribution, we cannot look at this since we have at most two observations within a market and often only one. The high frequency price surveys are a single price per market. For the trader surveys often only one or at most two local rice traders were surveyed in the market.

4 Empirical Strategy

4.1 Regression Discontinuity Design

The design of the EU program allows us to use an RDD[20] to identify the causal effect of rural road rehabilitation on transport costs and rural market prices.[21] We have a small number of

[19] Gari is a form of processed cassava similar in aspect to kuskus or bulghur, common throughout most of West Africa. Gari is obtained from peeling and grating cassava tubers often using manual equipment.

[20] We refer the reader to Imbens and Lemieux (2007) and Lee and Lemieux (2010) for extensive reviews of the RDD.

[21] Our main outcomes of interest are measured either at the road level (transport costs) or at the market level (market prices). In addition, since we do not have baseline (pre-intervention) data for market prices, we use instead road level data collected from household surveys in Enumeration Area (EAs) around the project roads during the 2004 Census. We also use Chiefdom level data collected from an agricultural household survey for the heterogeneous treatment effects analysis. For the sake of clarity, in this section we only refer to our outcomes as being road-level

clusters for the RDD, though a large number of observations, especially when using the high frequency price survey data. This RDD therefore resembles the geographic or boundary RDD studies (for example, see Dell (2010)). Later, we also conduct a number of robustness checks to deal with the limitations on the number of clusters.

In what follows, we describe the identification problem using the standard Rubin (1974) potential outcomes framework. Define $y_i(1)$ as the potential outcome for road i when the matched road is rehabilitated by the EU program and $y_i(0)$ when it is not rehabilitated. Then the (sub) population parameter of interest is $\Delta = E[y_i(1) - y_i(0)]$, the average treatment effect (ATE). The basic identification problem arises because the econometrician only observes the realized outcome based on the actual rehabilitation status T_i of the road:

$$y_i = T_i \cdot y_i(1) + (1 - T_i) \cdot y_i(0) \tag{11}$$

An OLS framework would lead to an inconsistent estimate of Δ in the presence of unobservable covariates that are correlated both with the outcome and with the rehabilitation status. With multiple rounds of data, a difference-in-difference estimator would be biased if changes in the rehabilitation status are correlated with changes in other unobservable variables.[22]

Our RDD relies on the comparison between roads "just above" and roads "just below" the rehabilitation cutoff. In the case of perfect correspondence between the rehabilitation plan and the actual rehabilitation status, this empirical strategy would identify the average treatment effect (ATE) around the cutoff. This ATE is local in the sense that results around the treatment effect at the cutoff cannot be generalized to other points in the domain of the forcing variable. In the context of this study, we argue that our empirical design identifies the marginal effect of a program expansion, which is a policy relevant local average treatment effect.

We define S_i^N as the road score, normalized to zero at the mid-point between the first road below the cutoff and the first road above the cutoff.[23] Our empirical analysis starts with a graphical approach. For each of the variables of interest, we plot the bin level means of the outcome and include a linear fit of all the underlying data. We restrict the graphs to be within our chosen main specification bandwidth (see below) so that the graphs are easily comparable to the parametric results. For the parametric estimation, we restrict our attention to roads that are "close" to the cutoff, i.e. the sample of roads whose score is within h points from the cutoff ($S^N \in [-h, h]$). We use one main bandwidth as our preferred specification, $h = 0.15$, which delivers a subsample of 31 roads. This bandwidth of $h = 0.15$ is close to the Imbens and Kalya-

or market-level. However, the reader should bear in mind that some of the variables used for baseline checks were actually collected at the household level and appropriately aggregated.

[22]Studies using a differences-in-differences approach include Ali (2011), Bakht, Khandker and Koolwal (2009), Khandker and Koolwal (2011), Bell and van Dillen (2012), and Mu and Van de Walle (2007)).

[23]Our results are similar if we normalize the cutoff to be at the first treated road in each district. These results are available upon request.

naraman (2009) optimal bandwidth across a range of our outcomes at the road-level. As Lee and Lemieux (2010) mention, optimal bandwidth algorithms may suggest bandwidths that are larger than the rule of thumbs used by many researchers. Since we have a small sample size, we choose the optimal IK bandwidth as our main specification. We also report results in our main tables for two additional bandwidths, ($h = 0.075$ and $h = 0.3$) which span half and double the preferred bandwidth, and deliver subsamples of 18 and 38 roads, respectively. For our transport cost variables, where our outcomes are at the road level, we do not report results for the $h = 0.075$ bandiwdth as these specifications only have 18 observations and are therefore not particularly meaningful.

For the preferred bandwidth and the two alternatives, we run a local-linear regression of the form:

$$y_{ik} = \gamma_0 + \gamma T_i + \gamma_R T_i * S_i^N + \gamma_L (1 - T_i) * S_i^N + \delta_k + \epsilon_{ik} \tag{12}$$

where y_{ik} is a road-level outcome, i denotes the road and k the district. We control for district fixed effects in the road level specifications and present heteroskedasticity robust standard errors.

For market-level outcomes (prices), the regression model is:

$$y_{ijkt} = \gamma_0 + \gamma T_i + \gamma_R T_i * S_i^N + \gamma_L (1 - T_i) * S_i^N + \delta_k + \mu_t + \epsilon_{ijkt} \tag{13}$$

where i denotes the road that the market is close to, j is the market, k is the district (we control for both the district in which the road is located as well as for the district the market is in, if different) and t is the survey round. For the trader survey, our regressions are at the trader level and we have multiple traders per market.

In addition to the local-linear regressions, we use the full sample of 47 roads and include polynomial approximations in S_i^N. We use third order polynomials, though we also show robustness to this.

When running the market-level regressions, we adjust our standard errors for two way clustering, allowing for clustering at the road level as well as at the market level. This is important since some markets match to multiple roads. There are 82 unique markets in our surveys. On average, we have about 6 markets matching to each road. Approximately 48% of markets match to just one road. The others match to two or more roads, with the average being about 2.8 roads per market. We also weight the regressions by the inverse of the distance between the road and the market in question.

We look not only at the treatment effects of the improved roads but also the heterogeneity in these effects along four specific dimensions: distance between the market and the closest town, harvest of the relevant crop (rice or cassava), the fraction of households selling the relevant crop and cell phone penetration. For the heterogeneity analysis we use a dummy variable for whether the market is above the median value for the relevant variable. We therefore report results from these specifications as well as specifications where we control for these heterogeneity variables.

4.2 Testing the Validity of the Identification Strategy

The above RDD relies on the assumption that there is no manipulation of the theoretical rehabilitation status around the threshold. One potential challenge to identification therefore comes from the following two compliance issues briefly discussed in Section 3.1.2:

1. In Kenema district, there is a discrepancy between the rehabilitation plan and the actual status - an additional road was treated. This implies that the average treatment effect of the actual rehabilitation status cannot be estimated. Instead, we present the (local) Intent-To-Treat (ITT) estimator.[24]

2. In Kambia district, the same score was assigned to two roads, but only one road was rehabilitated without a clear rule for the event of a tie break. To complicate matters, across the whole sample, these are the two roads closest to the cutoff on either side, giving them the highest weight in a classic RDD. Since we lack a clear ranking protocol for this specific case, we present results after dropping these two roads from the sample.[25]

In addition, we adopt two standard strategies to test for the presence of manipulation. First, we test for discontinuity in the density of the forcing variable (McCrary (2008)). Second, we inspect whether baseline covariates show discontinuities around the score cuttoff. Figure 2 presents the results of the McCrary test.[26] The observed discontinuity is well within the confidence interval. In addition, if anything, the jump is downward while any manipulation would predict a jump upward. Finally, given the low number of observations at the extreme values or tails, the density is not well estimated at these tails. Our density test is, therefore, likely to have low power.

The analysis of covariate balance at the cutoff relies on three data sources. For a subset of variables (the most relevant ones), we also show graphical results. Table 3a focuses on variables collected by the EU as part of their baseline assessment of the roads and directly entering the scoring index. We look at just the population per km graphically - see Figure 3a. Both the figure and Table 3a show no significant discontinuity at the cutoff (only one coefficient of the twenty is

[24] LATE results are available on request.

[25] This is akin to the recent donut RDD (see, for example, Barreca et al. (2011)). In one of the robustness checks later in Section 5.2.4, we include these roads and show our results are robust to this.

[26] For our test we use a binsize of 0.025 and a bandwidth of 0.15. Our estimate of discontinuity at the cutoff is -0.325 with a standard error of 0.684.

significant). Table 3b presents other baseline characteristics of the roads, including variables collected by EDA during the prioritization process that do not enter the score, and the agricultural and education variables collected during the 2004 Census. Unfortunately, the census has limited agricultural information but we present results for the available variables - the fraction of households involved in agriculture, the fraction of individuals involved in agriculture, literacy and education of the household head. We keep EAs within 2 km of the roads and we aggregate the data to the road level for these tests. We also graphically show results for the fraction of individuals in farming and the education of the household head in Figures 3b and 3c. Neither the figures nor the regressions show evidence of discontinuities at the cutoff - in Table 3b, none of the 28 coefficients are significant.

In Table 3c, we focus on the variables used for the heterogeneity analysis. This includes four variables collected during the AHTS in early 2010 as proxies of σ, the distance from the market to the closest urban town (as a proxy for x in the heterogeneity analysis) and a measure of cell phone penetration, also from the AHTS. As proxies of σ, we use the average rice and cassava harvests per household and the fractions of households selling rice and cassava.[27] Although these variables were not collected at baseline in the strict sense, the harvest variables can be considered predetermined as the relevant farmer decisions (such as acreage planted and input use) were made the previous year, prior to any road rehabilitation. Because harvest data may be noisy, we also look at the extensive margin sale choice as a proxy for σ. Since the majority of the population relies on subsistence farming for the staple crops, the share of producers who enter the market economy is a reasonable measure of the average surplus of rice. As a measure of cell phone penetration, we use the fraction of households that own a cell phone. We use chiefdom-level averages of the agricultural and cell phone variables for the chiefdom in which a given market is located. Chiefdom-level data are less subject to endogeneity concerns since the roads typically considered affect a small fraction of the population of each chiefdom.[28]

Table 3c reports the results. In general, we do not find much evidence of discontinuities in these variables. For three of the six variables, one specification shows an effect that is both economically and statistically significant (for example, in the tight bandwidth linear specification, the fraction of households selling cassava is more than 50% lower in the treatment group than in the control group). The polynomial specification is responsible for two of the three problematic coefficients. Due to the small sample size in these cells, we think that the polynomial is not a good approximation to the data as it overfits leading to an overestimate of the magnitude of the coefficients. Graphically, Figure 3d shows results for the fraction of households selling rice with little evidence of a discontinuity.

[27]For this table, we use the continuous version of these variables. In the heterogeneity analysis, we use dummies for whether the value of the variable is above or below the median, as described later in the paper.

[28]Chiefdoms are the third-level administrative unit in Sierra Leone, coming after provinces and districts. There are 149 chiefdoms throughout the country.

5 Results

We now discuss our empirical results. We first present estimates of the effects of the road improvements on transport costs and speed, and then for the comparative statics for rural market prices that we derived in Section 2. The comparative statics presented in the theory section focus on a change in crop prices with respect to a change in τ, the rural transport costs. The empirical results are for an *improvement* in road quality that *reduces* rural transport costs.

5.1 Speed and Transport Costs

Figures 4a and 4b present a graphical analysis of the impact of the program on our two primary measures of transport costs: travel speed and (log) travel fares per km. As mentioned above, for the graphs, we show the data within the main bandwidth, $h = 0.15$ - we show bin level means for the data and a linear fit of all the data. Table 4 shows the results from the parametric regressions on these variables according to the specifications outlined in Section 4. However, the results from the $h = 0.075$ bandwidth for these road level outcomes are not meaningful as the sample size is too small and given the number of controls for the RDD specification, we are left with too few degrees of freedom. Looking at the impact of road quality improvements on speed, the bin means show a jump at the discontinuity (see Figure 4a), but the flexible polynomial specification is driven up at the left of the discontinuity. The parametric analysis in Table 4 confirms this intuition: the wide ($h = 0.3$) bandwidth local linear specifications point at an increase in speed across the cutoff. The results are also robust to the inclusion of controls we later use for the heterogeneity analysis. The polynomial is less robust, but is likely to be overfitting the data. The discontinuity in transport fares is visible (though noisy) in Figure 4b and in Table 4: an improvement in road quality has a significantly negative impact on fares. In the local linear regression with the optimal bandwidth ($h = 0.15$), the road improvements lead to a 59% reduction in transport costs per km.

5.2 Rural Market Prices

5.2.1 Basic Price Effects

We now look at the effect of the road improvements on crop prices. First, we relate our empirical approach to the theoretical framework above. The impact of rural road rehabilitation corresponds to the first comparative static of interest we presented in Section 2, $\frac{\partial p^S}{\partial \tau}$, in Table 1. Since the theoretical models derive predictions with respect to transport costs (not road quality), a negative $\frac{\partial p^S}{\partial \tau}$ implies that improvements in road quality have a positive effect on prices, and vice versa. If our empirical results are consistent with any given model, the sign of our regression coefficients should be the *opposite* of the theoretical predictions.

Our price results focus on the two main staple crops produced domestically, rice and cassava. In our data, rice and cassava are available 85% and 96% of the time, respectively, and both crops are sold in all markets at some point during the year. Before looking at prices, we first analyze the effects of the road improvement program on the extensive margin of crop availability in markets. The RDD treatment effect on availability of local rice is -0.10 with a standard error of 0.07. For cassava, the effect is -0.04 with a standard error of 0.06 (detailed results available upon request). We interpret this as evidence that market availability on the extensive margin was not different across treatment and control roads, although we do not have data on quantities traded that would allow us to further test this.

Figure 5 and Table 5 (columns (1) and (2)) show that road rehabilitation leads to a substantial reduction in the price of rice in the trader data. The graphical analysis shows a discontinuity in the price of rice at the cutoff. The price decrease is significant across all specifications (columns (1) and (2) of Table 5). In the rice price data from the high frequency surveys, evidence for a treatment effect in the form of a price reduction is much weaker (see Figure 6 and Table 5, columns (3)-(4)). While still negative in the tight bandwidth, the point estimates in these regressions are much smaller and mostly not significant. The results for rice from the high frequency data are different to those in the trader survey. One reason for this may be the difference in timing of the two surveys. The trader survey is conducted just after harvest, while the high frequency surveys are collected every month. We do not have enough sample size to look at just the harvest period in the high frequency data as we only have one year (hence one harvest season) of data. For cassava there is no specific harvest season. Cassava can remain in the ground for multiple seasons, can be harvested any time and is usually only harvested for immediate consumption or sale (it has to be processed immediately it is harvested).

Figure 7 and Table 5 (columns (5) and (6)) show price effects for cassava, based on the monthly price surveys only as the trader surveys did not cover cassava. Table 5 shows a large price drop in cassava. In the optimal bandwidth specification (top panel in column (5)), the road rehabilitation significantly reduces prices of cassava by 17.8%. This result is robust to different bandwidths, a polynomial specification, and to the inclusion of controls. The effect on cassava prices is larger than the effect on rice prices. We expect this to be the case as cassava is usually processed at the market site rather than on the farm,[29] and raw cassava is more expensive to transport than unprocessed (husk or threshed) rice.[30] Hence, cassava prices should be more responsive to changes in road infrastructure.

[29] In the AHTS (2011), only 2% of households and 8% of villages reported being equipped with at least one cassava grater; 0.05% of households and 8% of villages were equipped with a mechanized rice mill.

[30] We do not have accurate data on the transport cost of unprocessed cassava. However, raw cassava tubers are more voluminous, and hence more expensive, holding volume constant to transport than most other crops. In addition the processing rate to transform raw cassava into *gari* is low: 1 unit of unprocessed cassava yields 0.36 units of *gari* based on the AHTS (2011) data, while the typical milling rate for rice is 0.5. In other words, producers must transport larger volumes of raw cassava than rice to the marketplace to sell the same volume of the processed crop.

In summary, Table 5 provides evidence of price reductions for both rice and cassava in response to the road improvements. We interpret this as evidence that the improvements in infrastructure have primarily facilitated access to rural markets for producers, as opposed to reducing transport costs on rural roads for traders. More formally, using the notation from our theoretical setup, these results imply that, in our sample, $\alpha > \beta$, which is consistent with the qualitative evidence that, on average, city traders' transport costs are primarily determined by the quality of the major roads, as opposed to rural roads. In our earlier terminology, the supply effect prevails over the demand effect. This importance of the supply effect (versus the demand effect) is inconsistent with a basic model of Bertrand competition. In the Bertrand framework, a change in transport costs affects the equilibrium price only through β, the costs for the trader. Similarly, the Cournot case with endogenous entry predicts that a reduction in transport costs would unambiguously increase prices. These predictions are not borne out in the empirics.

We also conduct a back of the envelope exercise to have a sense of the effects of the road improvements on farmer net revenues (i.e., revenues net of transport costs). Using our results on the decreases in transport fares, we can compute the total savings to farmers on transport. The savings amount to about $2 assuming that a farmer travels half the length of the average improved road. Given the price reduction for cassava that we find and using the data from the ATS on cassava harvests and sales, we can compute the revenue change for farmers. We find that farmers experience approximately a 7% change in their net revenue (revenue from cassava minus the transport costs). This calculation assumes about five trips to the market per year for a farmer. If the number of trips is instead seven, the change in net revenue for the farmer is 39%.

5.2.2 Heterogenous Price Effects

We now focus on the heterogeneity in these price responses to the road improvements. The sign of the heterogeneity in these effects can shed light on the underlying market structure and allow us to empirically test between different classes of models. Using insights from the theory, our analysis of heterogeneous effects focuses on two market characteristics: the distance between the rural market and the closest urban center (the variable x in the theory) and crop-specific productivity around the markets (the variable σ in the theory). We proxy the latter with Chiefdom level measures of harvests and sales. For this analysis, we work with dummy variables that indicate whether a certain market is above or below the median value of each of our heterogeneity variables. Using these binary indicators allows us to present the results in an intuitive way and to quantify the economic magnitude of the interactions easily.

In Table 6 (columns (1) and (2)), we present our heterogeneity analysis of price effects based on the distance between markets and the nearest large town. The price reductions induced by road quality improvements are always stronger (i.e., more negative) for markets that are further away from large towns. The sign of the interaction term of treatment and the dummy indicating the market is far from urban centers is negative and statistically significant in all four specifications for rice, and all but the wide-bandwidth local linear regression for cassava. By contrast, the sign of the treatment coefficient is always positive, and significant in all cases for rice, but never for cassava. Based on this hypothesis, we also report one-sided p-values on the treatment interaction coefficient in each panel, all eight of which are significant at the 10% level (and seven are significant at the 1% level).

Next, we examine the heterogeneous impacts on crop prices by the chiefdom-level average household harvest as a proxy for productivity (columns (3) and (4)). For rice, we find that the treatment effect is negative in low-productivity areas, and in fact, positive in the high-productivity areas, indicating a stronger demand effect in these areas. With respect to rice, the coefficient of treatment interacted with high-productivity areas is statistically significant in the optimal and tight bandwidths, but not significant in the other two specifications. We find similar results for cassava, with a strongly negative treatment effect in low-productivity markets (significant in the tight bandwidth and polynomial specifications) and a coefficient that is positive and statistically different from zero in two specifications in the high-harvest areas. The one-sided p values are significant in four of the eight specifications.

In columns (5) and (6), we present evidence of treatment effect heterogeneity by a second proxy of farmer productivity, the share of farmers selling any of their harvest. The price reduction induced by improvements in road quality is significantly weaker in markets with a higher density of sellers. For rice, in markets with a high density of sellers, the price effects are positive. For both crops, the difference in the percentage effect is economically sizable, though it is larger for cassava. The significance of the interaction term, as well as the one-sided p-values, indicate that the effects across low and high seller density markets are significantly different from each other for all specifications for cassava, and all except the wide-bandwidth specification for rice.

Summarizing these results, we find evidence that market-specific characteristics, both on the demand side (distance from major market centers) and on the supply side (productivity), significantly affect the magnitude and the direction of the price effects of improvements in rural road infrastructure. Turning to the models presented in Section 2, these findings are inconsistent with the bilateral bargaining framework and the Cournot model with an exogenous number of traders.[31] In the bilateral bargaining setting, the productivity parameter affects the size of the surplus but does not affect the optimal solution to the bargaining problem. In addition, the distance between the rural market and the urban center, x, affects the outside option of the city-traders but does not affect the impact of rural road quality on the bargaining solution. The Cournot model with an exogenous number of traders also predicts that neither x nor σ affect the price derivative with respect to rural transport costs.

[31] The Bertrand model and the Cournot model with an endogenous number of traders were ruled out on the basis of our main price effects in Table 5.

Our empirical findings are therefore only consistent with a model with search frictions, as formalized by Chau, Goto and Kanbur (2009). In this framework, a reduction in rural road transport costs has both demand and supply effects on prices. It also predicts that more isolated markets have lower entry and hence more imperfect pass-through and that markets with higher productivity have lower real search frictions and hence stronger demand effects. We find evidence of both forms of heterogeneity and in the directions predicted by a search framework.

5.2.3 Additional Evidence in Support of Search Costs

To look more directly at search costs, we present additional results that make use of data on cell phone access. To measure access to cell phones, we use the average cell phone ownership in the Chiefdom in which the market is located. As with the earlier heterogeneity results, we use a dummy for whether the market has below or above median cell phone ownership. The intuition here is to test whether there is heterogeneity in our price effects by this measure of cell phone penetration. Cell phones would allow farmers and traders to gather information in prices, to coordinate on times to meet, and to generally explore outside options more easily. Therefore, we expect that higher cell phone prevalence would be associated with lower search costs and hence that our price effects would be muted or less negative in areas with better cell phone penetration. These results are reported in Table 7. As a framework with search costs would predict, we find that the price effects are less negative (and in some cases even positive) in areas with better cell phone penetration, since the coefficients on the interaction are positive. We find this across specifications for cassava prices, but less robustly across specifications for rice prices.

5.2.4 Robustness Checks

Given our small sample size and empirical design, we report three different sets of robustness checks on our main results: alternative specifications, alternative samples, and a small sample correction. We report all robustness check results for the main price effects in Table 8 (both with and without the heterogeneity controls) and for the heterogeneous effects in Table 9.

In Panel A of Tables 8 and 9, we present results from three additional specifications: (i) one that controls for second-order polynomials in the score, (ii) one that uses a triangle weight in the local linear regression (i.e., a weight that places less emphasis on observations further from the cutoff), and (iii) one that uses continuous heterogeneity variables (reported only in Table 9) instead of the 'greater than median' dummies we use in Table 6. As Panel A in each of Tables 8 and 9 shows, our main results are robust to these alternative specifications. In some cases we lose precision in our estimates, but the coefficients do not change significantly.

With respect to alternative samples, we present four additional specifications: (i) one that includes the two roads at the cutoff in Kambia District, (ii) one that restricts the sample to the closest market to each road and therefore has no weights, (iii) one that restricts the sample to markets within 5km of each road and does not weight by the market-distance to the road, (iv) one that excludes markets that are in more urban areas, and (v) one that excludes markets that match to more than four roads. Looking at Panel B in Tables 8 and 9, our results are robust across these alternative samples though we lose power in specifications with low sample sizes.

Finally, Panel C in Tables 8 and 9 includes a robustness check to address the sample size and low number of clusters. Only 47 roads were considered for rehabilitation, but since we have market-level data, our results are two-way clustered by market and road. Our concern is the road-level clustering. From the applied literature (see Cameron, Gelbach and Miller (2008) and Angrist and Pischke (2008)), it seems that 47 clusters is not small enough to be a concern, nor is 31 (the number of roads in our preferred bandwidth specification). However, as a check, we implement the wild bootstrap that Cameron, Gelbach and Miller (2008) propose for small numbers of clusters. Since our concern is clustering at the road-level, as a preliminary step, we show that one-way clustering by road does not change our results for the preferred bandwidth specification (Panel C). We then report the 95% confidence interval from a wild bootstrap routine based on clustering by road only. The wild bootstrap confidence bands support our main results.

6 Conclusion

Road infrastructure projects represent a large share of current foreign aid and government expenditure in Sub-Saharan Africa. Promoters of these investments argue that enhancing market access is a prerequisite for agricultural development and economic growth. As such, the assessment of the impact of local improvements in rural road quality has immediate policy relevance. In addition, any empirical study focusing on these policies should explicitly assess the role of market structure and hence the heterogeneity in impacts across markets with different characteristics, such as the proximity of the market to urban centers, agricultural productivity and cell phone access.

In this paper, we make two contributions relative to the existing literature. First, we use the specific design of a rural road rehabilitation program in Sierra Leone to estimate the causal impact of road quality on rural market prices of rice and cassava, the two most important staple crops in the country. We also estimate how this response varies with specific market characteristics. Second, we use these empirical findings to test between alternative stylized frameworks of intermediated trade which describe the interaction between rural producers, intermediaries and final consumers. Specifically, we model responses to a change in rural road transport costs under the following four settings: (i) Bertrand traders' oligopsony, which leads to perfect competition outcomes; (ii) bilateral bargaining, which models the case of rural monopsonies; (iii) Cournot oligopsony, both with and without an endogenous number of traders; and (iv) a basic search framework à la Mortensen (2003). We show that these frameworks deliver different predictions on how prices respond to a reduction in rural transport costs. Comparing these theoretical predictions to our empirical findings, we find support for the model with search frictions but not for the other frameworks of trader competition. In addition, we present additional evidence in support of search costs using data on cell phone penetration.

The evidence on search frictions is consistent with a recent literature on the effects of information on prices (see Jensen (2007), Aker (2010), and Goyal (2010)). However, relative to this literature, we show that search frictions which determine the nature of traders' competition also have an effect on how the local economy responds to improvements in infrastructure. More generally, we point out that the structure of the market for agricultural commodities will affect the direction and the magnitude of price response to such investments, thus affecting the size of the gains for different types of agents. We believe our results could inform the decisions of policymakers considering similar improvements in infrastructure as well as a range of other policies that would impact agricultural trade, such as price subsidies, agricultural export promotion interventions, credit-provision policies targeting traders, and more major road projects. In addition, finding evidence consistent with the presence of search frictions implies that there may be strong complementarities between roads (or other infrastructure) projects and policy interventions that may reduce search frictions, such as the expansion of mobile phone coverage.

Possible extensions of this research would look at the longer-term effects of the rural roads improvements. Our study focused on the short-term impacts of these improvements since our surveys were conducted between one and two years after the completion of the rehabilitation program. Given the characteristics of these roads, i.e. that they are small dirt roads, we potentially expect the infrastructure to degrade over time and hence the impact of the rehabilitation to be more limited as this degradation occurs.

7 Appendix 1: Formula for Score

The score of road *i* in district *k* is given by:

$$score_i = 0.4 * \frac{ep_i}{ep\_max_k} + 0.2 * \frac{pd_i}{pd\_max_k} + 0.2 * \frac{ra_i}{ra\_max_k} + 0.1 * \frac{sv_i}{sv\_max_k} + 0.1 * \frac{l_i}{l\_max_k} \quad (14)$$

where: ep_i is economic productivity per kilometer of road *i*, ep_max_k is the maximum economic productivity in district *k*, pd_i is population density around road *i*, pd_max_k is the maximum population density in dsitrict *k*, ra_i is the baseline road condition assessment of road *i*, ra_max_k is the maximum baseline road condition in district *k*, sv_i is the social value indicator of road *i*, sv_max_k is the maximum social value in district *k*, l_i is the length of road *i*, l_max_k is the maximum road length in district *k*.

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Figure 1: District Maps of Sierra Leone

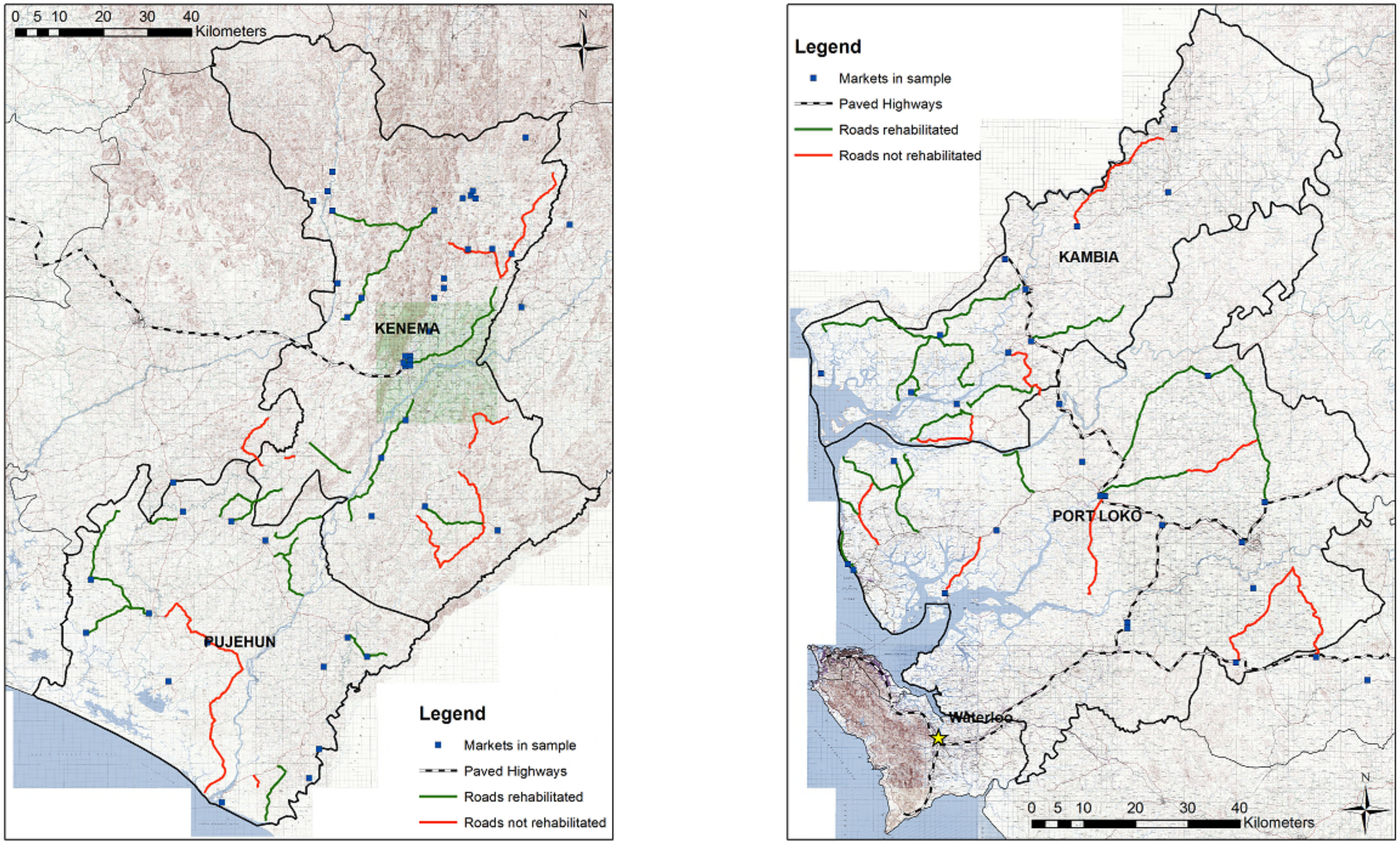


Figure 2: McCrary (2008) Density Test

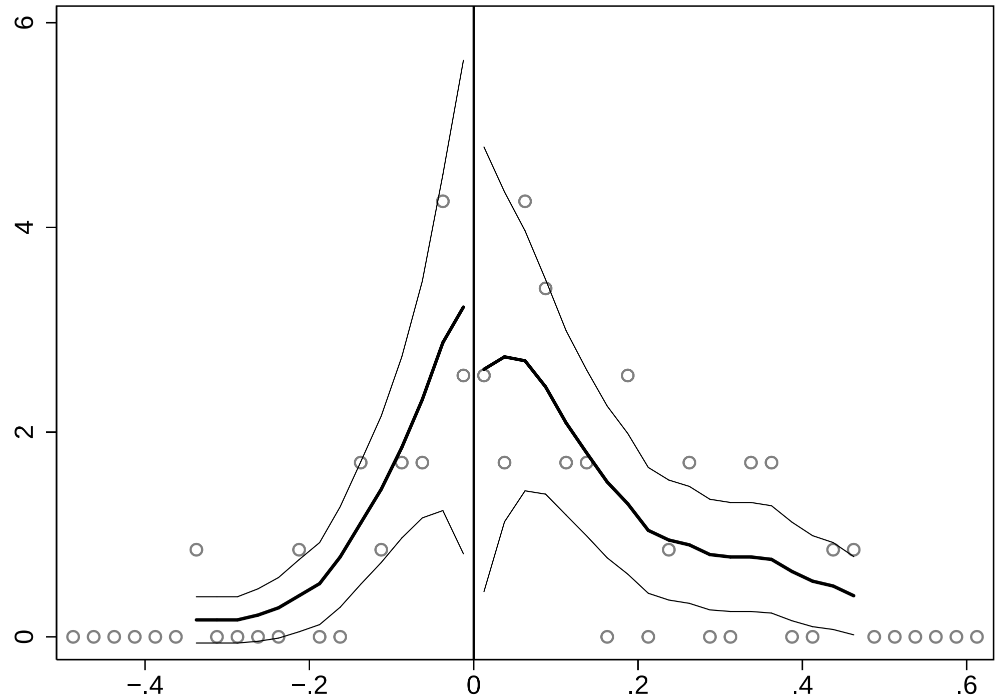
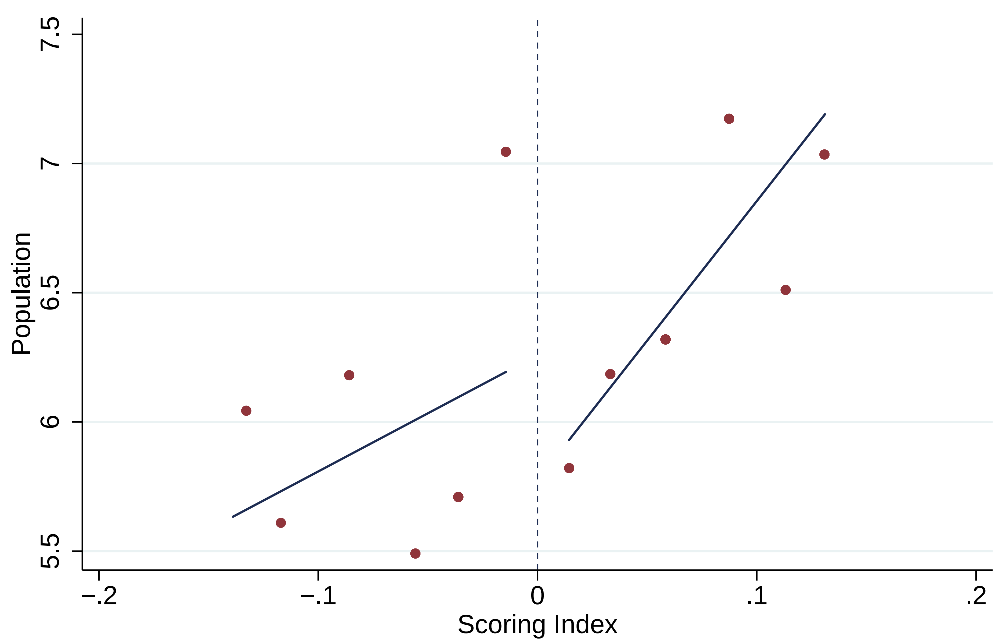
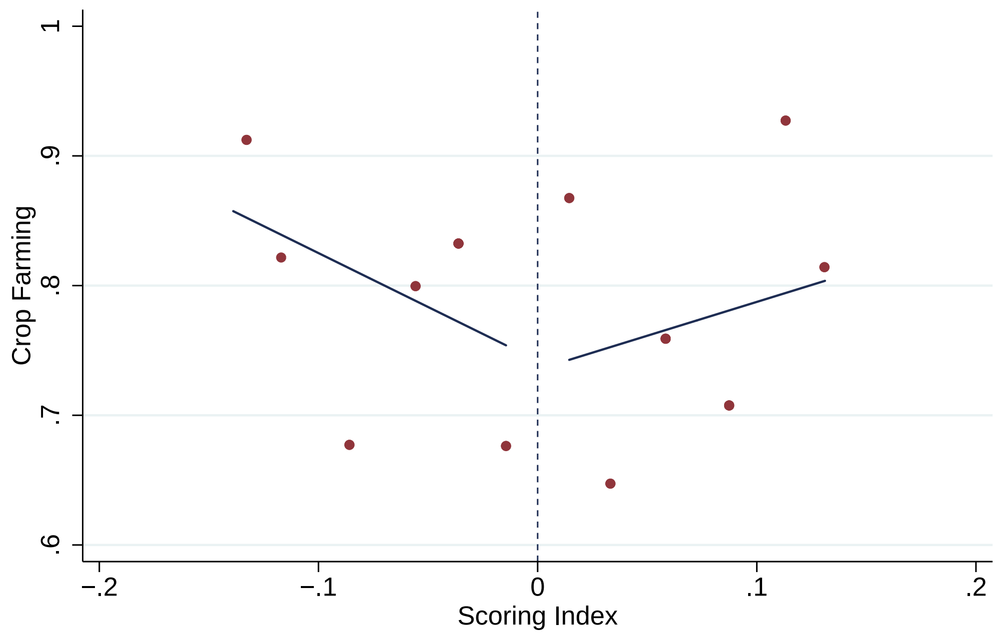


Figure 3a: Baseline: Population per km



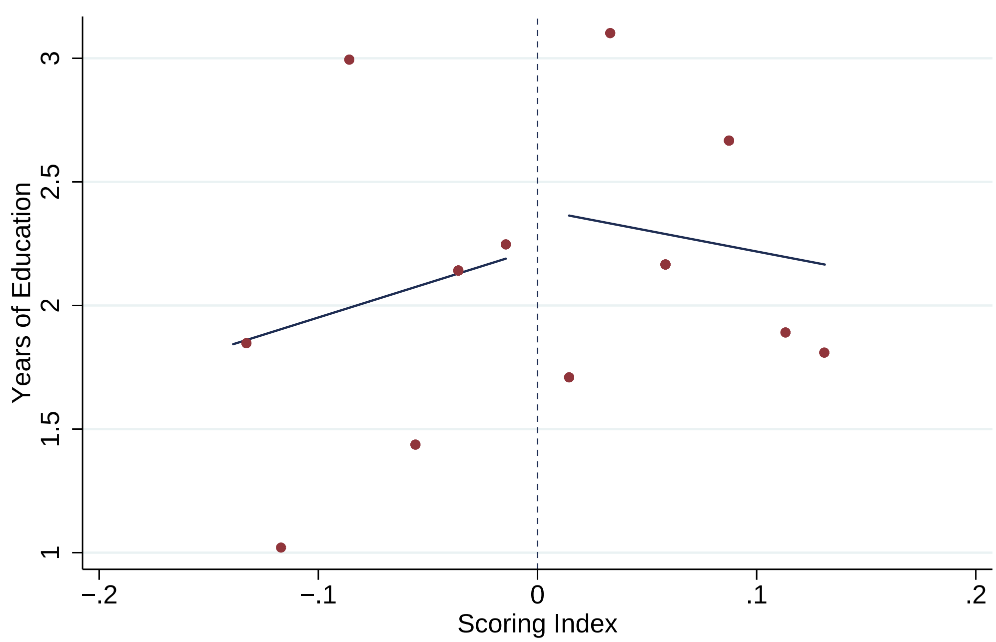
The solid line is a linear fit of the data at the road level.
The scatter represents bin−level means of the outcome (bin size is .025).

Figure 3b: Baseline: Fraction of Individuals in Crop Farming



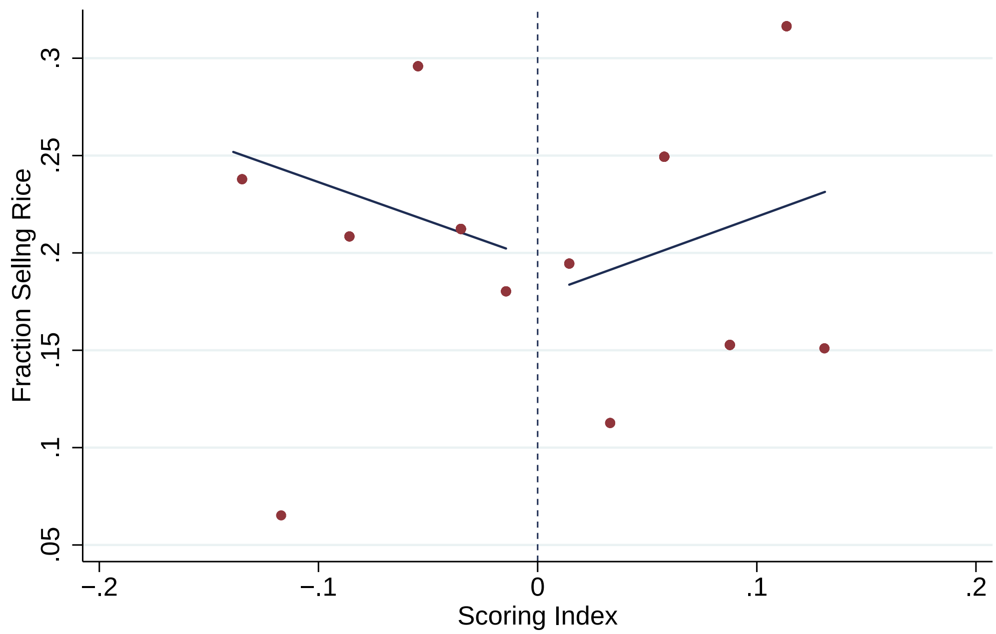
The solid line is a linear fit of the data at the road level.
The scatter represents bin−level means of the outcome (bin size is .025).

Figure 3c: Baseline: Education of HH Head)



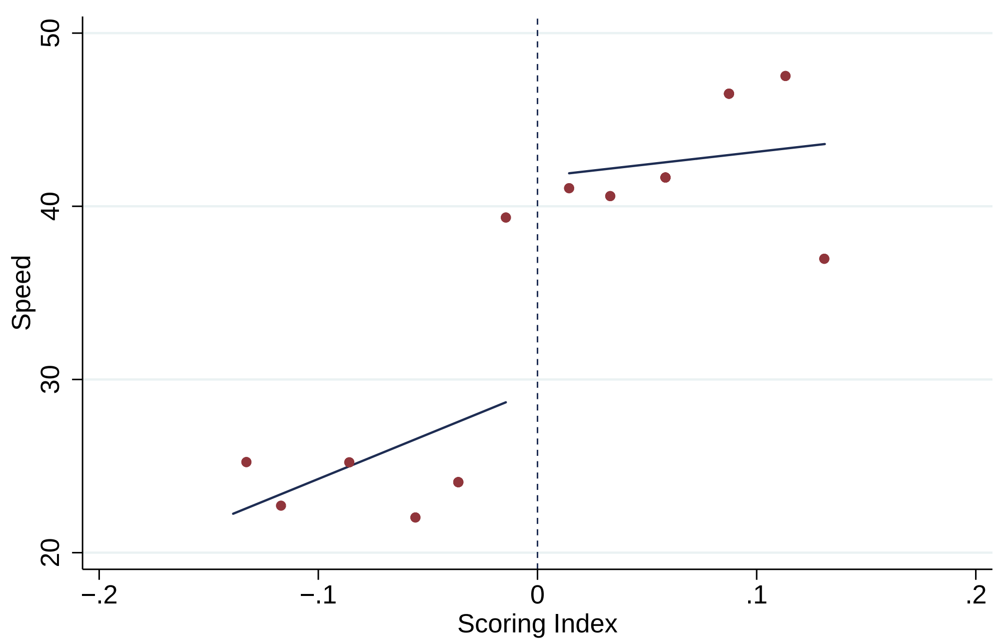
The solid line is a linear fit of the data at the road level.
The scatter represents bin−level means of the outcome (bin size is .025).

Figure 3d: Baseline: Fraction of HHs Selling Rice



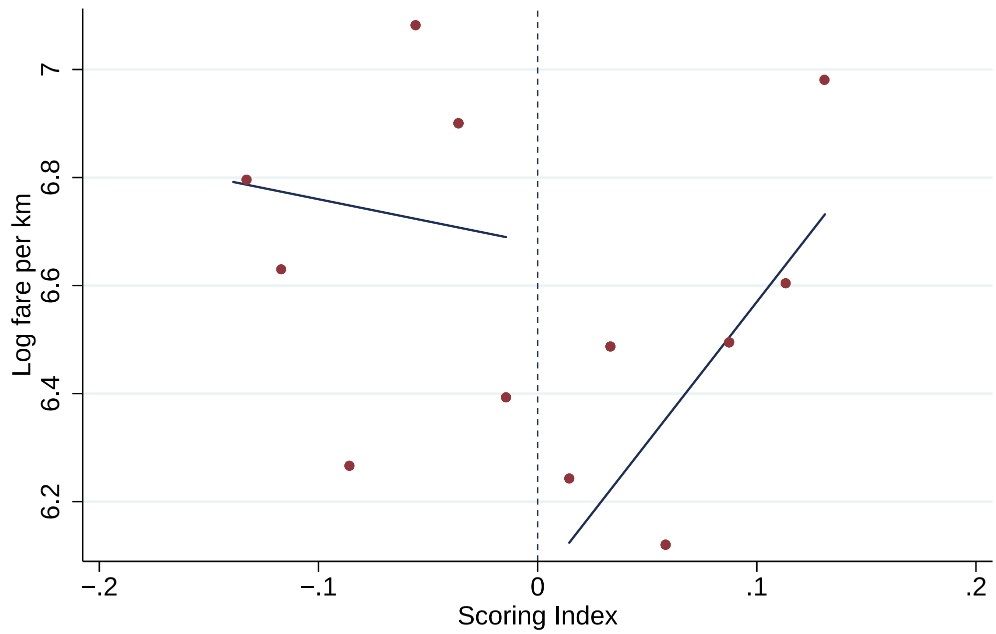
The solid line is a linear fit of the data at the road level.
The scatter represents bin−level means of the outcome (bin size is .025).

Figure 4a: First Stage: Speed (km/h)



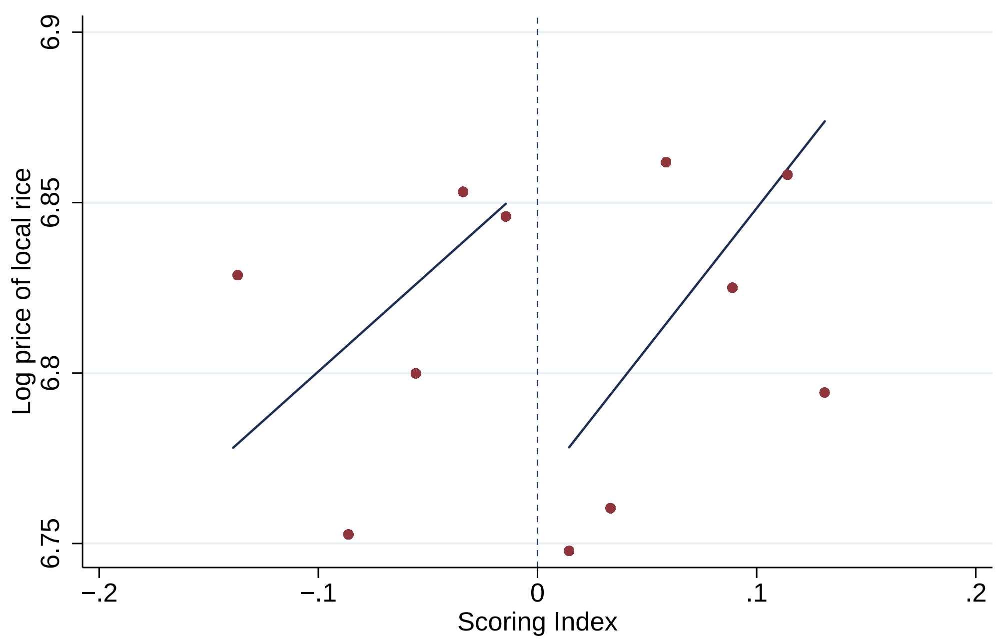
The solid line is a linear fit of the data at the road level.
The scatter represents bin−level means of the outcome (bin size is .025).

Figure 4b: First Stage: Log Motorbike Fare (per km)



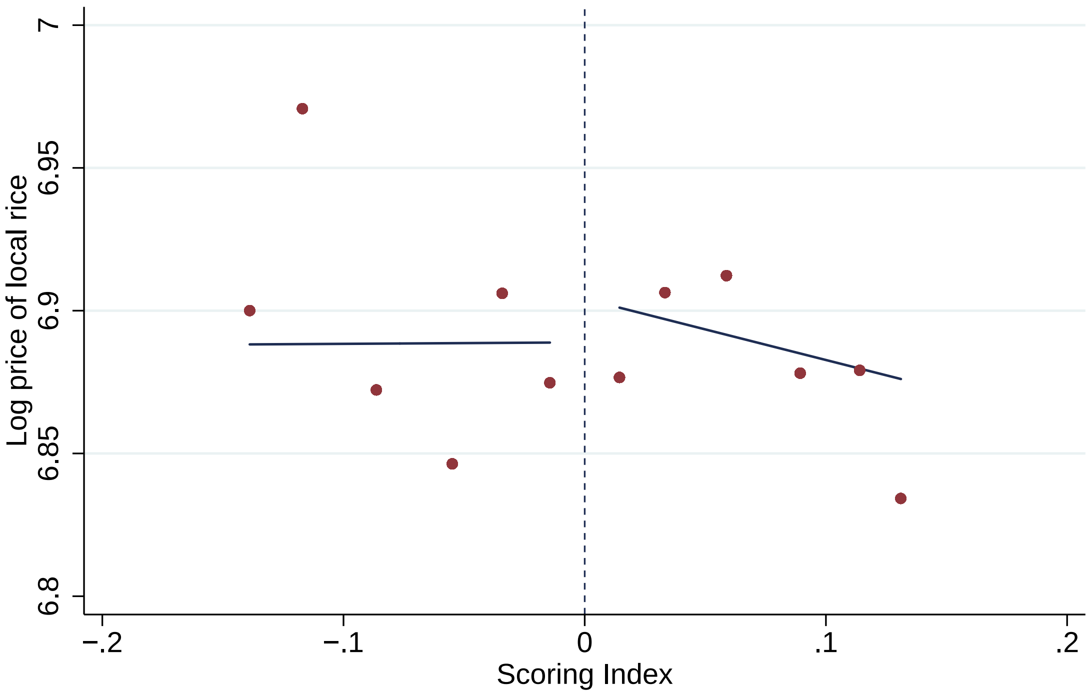
The solid line is a linear fit of the data at the road level.
The scatter represents bin−level means of the outcome (bin size is .025).

Figure 5: Trader Survey: Log Price of Local Rice



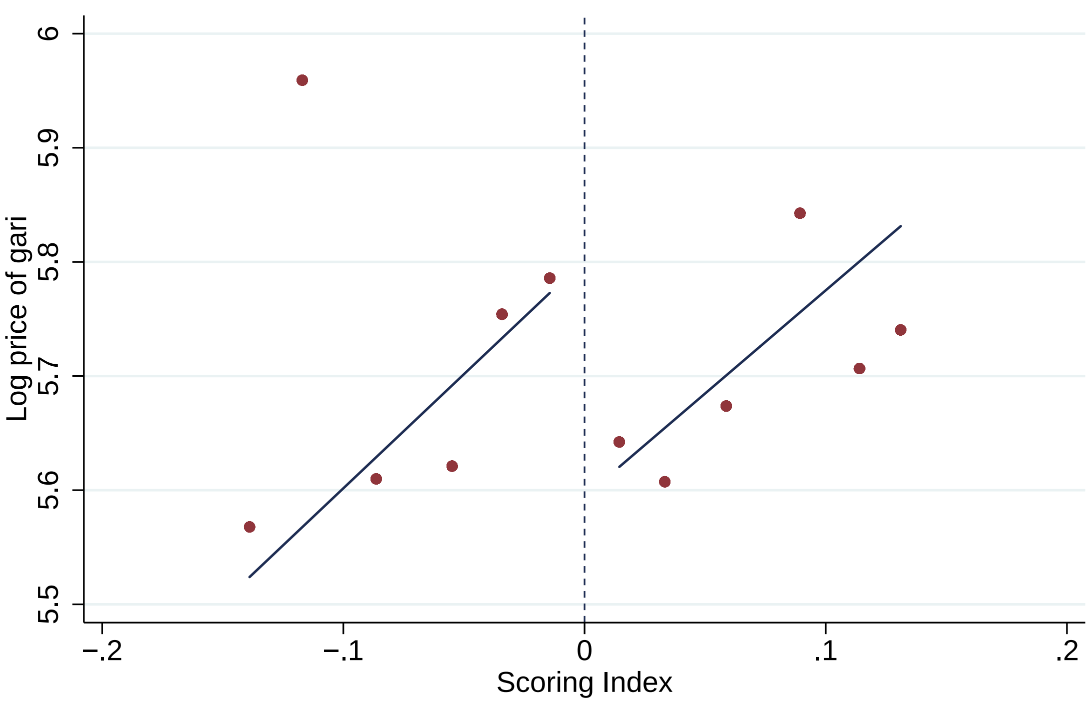
The solid line is a linear fit of the data at the road−market level.
The scatter represents bin−level means of the outcome (bin size is .025).

Figure 6: High Frequency Price Survey: Log Price of Local Rice



The solid line is a linear fit of the data at the road−market level.
The scatter represents bin−level means of the outcome (bin size is .025).

Figure 7: High Frequency Price Survey: Log Price of Cassava (Gari)



The solid line is a linear fit of the data at the road−market level.
The scatter represents bin−level means of the outcome (bin size is .025).

Table 1: Theory Comparative Statics and Empirical Results

Comp. Statics	**Bertrand**	**Bilateral Bargaining**	**Cournot Exogenous** M	**Cournot Endogenous** M	**Search Frictions**	**Empirical Results**	**Regression Coefficient** $(-\frac{\partial p}{\partial \tau})$
$\frac{\partial p}{\partial \tau}$	< 0	$\gtreqless 0$	$\gtreqless 0$	< 0	$\gtreqless 0$	> 0	Treat < 0
$\frac{\partial^2 p}{\partial \tau \partial x}$	$= 0$	=0	=0	$= 0$	> 0	> 0	Treat*Distance< 0
$\frac{\partial^2 p}{\partial \tau \partial \sigma}$	$= 0$	$= 0$	$= 0$	> 0	< 0	< 0	Treat*Harvest per hh> 0; Treat*% Selling> 0

Table 2: Summary Statistics

	Mean	SD	Obs
EA-Level 2004 Census Data			
Proportion farming (all individuals over 10 years)	0.68	0.36	1373
Proportion farming (all households)	0.78	0.32	1373
Proportion literate (all individuals over 12 years)	0.31	0.19	1374
Years of education (HH heads)	2.86	2.26	1369
Roads Baseline Data			
Log population per km	6.53	0.93	45
Log economic production per km	18.60	1.01	45
Road assessment	17.24	3.81	45
Social value	9.56	2.15	45
Number of bridges (excluding palm logs)	3.21	4.07	45
Number of palm log crossings	2.80	5.01	45
Number of culverts	18.29	17.05	45
Road length (km)	20.61	14.72	45
Score rescaled at midpoint	0.08	0.17	45
Chiefdom-Level AHTS Data			
Proportion of HHs selling rice	0.20	0.13	34
Proportion of HHs selling cassava	0.37	0.20	34
Log HH rice harvest (kg)	6.15	0.51	34
Log HH cassava harvest (kg)	7.18	0.53	34
Roads Endline: First Stage			
Total travel fare (one way)	16100	12085	45
Travel fare per km (one way)	900	558	45
Average speed (kph)	36.26	10.42	44
Trader Data			
Local rice purchase price	774.84	90.08	149
Local rice sale price	931.14	105.46	118
Market-Level Price Survey Data			
Price of cassava/gari	339.71	99.92	787
Price of local rice	996.51	143.06	764
Cassava/gari available (proportion of mkts)	0.95	0.21	918
Local rice available (proportion of mkts)	0.84	0.37	918
Number of traders per market (cassava/gari)	9.37	11.31	918
Number of traders per market (local rice)	9.05	9.90	918
Log distance (km) to nearest large town	2.60	1.40	78

Note: All prices are in SLL (Sierra Leonean Leones).
The relevant exchange rate was approximately $1=4300 SLL.
Total travel fare is for a motorbike ride along the entire distance of the road.
Outliers (top 1% of observations) are removed from price data.
All prices are in cups unless otherwise indicated.
Conversion rates are approximately 4 (5) cups of rice (cassava) per kg.

Table 3a: Pre-Rehabilitation Analysis: Score Components

	(1) Population per km	(2) Production per km	(3) Road Assessment	(4) Social Value	(5) Road Length
Preferred LLR (h=.15)					
Treatment	-0.537	0.342	-0.072	-1.008	15.694
	[0.409]	[0.328]	[2.264]	[1.599]	[17.433]
Mean for Control	5.977	17.863	17.143	8.857	23.199
Observations	31	31	31	31	31
LLR (h=.075)					
Treatment	-1.578***	0.006	2.897	-0.229	11.099
	[0.430]	[0.553]	[3.310]	[3.038]	[28.657]
Mean for Control	5.958	17.681	18.667	9.444	22.943
Observations	18	18	18	18	18
LLR (h=.3)					
Treatment	-0.213	0.232	1.641	-0.457	4.988
	[0.314]	[0.223]	[1.644]	[1.137]	[10.770]
Mean for Control	5.967	17.902	17.067	8.733	22.306
Observations	38	38	38	38	38
3rd Order Polynomial					
Treatment	-0.789	0.085	0.862	-1.065	24.238
	[0.530]	[0.488]	[2.929]	[2.356]	[23.118]
Mean for Control	5.935	17.889	16.750	8.750	21.074
Observations	45	45	45	45	45

Note: Road assessment is a 1-5 score assigned by EDA that measures the pre-existing condition of the selected road based on seven parameters (culverts, bridges, drainage, pavement surface, vertical/ horizontal alignment, and riding quality).
Social value is a 1-5 score assigned by EDA based on the conditions of schools, health centers, wells and toilets in the catchment area of the road.
LLR is short for local linear regression.
All specifications include district fixed effects.
Heteroskedasticity-robust standard errors reported in brackets.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 3b: Pre-Rehabilitation Analysis: Road Characteristics

	(1) Number of Bridges	(2) Number of Palmlog Bridges	(3) Number of Culverts	(4) Prop of HHs Crop Farming	(5) Prop of Indiv Crop Farming	(6) Literate HH Head Dummy	(7) HH Head Years of Education
Preferred LLR (h=.15)							
Treatment	2.801	-2.242	4.647	-0.036	0.003	0.040	0.284
	[5.263]	[4.466]	[11.778]	[0.097]	[0.125]	[0.059]	[0.582]
Mean for Control	3.857	4.552	15.430	0.880	0.794	0.239	2.056
Observations	31	31	31	31	31	31	31
LLR (h=.075)							
Treatment	0.578	-5.051	-9.375	0.100	0.190	-0.059	-0.249
	[11.257]	[4.421]	[9.420]	[0.136]	[0.172]	[0.067]	[0.694]
Mean for Control	4.778	3.525	14.336	0.890	0.790	0.240	2.008
Observations	18	18	18	18	18	18	18
LLR (h=.3)							
Treatment	0.130	-3.645	2.613	-0.003	0.001	0.033	0.212
	[3.499]	[3.427]	[8.724]	[0.070]	[0.090]	[0.039]	[0.398]
Mean for Control	3.800	4.248	15.735	0.886	0.804	0.238	2.035
Observations	38	38	38	38	38	38	38
3rd Order Polynomial							
Treatment	2.287	3.863	-0.263	-0.065	-0.001	0.038	0.640
	[7.704]	[6.487]	[15.785]	[0.149]	[0.185]	[0.090]	[0.880]
Mean for Control	3.563	3.983	15.001	0.890	0.810	0.237	2.021
Observations	45	45	45	45	45	45	45

Note: Columns (4)-(7) based on 2004 Census data.
Note: A culvert is a pipe or drain allowing water to flow under a road.
LLR is short for local linear regression.
All specifications include district fixed effects.
Heteroskedasticity-robust standard errors reported in brackets.
* p<0.1, ** p<0.05, *** p<0.01

Table 3c: Pre-Rehabilitation Analysis: Farming Activity and Harvests

	(1) Log Market Distance to Big Town	(2) Chiefdom Frac of HHs Selling Rice	(3) Chiefdom Frac of HHs Selling Cassava	(4) Log Rice Harvest	(5) Log Cassava Harvest	(6) Chiefdom Phone Access
Preferred LLR (h=.15)						
Treatment	-0.518	-0.031	-0.063	-0.005	0.166	-0.062
	[0.341]	[0.027]	[0.061]	[0.168]	[0.112]	[0.054]
Mean for Control	9.707	0.218	0.389	6.197	7.307	0.353
Observations	104	65	65	65	65	65
LLR (h=.075)						
Treatment	-0.670	0.007	-0.256***	-0.197	0.060	-0.059
	[0.623]	[0.054]	[0.067]	[0.219]	[0.280]	[0.104]
Mean for Control	9.857	0.223	0.405	6.202	7.253	0.360
Observations	64	41	41	41	41	41
LLR (h=.3)						
Treatment	-0.702*	-0.027	-0.016	-0.040	0.081	-0.029
	[0.365]	[0.021]	[0.045]	[0.157]	[0.103]	[0.033]
Mean for Control	9.707	0.218	0.389	6.197	7.307	0.353
Observations	129	77	77	77	77	77
3rd Order Polynomial						
Treatment	-2.292**	-0.018	-0.165	-0.727**	-0.314	-0.066
	[1.058]	[0.036]	[0.168]	[0.285]	[0.322]	[0.091]
Mean for Control	9.707	0.218	0.389	6.197	7.307	0.353
Observations	156	91	91	91	91	91

Note: All data is from the 2010 AHTS.
Distance data (km) is at the market-road level. Harvest data (kg) is at the chiefdom-road level.
LLR is short for local linear regression.
All specifications include road-district and market-district fixed effects.
Standard errors two-way clustered by road and market reported in brackets in column (1).
Standard errors two-way clustered by road and chiefdom reported in brackets in columns (2)-(5).
* p<0.1, ** p<0.05, *** p<0.01

Table 4: First Stage Analysis (Transport Fares and Road Speed)

	Average Speed (kph)		Log Fare/km	
	(1)	(2)	(3)	(4)
Preferred LLR (h=.15)				
Treatment	12.085**	12.769**	-0.594**	-0.610***
	[5.345]	[5.282]	[0.236]	[0.203]
Mean for Control	26.196	26.196	6.729	6.729
Heterogeneity Controls		X		X
Observations	31	31	31	31
LLR (h=.3)				
Treatment	16.122***	16.350***	-0.149	-0.178
	[4.881]	[4.704]	[0.214]	[0.215]
Mean for Control	26.732	26.732	6.789	6.789
Heterogeneity Controls		X		X
Observations	38	37	38	37
3rd Order Polynomial				
Treatment	-4.274	-3.674	-0.836**	-0.980**
	[8.509]	[8.498]	[0.325]	[0.419]
Mean for Control	26.732	26.732	6.805	6.805
Heterogeneity Controls		X		X
Observations	44	43	45	44

Note: Fares are one-way motorbike fares in SLL (Sierra Leonean Leones).
The relevant exchange rate was roughly $1=4300 SLL.
Average speed measured in kilometers per hour along the entire road.
Heterogeneity controls include cassava/rice sales indicators/harvests measured for EAs within 2km of the roads.
LLR is short for local linear regression.
All specifications include district fixed effects.
Heteroskedasticity-robust standard errors reported in brackets.
* p<0.1, ** p<0.05, *** p<0.01

Table 5: Effects on Prices from Trader and High Frequency Surveys

	Log Local Rice Price		Log Local Rice Price		Log Cassava Price	
	(1)	(2)	(3)	(4)	(5)	(6)
Preferred LLR (h=.15)						
Treatment	-0.116**	-0.105***	0.006	0.005	-0.178**	-0.141**
	[0.058]	[0.029]	[0.029]	[0.016]	[0.086]	[0.058]
Mean for Control	6.831	6.831	6.889	6.889	5.703	5.703
Heterogeneity Controls		X		X		X
Observations	190	188	896	883	918	906
LLR (h=.075)						
Treatment	-0.178***	-0.174***	-0.030	-0.059**	-0.227*	-0.254***
	[0.066]	[0.047]	[0.048]	[0.027]	[0.125]	[0.074]
Mean for Control	6.843	6.843	6.887	6.887	5.728	5.728
Heterogeneity Controls		X		X		X
Observations	124	122	599	586	595	583
LLR (h=.3)						
Treatment	-0.074*	-0.069**	0.005	-0.004	-0.159*	-0.099*
	[0.045]	[0.031]	[0.021]	[0.021]	[0.089]	[0.052]
Mean for Control	6.831	6.831	6.889	6.889	5.703	5.703
Heterogeneity Controls		X		X		X
Observations	237	233	1099	1073	1112	1088
3rd Order Polynomial						
Treatment	-0.165***	-0.168***	-0.000	-0.058	-0.403**	-0.341***
	[0.058]	[0.044]	[0.055]	[0.052]	[0.170]	[0.063]
Mean for Control	6.831	6.831	6.889	6.889	5.703	5.703
Heterogeneity Controls		X		X		X
Observations	298	292	1314	1275	1338	1302

Note: Annual trader data (cols (1)-(2)); monthly high frequency price data (cols (3)-(6)).
All prices in SLL (Sierra Leonean Leones) per cup.
Heterogeneity controls include log distance to the nearest major town, and rice and cassava sales fractions and harvest amount medians.
LLR is short for local linear regression.
All specifications include round, road-district, and market-district fixed effects.
Standard errors two-way clustered by road and market reported in brackets.
* p<0.1, ** p<0.05, *** p<0.01

Table 6: Heterogeneity by Access to Towns, Agricultural Production and Density of Rice Sellers Near Roads

	Distance		Harvest		Seller Density	
	(1) Log Rice Price	(2) Log Cassava Price	(3) Log Rice Price	(4) Log Cassava Price	(5) Log Rice Price	(6) Log Cassava Price
Preferred LLR (h=.15)						
Treatment	0.085***	0.002	-0.022	-0.115	-0.040	-0.275**
	[0.024]	[0.033]	[0.036]	[0.071]	[0.040]	[0.108]
Treat * Above Median	-0.162***	-0.345***	0.065*	0.064	0.095**	0.236**
	[0.047]	[0.104]	[0.039]	[0.080]	[0.039]	[0.113]
One-sided p-value	0.000	0.000	0.048	0.212	0.008	0.018
Mean for Control	6.889	5.703	6.889	5.703	6.889	5.703
Observations	896	918	883	906	883	906
LLR (h=.075)						
Treatment	0.107***	0.051	-0.138**	-0.404**	-0.121*	-0.476***
	[0.040]	[0.068]	[0.070]	[0.178]	[0.072]	[0.115]
Treat * Above Median	-0.210***	-0.535***	0.178**	0.410**	0.176**	0.490***
	[0.073]	[0.129]	[0.076]	[0.188]	[0.078]	[0.132]
One-sided p-value	0.002	0.000	0.009	0.015	0.012	0.000
Mean for Control	6.887	5.728	6.887	5.728	6.887	5.728
Observations	599	595	586	583	586	583
LLR (h=.3)						
Treatment	0.072***	0.002	-0.008	-0.254	-0.007	-0.278***
	[0.022]	[0.023]	[0.036]	[0.185]	[0.034]	[0.102]
Treat * Above Median	-0.128***	-0.186	0.019	0.219	0.040	0.308***
	[0.037]	[0.136]	[0.040]	[0.191]	[0.037]	[0.117]
One-sided p-value	0.000	0.086	0.318	0.126	0.136	0.004
Mean for Control	6.889	5.703	6.889	5.703	6.889	5.703
Observations	1099	1112	1073	1088	1073	1088
3rd Order Polynomial						
Treatment	0.135**	0.107	-0.053	-0.362***	-0.138***	-0.584***
	[0.055]	[0.075]	[0.065]	[0.095]	[0.033]	[0.101]
Treat * Above Median	-0.242***	-0.552***	0.065	0.420***	0.205***	0.556***
	[0.092]	[0.089]	[0.063]	[0.134]	[0.049]	[0.123]
One-sided p-value	0.004	0.000	0.151	0.001	0.000	0.000
Mean for Control	6.889	5.703	6.889	5.703	6.889	5.703
Observations	1314	1338	1275	1302	1275	1302

Note: All data is from high frequency price surveys.
All prices in SLL (Sierra Leonean Leones) per cup.
LLR is short for local linear regression.
All specifications include round, road-district, and market-district fixed effects.
One sided p-values are calculated on the interaction term (>0 for distance, <0 for harvest and seller density).
Heteroskedasticity-robust standard errors for all narrow bandwidth (h=.075) regressions. Standard errors two-way clustered by road and market for cassava price regressions, except the h=.075 specification.
For rice price (distance heterogeneity) regressions, we use heteroskedasticity-robust standard errors as there are too few clusters to allow for two-way clustering. Standard one-way clustering at either the road level or market level produces standard errors that are uniformly smaller than those reported.
* p<0.1, ** p<0.05, *** p<0.01

Table 7: Heterogeneity by Mobile Phone Penetration

	(1) Log Rice Price	(2) Log Cassava Price
Preferred LLR (h=.15)		
Treatment	-0.038	-0.233**
	[0.033]	[0.091]
Treat * Above Median	0.084**	0.242**
	[0.040]	[0.106]
One-sided p-value	0.019	0.011
Mean for Control	6.889	5.703
Observations	883	906
LLR (h=.075)		
Treatment	-0.082	-0.386***
	[0.061]	[0.099]
Treat * Above Median	-0.069	0.675***
	[0.091]	[0.178]
One-sided p-value		
Mean for Control		
Observations	586	583
LLR (h=.3)		
Treatment	-0.027	-0.238***
	[0.024]	[0.087]
Treat * Above Median	0.036	0.346***
	[0.045]	[0.116]
One-sided p-value	0.210	0.001
Mean for Control	6.889	5.703
Observations	1073	1088
3rd Order Polynomial		
Treatment	-0.071	-0.451***
	[0.056]	[0.145]
Treat * Above Median	-0.131	1.297***
	[0.193]	[0.442]
One-sided p-value	0.751	0.002
Mean for Control	6.889	5.703
Observations	1275	1302

Note: All data is from high frequency price surveys.
All prices in SLL (Sierra Leonean Leones) per cup.
LLR is short for local linear regression.
All specifications include round, road-district, and market-district fixed effects.
One sided p-values are calculated on the interaction term (>0 for distance, <0 for harvest and seller density).
Heteroskedasticity-robust standard errors for all narrow bandwidth (h=.075) regressions. Standard errors two-way clustered by road and market for cassava price regressions, except the h=.075 specification.
* p<0.1, ** p<0.05, *** p<0.01

Table 8: Robustness Checks: Main Effects on Prices

	Log Local Rice Price		Log Local Rice Price		Log Cassava Price	
	(1) Basic	(2) Het Controls	(3) Basic	(4) Het Controls	(5) Basic	(6) Het Controls
A: Alternative Specifications						
Paper Spec: 2nd Poly						
Treatment	-0.140**	-0.120***	0.005	-0.020	-0.218	-0.113
	[0.066]	[0.044]	[0.036]	[0.039]	[0.135]	[0.074]
Observations	298	292	1314	1275	1338	1302
Triangle Weight						
Treatment	-0.082	-0.074***	0.027	0.033**	-0.079	-0.077**
	[0.050]	[0.028]	[0.032]	[0.016]	[0.067]	[0.036]
Observations	190	188	896	883	918	906
B: Alternative Samples						
All Roads						
Treatment	-0.100**	-0.073**	0.015	0.024	-0.169***	-0.095*
	[0.048]	[0.031]	[0.023]	[0.016]	[0.063]	[0.050]
Observations	203	201	970	957	995	983
Closest Market (unw)						
Treatment	-0.123*	-0.179**	0.030	0.027	-0.179**	-0.161***
	[0.074]	[0.073]	[0.026]	[0.027]	[0.077]	[0.061]
Observations	56	56	282	282	284	284
Markets w/in 5km (unw)						
Treatment	-0.085	-0.063*	0.032	0.018	-0.122*	-0.080
	[0.061]	[0.033]	[0.028]	[0.027]	[0.073]	[0.061]
Observations	82	82	438	438	459	459
Drop Town Markets						
Treatment	-0.131**	-0.127***	-0.002	-0.000	-0.198**	-0.172***
	[0.056]	[0.022]	[0.030]	[0.018]	[0.091]	[0.052]
Observations	163	161	733	720	753	741
Drop Multimatch (>4) Markets						
Treatment	-0.131**	-0.127***	0.001	0.010	-0.168*	-0.132**
	[0.056]	[0.022]	[0.029]	[0.016]	[0.092]	[0.058]
Observations	163	161	778	765	780	768
C: Small Sample Corrections						
One-way Cluster (Road)						
Treatment	-0.116**	-0.105***	0.006	0.015	-0.178**	-0.126**
	[0.051]	[0.027]	[0.028]	[0.018]	[0.080]	[0.053]
Wild Bootstrap Coeff 95% CI	-0.21, -0.04	-0.15, -0.06	-0.05, 0.06	-0.02, 0.05	-0.33, -0.03	-0.23, -0.02
Observations	190	188	896	883	918	906

Note: All specifications are local linear regressions at the preferred (h=.15) bandwidth unless otherwise indicated. Wild bootstrap coefficient confidence intervals based on 400 iterations.

Table 9: Robustness Checks: Heterogeneity

	Distance		Harvest		Seller Density	
	(1) Log Rice Price	(2) Log Cassava Price	(3) Log Rice Price	(4) Log Cassava Price	(5) Log Rice Price	(6) Log Cassava Price
A: Alternative Specifications						
Paper Spec: 2nd Poly						
Treatment	0.087***	0.061*	-0.054	-0.422	-0.064	-0.438***
	[0.033]	[0.036]	[0.049]	[0.273]	[0.052]	[0.100]
Treat * Above Median	-0.156***	-0.369**	0.088	0.466*	0.101*	0.564***
	[0.057]	[0.149]	[0.056]	[0.277]	[0.060]	[0.126]
One-sided p-value	0.003	0.007	0.057	0.046	0.047	0.000
Observations	1314	1338	1275	1302	1275	1302
Triangle Weight						
Treatment	0.089***	0.018	-0.012	-0.042	-0.036	-0.180**
	[0.019]	[0.023]	[0.028]	[0.043]	[0.038]	[0.086]
Treat * Above Median	-0.160***	-0.266***	0.073**	0.019	0.101**	0.173*
	[0.042]	[0.086]	[0.031]	[0.045]	[0.039]	[0.089]
One-sided p-value	0.000	0.001	0.010	0.335	0.005	0.025
Observations	896	918	883	906	883	906
Continuous Het Vars						
Treatment	0.183	1.009**	0.290	-0.982***	-0.023	-0.390**
	[0.124]	[0.497]	[0.221]	[0.306]	[0.056]	[0.178]
Treatment Interaction	-0.019	-0.121**	-0.047	0.123***	0.085	0.505*
	[0.014]	[0.056]	[0.035]	[0.035]	[0.165]	[0.287]
One-sided p-value	0.087	0.015	0.912	0.000	0.302	0.039
Mean of Het Variable	9.390	9.373	6.207	7.244	0.230	0.408
Observations	896	918	883	906	883	906
B: Alternative Samples						
All Roads						
Treatment	0.070***	-0.038	-0.003	-0.075	-0.031	-0.277***
	[0.017]	[0.029]	[0.041]	[0.059]	[0.042]	[0.105]
Treat * Above Median	-0.148***	-0.304***	0.023	0.007	0.080*	0.189*
	[0.044]	[0.099]	[0.045]	[0.070]	[0.042]	[0.108]
One-sided p-value	0.000	0.001	0.307	0.460	0.030	0.041
Observations	970	995	957	983	957	983
Closest Market (unw)						
Treatment	0.066**	-0.075**	0.017	-0.242	0.020	-0.245**
	[0.033]	[0.038]	[0.045]	[0.315]	[0.062]	[0.103]
Treat * Above Median	-0.096	-0.252**	0.035	0.139	0.023	0.181*
	[0.059]	[0.121]	[0.063]	[0.322]	[0.065]	[0.109]
One-sided p-value	0.053	0.019	0.290	0.333	0.360	0.049
Observations	282	284	282	284	282	284
Markets w/in 5km (unw)						
Treatment	0.080***	0.056**	-0.068***	-0.139**	-0.046	-0.265***
	[0.029]	[0.025]	[0.018]	[0.069]	[0.029]	[0.103]
Treat * Above Median	-0.183***	-0.369***	0.154***	0.126*	0.135***	0.220**
	[0.050]	[0.118]	[0.018]	[0.070]	[0.031]	[0.105]
One-sided p-value	0.000	0.001	0.000	0.036	0.000	0.018
Observations	438	459	438	459	438	459

Drop Town Markets						
Treatment	0.088***	0.009	-0.028	-0.196***	-0.042	-0.312***
	[0.031]	[0.039]	[0.038]	[0.071]	[0.042]	[0.100]
Treat * Above Median	-0.165***	-0.352***	0.054	0.136*	0.084**	0.273***
	[0.051]	[0.108]	[0.036]	[0.076]	[0.039]	[0.105]
One-sided p-value	0.001	0.001	0.066	0.037	0.016	0.005
Observations	733	753	720	741	720	741
Drop Multimatch (>4) Markets						
Treatment	0.085***	0.002	-0.019	-0.115	-0.038	-0.279**
	[0.024]	[0.033]	[0.037]	[0.070]	[0.040]	[0.111]
Treat * Above Median	-0.177***	-0.431***	0.053	0.088	0.082**	0.261**
	[0.054]	[0.066]	[0.046]	[0.078]	[0.041]	[0.114]
One-sided p-value	0.001	0.000	0.124	0.131	0.022	0.011
Observations	778	780	765	768	765	768
C: Small Sample Corrections						
One-way Cluster (Road)						
Treatment	0.085***	0.002	-0.022	-0.115	-0.040	-0.275***
	[0.024]	[0.036]	[0.034]	[0.072]	[0.040]	[0.095]
Treat * Above Median	-0.162***	-0.345***	0.065*	0.064	0.095**	0.236**
	[0.047]	[0.088]	[0.038]	[0.086]	[0.042]	[0.102]
One-sided p-value	0.000	0.000	0.045	0.228	0.012	0.010
Wild Bootstrap Coeff 95% CI (Lower)	-0.21, -0.12	-0.51, -0.19	-0.01, 0.14	-0.11, 0.23	0.02, 0.17	0.05, 0.41
Observations	896	918	883	906	883	906

Note: All specifications are local linear regressions at the preferred (h=.15) bandwidth unless otherwise indicated.
Two-way clustered standard errors except rice price/distance heterogeneity regressions and one-way cluster spec.
All one-sided p-values are for the interaction term (>0 for distance, <0 for harvest and seller density).
Wild bootstrap interaction coefficient confidence intervals based on 400 iterations.