Essays in International Trade and Development

by

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To Mama and Papa,

the reason of what I become today.

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ABSTRACT

This dissertation contains three independent essays in international trade and development, with the aim of understanding the mechanisms through which trade impacts development.

The first chapter studies the monopsony power of agricultural intermediaries that arises as a result of trade costs and entry costs. The chapter examines how market power along agricultural value chains mediates the effects of policies on the welfare of farmers. Using microdata on farmers and rice mills in Thailand, I document heterogeneity in the spatial density of rice mills. I further provide reduced-form evidence that a one standard deviation increase in local competition among rice mills leads to a 7.7% increase in farmer prices. Informed by the empirical findings, I propose and estimate a quantitative spatial model that accounts for the market power and entry-location choices of intermediaries. I then simulate two policy counterfactuals. I find that gains to farmers from a country-wide improvement in road infrastructure are regressive: the percentage increase in income of the top decile farmers is on average 11% larger than that of the bottom decile. Changes in the entry decisions of the rice mills further exacerbate the regressive effect, more than doubling the gap between the change in income of the top and bottom decile farmers. The second counterfactual simulation shows that the market power of intermediaries could lead to a lower than socially optimal level of technology adoption among farmers.

The second chapter, co-authored with Michelle Lam, studies the long-term effect of trade on development. We approach this question in the context of the ancient

Silk Road, examining whether the locations along the highland Silk Road continue to be relatively more developed than other locations in the highland region along the Inner Asia Mountain Corridor that were not on the ancient Silk Road. We proxy for modern development using high-resolution satellite imagery. To provide a causal effect between proximity to the Silk Road and modern development, we adopt a novel instrumental variable, using a simulated seasonal mobility pattern of the nomadic pastoralists from Frachetti et al. (2017) as an instrument for the locations of the Silk Road sites. We find a significant and robust positive relationship between proximity to Silk Road sites and modern development measures; an increase in the distance to the Silk Road by one standard deviation decreases the night lights intensity by 10.0%. Based on the elasticity of night lights with respect to GDP in the literature, this corresponds to a decrease in GDP of about 4.1%-9.7%.

The third chapter examines the dynamics of export entry and exit under uncertainty. Data from disaggregated international trade transactions often reveals a high degree of turnover among exporters, an observation at odds with a standard trade model with sunk cost of entry into the export market. The chapter examines what accounts for the high degree of turnover among exporters observed in the data. Using Chilean plant-level data from the manufacturing census, I establish that a third of the exporter turnover among plants arises from plants that export for only one year. I document the differences in productivity across different groups of exporting plants. I find that incumbent exporters are the most productive group, followed by export entrants who export beyond one year; one-year exporters are, on average, the least productive group among the exporting plants. I further show that there is no significant correlation between domestic sales growth and number of one-year exporters, indicating that the demand-side story cannot fully explain the existence of one-year exporters. Informed by these stylized facts, I propose a dynamic trade model with uncertainty in the cost of exporting and a heterogeneous productivity process across firms. I demonstrate that the predicted aggregate responses of the economy to external shocks in my proposed model are significantly different from those in existing models. On impact, following a temporary 10% exchange rate depreciation, the change in the export participation rate in my proposed model is three times smaller than that in the canonical model. Likewise, the hysteresis in my proposed model is significantly more attenuated.

Chapter I

Entry and Spatial Competition of Intermediaries: Evidence from Thailand's Rice Market

1.1 Introduction

How does market power along agricultural value chains mediate the effects of policies on the welfare of farmers? A large proportion of the population in developing countries relies on farming as a source of livelihoods, with agriculture accounting for 60% of employment in low-income countries and 29% in middle-income countries (World Bank, 2021). One of the prominent features of agriculture in developing countries is a large number of small farmers and a small number of intermediaries,[1] suggesting the possible existence of market power along the value chain. This is particularly true for many staple crops that need to be processed before they become edible, such as rice and wheat. The fixed cost and economies of scale arising from the intermediate processing activities give rise to large intermediaries; for instance, in the rice market, rice mills emerge. The local market concentration of these large-scale intermediaries contrasts with the fragmented nature of small-scale farmers. Therefore, intermediaries can potentially enjoy significant market power and suppress the prices that farmers receive. Furthermore, these intermediaries make strategic entry and

[1] For example, in Thailand, there are almost 4,000 times as many farmers as there are rice mills.

location choices, which are influenced by the heterogeneous local market sizes and transport costs, leading to heterogeneity in the spatial density of intermediaries across the country. Uneven distribution of intermediaries, in turn, results in variations in the level of local competition of intermediaries and possibly variations in the prices that farmers receive.

Assessing how policies impact farmer income requires understanding both how intermediaries' entry decisions change in response to those policies and how subsequent changes in the spatial density of intermediaries impact prices that farmers receive. For instance, consider an improvement in road infrastructure, which reduces trade costs. For a given spatial density of intermediaries, we would expect lower trade costs to increase the prices that farmers receive. However, the direction of the overall effect of this policy becomes ambiguous once we account for intermediaries' entry responses. On the one hand, because upward pressure on farmer prices means upward pressure on intermediaries' marginal cost, putting downward pressure on their profit margin, intermediaries may respond by exiting the market, leading to lower competition among intermediaries and lower farmer prices. On the other hand, higher farmer prices could incentivize farmers to increase their output. A higher quantity of rice traded means higher total profit for the intermediaries, which encourages more intermediaries to enter, increasing the spatial competition. Therefore, to understand the effects of shocks on the welfare of farmers, it is necessary to take into account both the intermediaries' entry-location decisions and the subsequent impact on their market power.

In this paper, I develop a framework to study the consequences of policies, such as an improvement in road infrastructure, on the welfare of farmers. I approach the question in the context of the rice market in Thailand, focusing on the market power of rice mills and its impact on farmers. I assemble a micro-level dataset on the locations of farmers and rice mills, prices, and rice production. In the first part of the paper, I begin by providing two motivating observations of the entry, exit, and spatial distribution of rice mills. First, I document the heterogeneity in the spatial distribution of rice mills; productive areas tend to have a higher density of mills on average, indicating that mills will only enter if they can achieve a certain level of scale, signifying the existence of economies of scale for rice mills and heterogeneity in the spatial competition among rice mills. Second, I show that there is an active margin of entry and exit of rice mills, which leads to changes in the density of rice mills and their spatial competition.

I then provide reduced-form, causal evidence that spatial competition among rice mills affects farmer prices. Similarly to Macchiavello and Morjaria (2021), I instrument for the local competition among rice mills using the productivity of the farmers in the neighboring area. Conditional on the farmer's own productivity, a farmer surrounded by more productive neighbors is surrounded by a larger number of mills and experiences a higher degree of competition among the mills (first stage). I establish that a one standard deviation increase in local competition results in a 7.7% increase in farmer prices[2] (second stage).

Next, I develop a quantitative structural model grounded in these empirical findings. I adopt a framework that captures both the uneven spatial distribution of rice mills and the effect of spatial competition among intermediaries on farmer prices. In the model, rice farmers grow rice on plots with heterogeneous productivity. Post-harvest, farmers optimally choose mills to sell the rice they have grown. The mills then sell rice to retailers at fixed and exogenous retail prices. Following Chatterjee (2020), I model the spatial market power of rice mills using a Nash bargaining framework, in which spatial market power arises because of the transport cost and

[2] I define farmer price to be the price that farmers receive from a mill. Farmer price is different from farm gate price, which is the farmer price subtracted by the cost of transporting rice from the farm to the mill.

the physical distances between rice mills. The price paid to the farmer is determined through Nash bargaining between the farmer and the rice mill. If the mill and the farmer cannot reach an agreement, the farmer transports and sells rice to another mill. Since transport is subject to trade costs, the threat point of the farmer in the Nash bargaining process is the value they would get if they sell rice to another mill after accounting for the transport cost. Larger distances between mills mean that farmers have lower threat points, resulting in lower equilibrium farmer prices. Therefore, mills situated in areas with a higher mill density have lower market power and pay higher prices to farmers.

Heterogeneity in the spatial distribution of rice mills arises because rice mills make strategic entry and location decisions that are influenced by the heterogeneity in market sizes and remoteness of the locations. To endogenize the entry decisions of mills, I employ a static entry game with incomplete information about the competitors' entry cost as in Seim (2006). While making entry-location decisions, mills face a trade-off between access to farmers and the level of competition. On the one hand, mills want to locate in places with higher quantity of rice in order to make higher profits. On the other hand, mills want to avoid locating close to other mills so that they face lower competition. In equilibrium, areas with higher aggregate rice output, which I term productive areas, can support a higher number of mills, leading to higher mill density. As a result, mills in productive areas face a higher level of local competition, and farmers in productive areas receive higher prices relative to those in unproductive areas.

Due to the interdependencies in the mills' decisions, solving the static entry game for an exact equilibrium is a computationally intractable problem. A mill's profit in a location depends on both the number of mills in that location and the number of mills in other locations. Therefore, while making an entry-location decision, mills have to consider all the potential location choices of all other potential entrants.

Since there are multiple locations and multiple potential entrants, the space of mills' actions becomes too large to be computationally feasible even when the number of locations and the number of potential entrants are not too large. To address this dimensionality challenge, I obtain an approximation of an equilibrium of the static entry game using the method proposed by Aguirregabiria and Vicentini (2016). In particular, I assume that the location-specific variable profit function is a second order polynomial in the number of entrants in each location. For a game with 180 locations and 2,000 potential entrants in this paper, this approach reduces the dimensionality down from over 2×10^{268} to under 7×10^{4}.

I quantify the model using micro-level data on locations of mills and farmers, prices, and rice production. I solve the model sequentially and estimate parameters in the Nash-bargaining problem and the entry game separately using a two-step procedure. In the Nash bargaining problem, the structural relationship between farmer prices, density of rice mills, and retail prices depends on the bargaining power of farmers and the transport costs. To estimate parameters governing this relationship, I first take the number and the locations of rice mills in the data as given, which pins down the distances between the rice mills. With the observed mill density in the data, I estimate parameters that determine farmer prices in the Nash bargaining problem using simulated method of moments. Specifically, I match coefficients of an auxiliary regression of farmer prices on the distance to the mill, the retail price, and the maximum alternative price within a 100 kilometer radius, as well as the parameters of the distribution of farmer prices in the data. With these estimated parameters in the Nash-bargaining problem, I then estimate the parameters in the entry problem to match the spatial distribution of rice mills observed in the data. Because the mill distribution is an equilibrium object in the entry game, I estimate the parameters using the nested fixed point maximum likelihood algorithm. Specifically, for a given set of parameters in the entry problem, I solve for a fixed point in the entry game and nest the fixed-point algorithm into the maximum likelihood routine.

I then use the estimated model to conduct two counterfactual experiments, which highlight how the intermediaries' entry decisions and their subsequent market power impact farmers' income. First, motivated by the strategic plan of the Department of Highways of Thailand for investment in road infrastructure, I simulate a country-wide reduction in trade costs. Second, motivated by ongoing projects in Thailand that promote new farming practices, I study how intermediaries impact farmers' decisions to adopt new technology. For each counterfactual scenario, I conduct two exercises. In the first exercise, I examine the effect on farmers' income while holding the number of mills in each location the same as the baseline scenario. Then, I study the change in farmers' income after allowing mills to change their entry-location decisions.

In the first counterfactual scenario, based on the Department of Highways' 2017 strategic plan, I simulate a 9.09% country-wide reduction in the iceberg trade costs. I find that the intermediaries' strategic entry decisions and spatial market power have substantial distributional consequences. While aggregate farmer income increases by 16.75%, the percentage increase in income of the top decile farmers is on average 25% larger than the percentage increase in income of the bottom decile. Productive locations attract a larger number of intermediaries, leading to lower market power of intermediaries. Therefore, a larger portion of the gains is passed from intermediaries to farmers in productive areas relative to farmers in unproductive areas.

Furthermore, changes in mills' entry-location decisions in response to the policy are regressive. A reduction in trade costs can affect mills' entry decisions in several ways. First, lower trade costs reduce the costs of accessing nearby mills and increase the threat points for farmers in the Nash bargaining, which force intermediaries to offer higher prices, reducing their per-unit profit. Second, lower trade costs increase the quantity of rice that farmers produce and trade to mills, increasing the total profit of rice mills. In unproductive locations, the increase in farmers' outputs is not sufficient to offset the effect of lower profit margin, leading to a net decline in profit. In contrast, in productive locations, the additional profit brought about by higher output exceeds the loss from a lower profit margin. Therefore, productive locations become relatively more attractive; the number of mills rises in productive locations and falls in unproductive locations. Consequently, the percentage increase in farmer prices in productive areas becomes larger than what would have been if there had been no entry response of intermediaries and vice versa. As a result, farmers in productive areas enjoy a larger percentage increase in income relative to unproductive farmers. Ignoring the entry response of intermediaries leads us to underestimate the gap between the percentage increase in income of the top decile and the bottom decile farmers by 53%.

In the second counterfactual analysis, I consider how intermediaries' entry decisions and spatial market power impact farmers' adoption of new technology. Based on an ongoing project in Thailand, I model farmers' decisions of whether to adopt a new agricultural technology that will increase their productivity by 30% with an upfront investment cost. I illustrate the existence of multiple equilibria, one of which results in a level of investment that is lower than socially optimal. Multiple equilibria arise because farmers' return to investment depends on the prices they receive, which in turn depends on the market power of the intermediaries. Because farmers are small relative to the rice market, they cannot individually directly influence the spatial distribution of rice mills. Likewise, farmers do not internalize how their individual investment decisions could collectively lead to a higher number of mills, which would increase farmer prices and return to investment. I demonstrate that if farmers believe that no other farmers will invest in the new technology, their estimated return will be sufficiently low that they believe it is not worthwhile to invest. On the other hand, if farmers collectively invest in the new technology, more intermediaries enter, driving up the return such that it would be worthwhile for 62% of the eligible farmers to invest. Because farmers do not internalize the strategic complementarity between their investment decisions and the intermediaries' entry decisions, farmers can end up in an equilibrium with a lower than socially optimal level of investment. Thus, subsidies for technology adoption could be welfare improving.

This paper contributes to the existing literature in several dimensions. The first is a growing body of work that examines the market power of intermediaries in agriculture. Tomar (2016) and Chatterjee (2020) estimate sizable welfare gains for the farmer as a result of policy reforms that reduce the market power of intermediaries. Nevertheless, experimental evidence on intermediary market structure shows mixed results; while results in Casaburi and Reed (2021) suggest a competitive intermediary sector, Bergquist and Dinerstein (2020) estimate significant market power of intermediaries. The majority of the existing literature focuses on measuring the market power among intermediaries within a particular marketplace without accounting for the spatial locations of the marketplace. While Chatterjee (2020) measures the competitiveness across marketplaces, in his paper, the locations of intermediaries are exogenously determined by the government and fixed across time. This paper contributes to the literature in two ways. Empirically, I provide reduced-form, causal evidence from the universe of intermediaries in a market with active entry and exit, showing that the interaction of economic geography and spatial competition among intermediaries result in variations in the local market power of intermediaries. When it comes to theory, instead of taking the intermediaries' locations as exogenously given, this paper endogenizes intermediaries' entry and location decisions. As I illustrate in my motivating observations, entry decisions of intermediaries could potentially be important as intermediaries are spatially unevenly distributed. Modeling the entry-location decisions allows me to examine how the extensive margin of intermediaries changes in response to external shocks and their distributional implications on farmers' income.

This paper also contributes to a growing literature in international trade that analyzes interdependencies in firm-level decisions. While many papers have studied the interdependencies in firm's entry decisions arising from granularity of firms (Eaton et al., 2012; Gaubert and Itskhoki, 2021; Gaubert et al., 2021), existing work limits the interactions across firms to be *within* a market. In such a case, a firm's decision to enter a market can be analyzed separately for each market by assuming sequential entry. Since there are no interdependencies in firms' decisions across markets, the problem remains computationally feasible. The other strand of spatial and trade literature has considered the interdependencies in sourcing decisions across suppliers *within* a firm. By focusing on interactions within a firm, Antras et al. (2017) are able to limit their analysis to instances where importing decision of a firm exhibits strategic complementarities across suppliers, which means that the addition of a supplier to a firm's sourcing strategy increases the marginal gain from adding another supplier. The complementarities in sourcing decisions of a firm allow the problem to be solved using an algorithm developed by Jia (2008). However, the approach cannot be extended to instances where firms' decisions are strategic substitutes. Hoang (2020) estimates the fixed costs and sunk costs of sourcing inputs using moment inequalities, which can be applied both when firms' decisions are strategic complements and strategic substitutes, but does not conduct any counterfactual analysis. This paper studies the location decisions of the rice mills, taking into account the strategic interactions both *across* mills and *across* locations. Interdependencies across locations mean that I cannot analyze the mills' entry decisions separately by locations. Likewise, interdependencies across mills mean that intermediaries' entry strategies are strategic substitutes. I overcome the combinatorial challenge in mills' entry decisions by adopting the approach proposed by Aguirregabiria and Vicentini (2016).

Additionally, this paper contributes to the literature that analyzes the distribution of gains from increased integration under variable markups. The majority of the existing literature focuses on the variable markups brought about by the producers

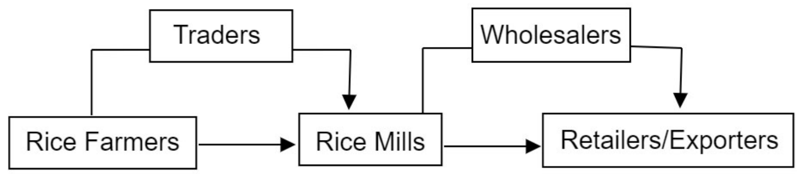
(Badinger, 2007; Edmond et al., 2015; Feenstra and Weinstein, 2017; Melitz and Ottaviano, 2008). While Chatterjee (2020) estimates gains from increased integration arising from changes in the spatial market power of intermediaries, the setting of the paper is in India, where locations of intermediaries are exogenously constrained by state licensing and where there are no entry responses of intermediaries. A novelty in this paper is that I examine how the strategic entry-location decisions and spatial variations in monopsony power of intermediaries impact the distribution of gains from increased integration. I show that if there is sufficiently large heterogeneity in underlying geographical features across space, strategic entry decisions of intermediaries will result in the varying spatial market power of intermediaries across space, leading to a regressive distribution of gains from increased integration.

The rest of the paper proceeds as follows. Section 1.2 describes the structure of the rice market in Thailand and the data sources. Section 1.3 presents motivating observations about the rice mills in Thailand and reduced-form evidence of the spatial market power of intermediaries that motivate my choice of model. In section 1.4, I develop a quantitative spatial model informed by the empirical findings. Section 1.5 describes how I recover structural parameters using the two-step estimation strategy. Section 1.6 presents findings from the two counterfactuals based on policies in Thailand. Section 1.7 concludes.

1.2 Background and Data

Rice is a staple crop in Thailand; 46% of the cropland in Thailand is devoted to rice production (Office of Agricultural Economics, 2019). Figure 1.1 shows the structure of the rice market in Thailand. Within the rice value chain, rice mills are the key players in the midstream-level activities. In this paper, I focus on the relationship between the farmers and the rice mills. The term intermediaries in this paper refers to rice mills. In Thailand, there are very few regulatory barriers that prevent businesses from entering the rice market. Therefore, rice mills are free to make their entry and location decisions based on the profitability and the entry cost.

Figure 1.1: Rice Market Structure



Examining how entry decisions of rice mills affect their spatial market power and the farmers requires micro-level geospatial data on the rice mills and farmers. Since there is no publicly available dataset, I assembled a micro-level dataset on the farmers, the rice mills, the general cropping patterns, and rice prices between 2008-2018 from various sources. I outline below the primary datasets that I use.

Rice Mills: Data on rice mills consists of the annual balance sheets of all firms registered with Thailand Standard Industrial Classification (TSIC) code for "rice milling" that are submitted to the Department of Business Development, Ministry of Commerce. This is an unbalanced panel from 2007-2019. I identify the locations of the mills from their registered addresses using Google Maps API.

Farmers: Farmer-level data on prices that farmers received, the input usage, and the quantity of rice sold are taken from the socio-economic and labor survey on agricultural households between 2008-2018. The survey was conducted annually by the Office of Agricultural Economics. I identify the locations of the farmers at the sub-district level.[3] The latitudes and the longitudes of the sub-districts are obtained from the Department of Provincial Administration and supplemented by Google Maps API.

[3]The administrative levels in Thailand are provinces, districts, and sub-districts. There are 77 provinces, 928 districts, and 7,435 sub-districts (Department of Environmental Quality Promotion, n.d.).

Rice Production and Yields: Data on rice production and yields come from the Office of Agricultural Economics. I have data on the monthly quantity of rice harvested at the province level between 2008-2018. Additionally, I have the annual quantity of rice at the district level between 2012-2018. I supplement this dataset with data from the 2003 and 2013 Agricultural Census and the 2008 and 2018 Agriculture Intercensal Survey provided by the National Statistical Office.

Retail Prices: I obtain data on retail prices from the Bureau of Trade and Economic Indices, Ministry of Commerce. Retail prices are collected on a monthly frequency and are available at the province level.

In addition, I supplement my dataset with high-spatial-resolution data. I obtain data on crop-suitability-index from the Global Agro-Ecological Zone (GAEZ) v.3 and data on area equipped with irrigation from AQUAMAPS. I further utilize the terrain ruggedness measure developed by Nunn and Puga (2012). Lastly, I obtain data on the population density from the Gridded Population of the World (GPWv4) provided by NASA Socioeconomic Data and Applications Center (SEDAC).

1.3 Characteristics of Thailand's Rice Market

In this section, I present key characteristics of rice mills and farmer prices in Thailand that motivate my choice of model. First, I provide two motivating observations about the endogenous entry and location decisions of the rice mills. I show that 1) there is a positive correlation between spatial density of mills and quantity of rice grown in the area, implying heterogeneity in the level of local competition among rice mills and the existence of economies of scale for rice mills, and 2) there is an active margin of entry and exit of rice mills. Having done so, I provide reduced-form, causal evidence that spatial competition among rice mills impacts farmer prices.

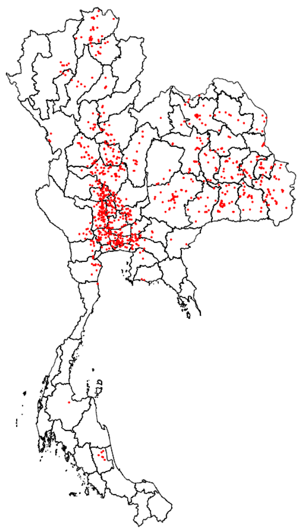
1.3.1 Entry, Exit, and Spatial Density of Rice Mills

I first present two observations about the rice mills in Thailand that motivate me to endogenize entry decisions of rice mills. First, there is an uneven spatial distribution of rice mills across the country. Figure 1.2(a) displays the locations of rice mills in 2018, while Figure 1.2(b) shows the quantity of rice harvested in each province in 2018. We can see a large number of mills concentrated in the central region and the northeastern region. In particular, Figure 1.2(c) shows a positive correlation between the density of rice mills and the quantity of rice grown, which is indicative of the existence of fixed costs and economies of scale. Although there is no regulatory barrier for rice mills to enter the rice market in Thailand, the presence of fixed costs means that mills would only enter if they can achieve a certain level of sales. Therefore, areas with more productive farmers will experience higher mill densities. Higher spatial density of rice mills in productive areas suggests that mills in productive areas face a higher level of spatial competition relative to those in unproductive areas. Therefore, the observed distribution of rice mills along with its positive correlation with the quantity of rice output are important features that the model should reflect.

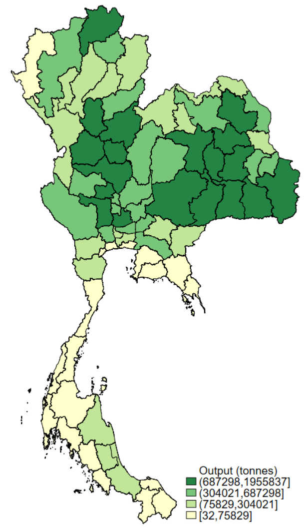
Second, there is an active margin of entry and exit of rice mills. Table 1.1 reports the summary statistics of the rice mills between 2007-2019. While there are on average about 1,011 mills operating each year, the margin of entry and exit fluctuates across the years; the net entry rate varies from -4.7% to 4.7%, resulting in the number of mills across the sample period that ranges between 944 and 1,084. Entry and exit of rice mills mean changes in spatial density of mills, impacting the rice mills' level of spatial competition and market power. Furthermore, there is heterogeneity in the entry and exit of rice mills across the provinces. Figure 1.3 displays variations in the average net entry rate of each province between 2008-2019, indicating heterogeneity in changes in spatial density of rice mills across the country. Given that changes in

Figure 1.2: Spatial Distribution of Rice Mills

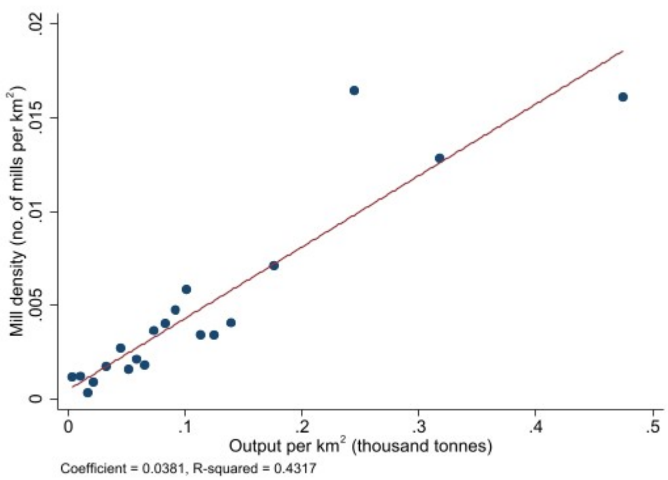
(a) Locations of Mills in 2018



(b) Output in 2018



(c) Binned Scatter Plot of Mill Density and Average Output per km^2 in Each Province



Notes: Panel (a) plots the locations of rice mills in 2018. Panel (b) shows the quantity of rice produced per province in 2018. Panel (c) shows a binned scatter plot of the average number of mills per km^2 in each province against the average output per km^2 (thousand tonnes) in each province between 2008-2018.

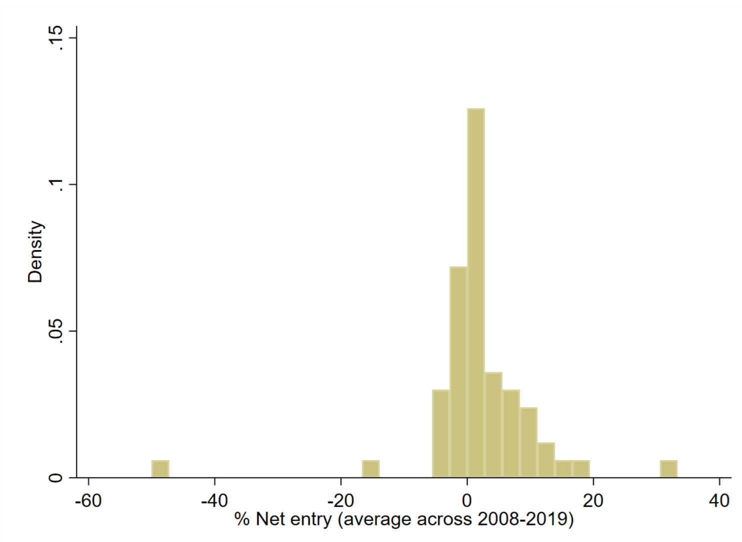
spatial density of mills may impact farmer prices, entry and exit form an important margin that the model needs to capture.

Table 1.1: Summary Statistics of Rice Mills

	Mean	Std. Dev.	Min	Max
No. of mills	1,010.85	45.14	944.00	1,084.00
% entering	8.23	2.33	5.65	13.24
% exiting	8.34	1.41	6.86	10.95
% net entry	-0.06	2.90	-4.65	4.72

Notes: This table reports the average of the total number of mills, entry rate, exit rate and net entry rate in Thailand between 2007-2019.

Figure 1.3: Histogram of Average % Net Entry in Each Province



Notes: Net entry rate of mills in each province, averaged across 2008-2019.

1.3.2 Spatial Competition and Farmer Price

Having shown that there are variations in the spatial distribution of rice mills across Thailand, I now provide reduced-form evidence that a higher density of rice mills results in higher prices that farmers receive. In a market with imperfect competition among rice mills, higher mill density means a higher level of local competition, which reduces the mills' market power. Therefore, farmers situated in areas with a higher density of rice mills benefit from higher competition among rice mills.

I first construct a measure that captures the degree of spatial competition among rice mills. I define local competition as the sum of the number of rice mills surrounding a farmer weighted by the inverse of the distances between the farmer and the mills. The local competition among rice mills that farmer f experiences is the sum of all the mills within 100 km radius from the farmer, where the weights are inverse to the distance between the farmer and the mills. Specifically,

$$COMP_{ft} = \sum_{m \in \mathcal{M}_{100\text{km},t}} \left\{ \frac{1}{distance_{fm}} \right\}, \tag{1.1}$$

where $\mathcal{M}_{100\text{km},t}$ is the set of all the mills situated within 100 km radius around farmer f at time t and $distance_{fm}$ is the geodesic distance between farmer f and mill m. A farmer situated close to a large number of rice mills will exhibit a higher competition measure. This measure is similar to the competition measure in Chatterjee (2020) and the market access measure in Donaldson and Hornbeck (2016).[4] As a robustness check, I also use an alternative measure of competition, defining local competition as simply the number of mills within a 100 km radius from the farmer.

Having constructed the competition measure, I can show the relationship between

[4]Chatterjee (2020) creates a competition measure for a marketplace as the weighted sum of other marketplaces within the same state since the Agriculture Produce and Marketing Committee Acts of Indian states prohibit farmers from selling their output to government-regulated marketplaces outside of their own state. There is no regulatory restriction on whom the farmers could sell the rice to in Thailand, though in practice, farmers generally sell rice to nearby mills. Therefore, I use 100 km as a cutoff for the competition measure. As robustness checks, I conduct the same analysis using an analogous competition measure with different distance cutoffs. Results can be found in Appendix A.1.1.

local competition and farmer prices using the following reduced-form specification:

$$p^f_{frct} = \beta_0 + \beta_1 COMP_{ft} + \beta_2' Z_{ft} + \gamma_r + \gamma_c + \gamma_t + \varepsilon_{frct} \; , \tag{1.2}$$

where p^f_{frct} is the log of price that farmer f in region r receives for crop type c at time t. Z_{ft} denotes other control variables. γ_r and γ_c controls for the region and crop-type[5] fixed effects, and γ_t controls for the time fixed effects. To allow spatial correlation, I adjust the standard errors as in Conley (1999).

Table 1.2 reports the results from the OLS regressions.[6] Column 1 reports the results when I only control for the fixed effects, namely the year fixed effects, the fixed effects for the month in which the farmers sell the majority of their crops, the region fixed effects, and the crop-type fixed effects. There is a positive and significant relationship between local competition and farmer prices; a one standard deviation increase in competition among rice mills corresponds to a 1.4% increase in price that farmers receive. To account for other factors that may influence farmer prices, I add in four more control variables. Since the local supply of rice could affect local price, I control for the quantity of rice that the farmer sells and the quantity of rice harvested in the province. I also control for land suitability for growing rice using the crop-suitability-index from the FAO GAEZ dataset. Likewise, I control for the distance between the farmer and Bangkok, which is the capital of Thailand and close to the largest port in Thailand. The results after controlling for other variables are shown in column 2. After controlling for other factors, a one standard deviation increase in local competition corresponds to a 2.3 % increase in farmer prices.

As robustness checks, I run the same regression using an alternative measure of local competition. Instead of using the measure constructed using equation (1.1), I use

[5] The crop types I am able to observe in the data are in-season white rice, out-of-season white rice, in-season sticky rice, and out-of-season sticky rice.

[6] The surveys in 2016-2018 do not contain data on the month in which farmers sell the majority of their rice. Therefore, I only use farmer prices in 2008-2015 in my regressions.

Table 1.2: OLS Results

	log(farmer price)			
	(1)	(2)	(3)	(4)
COMP (std)	0.014**	0.023***		
	(0.006)	(0.008)		
No. of mills (std)			0.036**	0.036**
			(0.014)	(0.015)
log(crop sold)		-0.006	-0.006	-0.006
		(0.005)	(0.005)	(0.005)
log(province-level output)		-0.012	-0.013	-0.012
		(0.008)	(0.008)	(0.008)
Crop-suitability-index		0.010*	0.008	0.009
		(0.006)	(0.006)	(0.006)
log(distance to BKK)		0.024	0.040*	0.040*
		(0.017)	(0.023)	(0.023)
log(distance to nearest mill)				0.003
				(0.003)
Year FE	Yes	Yes	Yes	Yes
Month-of-highest-sales FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Crop-type FE	Yes	Yes	Yes	Yes
N	54,323	54,252	54,252	54,252
R^2	0.509	0.511	0.512	0.512

Notes: This table reports the OLS estimates of equation (1.2). COMP (std) is the standardized competition measure constructed using equation (1.1). No. of mills (std) is the standardized number of mills within 100 km from the farmer. All regressions use data from 2008 to 2015. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwith of 1.5 degrees using Bartlett kernel. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

the number of rice mills within a 100 km radius from the farmer. Column 3 of Table 1.2 reports results when I use an alternative measure of competition. Column 3 shows that the positive and significant relationship between competition and farmer prices is not sensitive to the competition measure I use. I perform additional robustness checks using the average farmer prices betweeen 2016-2018 as an additional control variable and using alternative competition measures with different cutoffs. The results can be found in Appendix A.1.1.

Finally, one may be concerned that the higher prices received by farmers with higher competition measures may arise from lower transport costs for farmers situated closer to rice mills rather than from the higher local competition among the mills. Column 4 addresses this by controlling for the distance between the farmer and the nearest mill. The results indicate that this concern is unfounded. First, the coefficient of interest is not affected by the inclusion of the additional control variable. Second, after controlling for the number of mills within 100km from the farmer, the distance between the farmer and the nearest mill does not have a significant effect on the farmer prices.

Overall, the results from the OLS regressions indicate a positive and significant relationship between local competition among rice mills and farmer prices. Farmers who are located in areas with a higher spatial density of rice mills tend to receive higher prices on average.

However, despite controlling for observable characteristics, there could still be concerns over other unobserved heterogeneity. Ex-ante, it is unclear how the bias would affect the coefficient of interest. For example, the direction of the bias from the quality of rice could be positive or negative. On the one hand, areas that are more suited for growing rice may produce higher quality rice and receive higher prices, leading to an upward bias. On the other hand, areas suitable for growing rice may choose to grow varieties of rice that give higher yield at the cost of lower quality and receive lower prices, leading to a downward bias. Given this, I turn to an instrumental variable strategy to establish a causal relationship between local competition among rice mills and farmer prices.

Taking advantage of the fact that farmers are small, I instrument for local competition among rice mills using the neighboring farmers' productivity. The intuition behind the instrument can be explained as follows. Mills' entry decisions depend on the profitability of the location. The total profit of any given mill depends on the quantity of rice that the mill sells, which is dictated by the quantity of rice that the mill can buy from the farmers. As a result, areas that produce a higher quantity of rice attract a larger number of rice mills, leading to a higher density of mills and higher competition. Since an area comprises a large number of farmers, the overall quantity of rice produced in an area depends on the aggregate productivity of farmers in that area. Therefore, the local competition among rice mills that farmer f experiences depends not only on farmer f's own productivity, but also on the productivity of the neighboring farmers. In other words, two farmers who have the same productivity may face different levels of local competition among the mills if the productivity of their neighbors is different.

Given this intuition, conditional on farmer f's own productivity, competition among rice mills can be instrumented using the productivity of the neighboring farmers. To further illustrate this, consider Figure 1.4. The center of the circle is the location of farmer f. Farmer f's own productivity is the productivity of the land within 50 km from the farmer, represented by the inner yellow circle. The neighboring farmers' productivity is the productivity of the land between 50 km and 100 km from the farmer, represented by the outer orange ring.[7] I employ the productivity in the outer ring as the instrument competition, controlling for the productivity in the inner circle. My instrument is similar to the instrument used by Macchiavello and Morjaria (2021). The first stage is given by:

$$COMP_{frct} = \alpha_0 + \underbrace{\alpha_1 A_f^{50-100}}_{Instrument} + \underbrace{\alpha_2 A_f^{0-50}}_{Control} + \alpha_3' Z_{ft} + \gamma_r + \gamma_c + \gamma_t + \mu_{ft}, \tag{1.3}$$

where A_f^{50-100} is the productivity of neighboring area that lies between 50 km and 100 km from the farmer, and A_f^{0-50} is the productivity of the land within 50 km from the farmer, which is used as a control for farmer f's own productivity. The predicted

[7]For alternative distance cutoff for the farmer's own productivity and the neighboring area's productivity, see Appendix A.1.2.

competition measure is then used in the second stage:

$$p^f_{frct} = \beta_0 + \beta_1 \widehat{COMP}_{frct} + \underbrace{\beta_2 A_f^{0-50}}_{Control} + \beta_3' Z_{ft} + \gamma_r + \gamma_c + \gamma_t + \varepsilon_{frct}. \tag{1.4}$$

The exclusion restriction is that, conditional on farmer f's own productivity and other controls included in the regression, the instrument only affects farmer prices through competition among the rice mills.[8] In the regressions, I proxy for the productivity using FAO crop-suitability-index and the area equipped for irrigation.[9]

Table 1.3 reports the 2SLS estimates. Columns 1 and 2 report the results using the competition measure constructed using equation (1.1). Column 1 shows that the instruments strongly correlate with competition, with an F-stat of 24.5. Column 2 reports results from the second stage. A one standard deviation increase in local competition measure increases the farmer prices by 7.7 %. The IV estimate (0.074) is about three times as large as the OLS estimate (0.023) in Column 2 of Table 1.2. The downward bias in the OLS estimate can be explained by the measurement error or the unobserved heterogeneity as outlined earlier. Columns 3 and 4 show

[8] This exclusion restriction would be violated if the productivity of the neighboring area correlates with other factors, such as distance to local roads, that correlate with farmer prices. Appendix A.1 conducts additional robustness checks by controlling for terrain ruggedness and performing falsification exercises to show that the concern is unfounded.

[9] Specifically, I run the following first-stage:

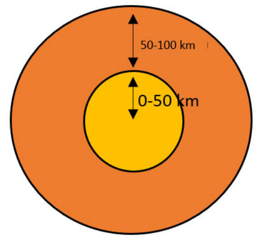
$$\begin{aligned} COMP_{frct} = &\alpha_0 + \underbrace{\alpha_1 Suit_f^{50-100} + \alpha_2 Suit_f^{50-100} \times Irri_f^{50-100} + \alpha_3 Irri_f^{50-100}}_{\text{Neighbors' productivity (instrument)}} \\ &+ \underbrace{\alpha_4 Suit_f^{0-50} + \alpha_5 Suit_f^{0-50} \times Irri_f^{0-50} + \alpha_6 Irri_f^{0-50}}_{\text{Own productivity (controls)}} \\ &+ \alpha_7' Z_{frct} + \gamma_r + \gamma_c + \gamma_t + \mu_{frct} \ , \end{aligned}$$

and the second stage:

$$\begin{aligned} p^f_{frct} = &\beta_0 + \beta_1 \widehat{COMP}_{frct} + \alpha_4 Suit_f^{0-50} + \alpha_5 Suit_f^{0-50} \times Irri_f^{0-50} + \alpha_6 Irri_f^{0-50} \\ &+ \beta_3' Z_{ft} + \gamma_r + \gamma_c + \gamma_t + \varepsilon_{frct} \ . \end{aligned}$$

where $Suit_f^{50-100}$ and $Irri_f^{50-100}$ represent the crop-suitability-index and the area equipped for irrigation of the land between 50 km and 100 km from the farmer. Similarly, $Suit_f^{0-50}$ and $Irri_f^{0-50}$ represent the crop-suitability-index and the area equipped for irrigation within 50km from the farmer.

Figure 1.4: Instrument for Local Competition



Notes: This figure illustrates the instrument for local competition among rice mills. The orange outer ring represents the productivity of the neighboring farmers, specifically the productivity of the farmers situated between 50 to 100 km from the farmer. This is used as an instrument for local competition. The inner yellow circle represents the farmer's own productivity, which is used as a control variable.

that the results are robust to an alternative measure of competition. A one standard deviation increase in the number of mills within 100 km from the farmer leads to a 7.1 % increase in farmer prices. Further robustness checks can be found in Appendix A.1. I check for sensitivity of the instrument to different distance cutoffs, control for terrain ruggedness, and conduct falsification exercises. Overall, my results are robust to different specifications and alternative measures.

To summarize, this section provides empirical evidence of the spatial competition among rice mills. First, I show that there are variations in the spatial density of rice mills across Thailand and that the density of rice mills positively correlates with the quantity of rice harvested in the area. Second, I show that there is an active margin of entry and exit of rice mills, which impact the density of rice mills. Having done so, I provide reduced-form, causal evidence that local competition among rice mills, which is driven by the mills' spatial density, has significant effects on the farmer prices.

Table 1.3: IV Results

	COMP (std)	log(price)	No. of mills (std)	log(price)
COMP (std)		0.074***		
		(0.020)		
No. of mills (std)				0.069***
				(0.027)
$Suit^{50-100}$ (std)	0.308***		0.205***	
	(0.043)		(0.060)	
$Suit^{50-100} \times Irri^{50-100}$ (std)	0.183***		0.073**	
	(0.038)		(0.037)	
$Irri^{50-100}$ (std)	0.232***		0.413***	
	(0.062)		(0.150)	
$Suit^{0-50}$ (std)	0.070	0.013	0.113***	0.012
	(0.064)	(0.008)	(0.039)	(0.010)
$Suit^{0-50} \times Irri^{0-50}$ (std)	0.067	0.007	0.073**	0.008
	(0.051)	(0.009)	(0.035)	(0.010)
$Irri^{0-50}$ (std)	0.405***	-0.048***	0.254***	-0.037**
	(0.124)	(0.015)	(0.064)	(0.015)
First-stage F-stats	24.514		38.837	
Hansen's p-value		0.870		0.222

Notes: This table reports the IV estimates of equations (1.3) and (1.4). COMP (std) is the standardized competition measure constructed using equation (1.1). No. of mills (std) is the standardized number of mills within 100 km from the farmer. All regressions include controls for quantity of crop sold, province-level output, distance to Bangkok, and fixed effects for year, month-of-highest-sales, region, and crop-type. All regressions use data from 2008 to 2015. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 1.5 degrees using Bartlett kernel. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1.4 Model

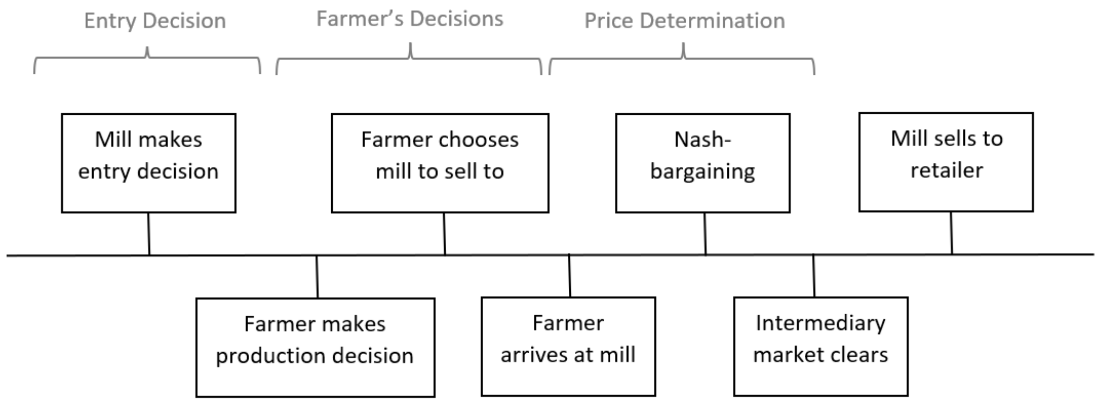
I now develop a spatial model of trade that captures the empirical findings in the previous section. In the model, the market power of rice mills is captured through a Nash bargaining framework. The density of mills matters for farmer prices because it affects the farmer's threat point in the Nash bargaining process. Variations in the density of rice mills arise because mills make strategic entry and location decisions, which I model using a static entry game with incomplete information.

1.4.1 Setup

The economy consists of two types of agents, the farmers and the mills, who are distributed across the Euclidean space $\mathbb{R}^2$. There are F plots of land at different geographical locations. Each plot of land, f, is owned by a representative farmer. I index the farmer by their plot of land. There are M potential entrants of rice mills. Let $\mathcal{M}$ be a set of mills that are operating. Each mill m is identified by the coordinates of their geographical location. Geography matters since the transportation of rice across space is subject to iceberg trade costs. $\tau_{ij} \geq 1$ units of rice must be shipped in order for one unit of rice from i to arrive at j. I assume that trade costs are symmetric (i.e. $\tau_{ij} = \tau_{ji}$) and that triangular inequality holds (i.e. $\tau_{ij} \leq \tau_{ik} \times \tau_{kj}$).

The timing of events is outlined in Figure 1.5. First, the mills make their entry and location decisions. The farmers then choose the quantity of rice to grow. After the rice has been harvested, the farmers choose which mill to sell their rice to. Once the farmers have arrived at the mill, the farmer prices are determined through Nash-bargaining. After the intermediary markets clear, the mills then sell the rice to the retailers.

Figure 1.5: Timing of Events



1.4.1.1 Farmers

Farmer produces rice according to the production function:

$$y_f = A_f \overline{H}_f^{\gamma} \overline{L}_f^{\alpha} X_f^{\beta} \ , \tag{1.5}$$

where A_f is the total factor productivity of the land owned by farmer f, H_f is the amount of land, L_f is the quantity of labor, and X_f is the quantity of intermediate inputs. I assume that the production function has constant returns to scale, so $\alpha + \beta + \gamma = 1$. The amount of land and labor available to the farmer is fixed. I assume that the farmers are price takers in the intermediate input and the labor markets. Farmers optimally choose the quantity of input to maximize their income, producing the profit maximizing output y_f^*.

After the production has taken place, the farmer chooses mill m to sell their crop to in order to maximize their income. Since transporting rice from location f to m is subject to iceberg trade cost τ_{fm}, their maximization problem is given by:

$$\max_{m \in \{\mathcal{M}\}} \frac{p_m^f y_f^*}{\tau_{fm}} \ , \tag{1.6}$$

where p_m^f is the farmer price at mill m, and y_f^* is the profit-maximizing output.

1.4.1.2 Mills

Mills are price takers in the retail sector. Mill m buys a unit of rice from the farmer at a price p_m^f and sells it to the retailer at an exogenously given retail price p_m^r. Mills can have different retail prices, depending on their locations. I assume that there is no marginal cost; therefore, the per-unit profit for the mill from trading rice is $p_m^r - p_m^f$.

1.4.1.3 Price Determination

Price in the intermediary markets is determined by Nash bargaining as in Chatterjee (2020). Once farmer f has arrived at mill m, the initial transport cost from f to the m is sunk. The farmer could either sell their rice to mill m and receive p_m^f per unit of rice, or travel to another mill k and receive $\frac{p_k^f}{\tau_{mk}}$ since it is costly to transport crop from m to k. Therefore, for a farmer who has already arrived at mill m, the outside option is:

$$\underline{p}_m = \max_{k \in \mathcal{M} - \{m\}} \left\{ \frac{p_k^f}{\tau_{mk}} \right\} , \tag{1.7}$$

which is the highest value that farmers could get if they travel to another mill and sell their crop there. Farmer's outside option forms their threat point in the Nash bargaining problem. The outside option of the mill is 0.

The farmer price is determined by the Nash bargaining solution, which solves the following maximization problem:

$$\max_{p_m^f} \quad (p_m^f - \underline{p}_m)^{\delta} (p_m^r - p_m^f)^{1-\delta} , \tag{1.8}$$

where δ is the bargaining power of the farmer. The left-hand side bracket is the difference between the farmer price and the farmer's threat point. The right-hand side bracket is the per-unit profit that rice mills receive from this transaction. Solving the Nash bargaining problem provides an expression for the farmer price at each mill in terms of the threat point and the retail price:

$$p_m^f = (1-\delta)\underline{p}_m + \delta p_m^r \ . \tag{1.9}$$

We have one such equation for all $m \in \mathcal{M}$. The threat point $\underline{p}_m$ is a function of the farmer prices at all other locations, as defined by (1.7). Therefore, the equilibrium is a Nash-in-Nash solution, consisting of a vector of farmer prices that solves the fixed-point mapping (1.9). The fixed-point problem (1.9) is a contraction mapping and therefore has a unique solution.[10] Note that all farmers arriving at mill m have the same outside option $\underline{p}_m$. Therefore, all the farmers arriving at the same mill receive the same price. In other words, there is only one farmer price at each mill.

1.4.1.4 Entry Decision

Following the framework in Seim (2006), I model the entry and location decisions of rice mills as a static game of incomplete information. There are M potential entrants who simultaneously choose whether to enter and where to locate from a set of L possible locations. Location l is defined as a non-overlapping grid cell containing all points $\Big(x \in [\underline{x}_l, \overline{x}_l], y \in [\underline{y}_l, \overline{y}_l]\Big)$. Each mill can only choose to operate in one location in any given period. Upon entering location l, mill m randomly draws $x_m \sim U(\underline{x}_l, \overline{x}_l)$, $y_m \sim U(\underline{y}_l, \overline{y}_l)$. Intuitively, if one think of L as a set of possible districts; then, a mill can choose which district they want to locate in, but the exact co-ordinates within a district that they get depends on many exogenous factors such as the availability of land; therefore, each mill has their own unique co-ordinates. All distance calculations in the model use the mills' actual co-ordinates.

The variable profit of mill m in location l is $(p_l^r - p_{ml}^f)Q_{ml}$, where the retail price

[10] See Appendix A.2 for details.

p^r_l is exogenously given, the farmer price p^f_{ml} is determined from the Nash bargaining problem, and Q_{ml} is the quantity of rice that mill m buys from farmers. I assume that all the mills in the same location receive the same retail price. Let the spatial distribution of mills be represented by a vector $N = \{n_1, n_2, ..., n_L\}$, where n_l is the number of mills in location l. Conditional on N, the expected variable profit of a mill located in location l is given by:

$$vp^e_l(N, P^r, A, \overline{H}, \overline{L}) = \mathbb{E}\left[(p^r_l - p^f_{ml})Q_{ml}\right] \ , \tag{1.10}$$

where $P^r = \{p^r_1, p^r_2, ..., p^r_L\}$ is a vector of exogenously given retail price across locations and $A = \{A_1, A_2, ..., A_F\}$ is a vector representing the farmers' productivity, $\overline{H} = \{\overline{H}_1, \overline{H}_2, ..., \overline{H}_F\}$ is a vector representing the farmers' land endowment, and $\overline{L} = \{\overline{L}_1, \overline{L}_2, ..., \overline{L}_F\}$ is a vector representing the farmers' labor endowment. Note that $A, \overline{H}$, and $\overline{L}$ are all exogenous characteristics of the farmers that determine their output; therefore, for ease of notation, I omit $\overline{H}$ and $\overline{L}$ from the subsequent writing of the function vp^e_l.

The total profit is the variable profit minus the entry cost. Mills make location decisions based on total profit in each location. Conditional on N, the expected total profit of mill m in location l is:

$$\pi^e_{ml}(N, P^r, A) = vp^e_l(N, P^r, A) - ec_{ml} \ . \tag{1.11}$$

The cost of entry into location l for mill m is given by:

$$ec_{ml} = EC_l - \varepsilon^{EC}_{ml} \ , \tag{1.12}$$

where EC_l is the location-specific entry cost that is common for all mills and ε^{EC}_{ml} is the mill and location-specific cost that is private information of mill m. Because mills possess private information about their cost of entry, N is unknown ex-ante. Each mill has to form beliefs about their rivals' choices of locations. Since the mills are homogeneous apart from their private information, all mills have the same belief about all their rivals. Let $\overline{\Psi} = \{\overline{\psi}_1, \overline{\psi}_2, ..., \overline{\psi}_L\}$ be the mill's belief about their rivals' location strategy, where $\overline{\psi}_l$ is the probability a rival will choose to enter location l. The expected total profit for a mill located in location l without conditioning on N is:

$$\mathbb{E}_N\left[\pi^e_{ml}(N, P^r, A)\right] = \widetilde{vp}^e_l(\overline{\Psi}, P^r, A) - EC_l + \varepsilon_{ml} \ , \tag{1.13}$$

where $\widetilde{vp}^e_l(\overline{\Psi}, P^r, A) = \mathbb{E}_N\left[vp^e_l(N, P^r, A)\right]$ is the expected variable profit over the distribution of N. Note that since mills never know the realized variable profit vp_l prior to entering, they make all entry decisions based on $vp^e_l(N, P^r, A)$. Therefore, to avoid confusion, I henceforth refer to $vp^e_l(N, P^r, A)$ as the variable profit and $\widetilde{vp}^e_l(\overline{\Psi}, P^r, A)$ as the expected variable profit.

Given its beliefs, $\overline{\Psi}$, a mill chooses the entry-location decision that maximizes its expected profit. The best response of mill m is to locate in location l if:

$$\widetilde{vp}^e_l(\overline{\Psi}, P^r, A) - EC_l + \varepsilon_{ml} \geq \widetilde{vp}^e_{l'}(\overline{\Psi}, P^r, A) - EC_{l'} + \varepsilon_{ml'} \quad \forall l' \neq l \ . \tag{1.14}$$

Following the IO literature on entry of firms (Seim, 2006; Zhu and Singh, 2009; Datta and Sudhir, 2013; Aguirregabiria and Vicentini, 2016), I assume that the private information shocks are independently and identically distributed across mills and locations with type 1 extreme value distribution.[11] The probability that the best response of a mill is to locate in location l can then be expressed as multinomial logit

[11] This assumption is computationally attractive because it provides a closed-form expression for the mill's best response function. However, it comes at a cost since it implies that there is no spatial correlation in the private information.

probabilities:

$$\psi_l(\overline{\Psi}) = \frac{exp\left\{\lambda\left[\widetilde{vp}^e_l(\overline{\Psi}, P^r, A) - EC_l\right]\right\}}{1 + \sum\limits_{l'=1}^{L} exp\left\{\lambda\left[\widetilde{vp}^e_{l'}(\overline{\Psi}, P^r, A) - EC_{l'}\right]\right\}}\ , \tag{1.15}$$

where 1 in the denominator accounts for the option for a mill to not enter the market. λ is the scale parameter the captures the dispersion of the private information shock. The lower the value of λ, the higher the dispersion and the more disconnected the entry decision is to the expected profit.

The equilibrium is a symmetric Bayesian Nash equilibrium in which the mills' beliefs are consistent with other mills' best responses. Given that mills are homogenous apart from their private information shocks, in equilibrium, all mills have the same strategy. This gives us a system of L equations with L unknown that defines a fixed point mapping in the space of vector of entry-location probabilities:

$$\psi^*_l(\Psi^*) = \frac{exp\left\{\lambda\left[\widetilde{vp}^e_l(\Psi^*, P^r, A) - EC_l\right]\right\}}{1 + \sum\limits_{l'=1}^{L} exp\left\{\lambda\left[\widetilde{vp}^e_{l'}(\Psi^*, P^r, A) - EC_{l'}\right]\right\}}\ . \tag{1.16}$$

By Brouwer's fixed point theorem, an equilibrium exists. However, the equilibrium is not necessarily unique. Seim (2006) shows that there is a unique solution if the locations are not too homogeneous and if the degree of competition decreases with distance. This means that in my model, the iceberg trade cost must be sufficiently large. I check ex-post through simulations that the equilibrium appears to be unique.

1.4.2 Equilibrium Definition

Given the parameters α, β, γ, δ, and λ, iceberg trade cost function $\{\tau\}$, endowments $\{A_f, \overline{H}_f, \overline{L}_f\}_{f\in\{1,\ldots,F\}}$, intermediate input price w^X, and a vector of retail prices P^r, location-specific component of entry cost $\{EC_l\}_{l\in\{1,\ldots,L\}}$, and number of potential entrants M, an equilibrium is a set of entry location probabilities $\Psi^* = \{\psi_1^*, ..., \psi_L^*\}$, farmer prices $P^f = \{p_1^f, ..., p_{|\mathcal{M}|}^f\}$, intermediate input choices $\{X_1, ..., X_F\}$, and the mill choice for each farmer $\{\mu_1, ..., \mu_F\}$ such that:

1. Farmers optimally choose the quantity of intermediate input to maximize their incomes:

$$\max_{X_f} \quad \frac{p_{\mu_f}^f}{\tau_{f\mu_f}} A_f \overline{H}_f^{\gamma} \overline{L}_f^{\alpha} X_f^{\beta} - w^X X_f \qquad \forall f \tag{1.17}$$

2. Farmers make an optimal choice on which mill to sell their output:

$$\mu_f = \arg\max_{m \in \mathcal{M}} \frac{p_m^f y_f^*}{\tau_{fm}} \qquad \forall f \tag{1.18}$$

3. Farmer prices across all mills are the Nash-in-Nash equilibrium solution:

$$p_m^f = (1-\delta) \max_{k \in \mathcal{M}-\{m\}} \left\{ \frac{p_k^f}{\tau_{mk}} \right\} + \delta p_m^r \qquad \forall m \in \mathcal{M} \tag{1.19}$$

   which combines equations (1.9) and (1.7) into one equation.

4. Mill's entry-location probabilities, Ψ, across all locations satisfy the symmetric Bayesian Nash equilibrium given by equation (1.16).

1.4.3 Equilibrium Computation

I solve the model backward from the timeline in Figure 1.5. First, conditional on the retail prices and the number of mills at each location, I solve the Nash bargaining problem for the farmer prices as given by equation (1.19). Next, given the farmer price at each mill, I solve each farmer's optimal choice of mill as given by equation (1.18). Subsequently, I know the price that each farmer receives and can solve for each farmer's optimal choice of intermediate input, which gives me the quantity of rice each farmer produces. Finally, given the retail prices, farmer prices, farmers' outputs, and farmers' optimal mill choices, I solve for the mills' expected profit then solve for the Bayesian Nash equilibrium, which determines mills' entry-location decisions. In what follows, I describe how I compute the Bayesian Nash Equilibrium.

1.4.3.1 Bayesian Nash Equilibrium Computation

The Bayesian Nash equilibrium from the mills' entry problem is a solution to the fixed point problem in equation (1.16). Solving this requires knowledge of the expected variable profit, $\widetilde{vp}_l^e(\overline{\Psi}, P^r, A)$. Let $\mathbb{S} = \{N_1, ..., N_{|\mathbb{S}|}\}$ be a set of all possible combinations of the number of mills in each location. In theory, one can calculate the expected variable profit, $\widetilde{vp}_l^e(\overline{\Psi}, P^r, A)$, by computing the variable profit, $vp_l^e(N, P^r, A)$, for each $N_s \in \mathbb{S}$ and calculate the expected variable profit conditional on $\overline{\Psi}$, as $\widetilde{vp}_l^e(\overline{\Psi}, P^r, A) = \mathbb{E}_N\left[vp_l^e(N, P^r, A)\right]$. To do so, one would have to keep track of $|\mathbb{S}| \times L$ variable profits corresponding to each N to compute the expected variable profit. However, it is computationally infeasible to enumerate all possible configurations of N and solve for the corresponding $vp_l^e(N, P^r, A)$. To illustrate the extent of this dimensionality challenge, consider a small entry game with only 10 locations and 100 potential entrants. Even in such a small entry game, we already have $|\mathbb{S}| > 10^{13}$; this means that, in order to compute the exact expected variable profit, one would need to keep track of over $10^{13} \times L$ parameters.[12] Even in such a small entry game, the dimensionality of the space of mills' actions is already too large to be computationally feasible. In the data, I observe an average of 1,011 mills per year. Therefore, the number of potential entrants that I need to consider must be over a thousand,

[12] $|\mathbb{S}|$ is computed as follows. There are 10 locations, and potential entrants can choose not to enter, resulting in 11 options for potential entrants to choose from. Since mills are homogeneous apart from the private information shocks, the ordering does not matter. Therefore, this is equivalent to an unordered sampling with replacement; we are choosing from a set of 11 a hundred times such that repetition is allowed and such that order does not matter. The number of possible spatial configurations of N in this small game is $\binom{110!}{10!100!} > 10^{13}$. More generally, for a game with L locations and M potential entrants, the number of possible realizations of N is $\binom{(L+M)!}{L!M!}$.

posing a much larger dimensionality challenge than in the illustrative example above.

The literature generally approaches this computational issue by approximating the equilibrium. For example, in order to deal with the dimensionality problem in a dynamic entry game, Aguirregabiria and Vicentini (2016) approximate the best response functions of firms using an interpolation function that is second order polynomial in the number of firms and distances between firms. In the same spirit, I compute the approximated Bayesian Nash Equilibrium by approximating the variable profit function. As explained earlier, for a given set of retail prices and productive capacity of the farmer, the only information I need to compute the variable profit is the number of mills in each location. Since P^r and A are exogenously given, I write the expected variable profit conditional on N, $vp_l^e(N, P^r, A)$, from (1.10) as a function of N i.e. $vp_l^e(N, P^r, A) = F_{P^r,A,l}(N)$. For ease of notation, I omit P^r and A from subsequent writing of the variable profit and approximation functions; however, please note that the variable profit and the approximation function are specific to given P^r and A. I approximate the function $F_l(N)$ as a second order polynomial in the number of mills in each location:[13]

$$vp_l^e(N) \approx \beta_l^{(0)} + \sum_{k=1}^{L} \beta_{kl}^{(1)} n_k + \sum_{k=1}^{L} \beta_{kl}^{(2)} n_k^2 + \nu_l \quad \forall l. \tag{1.20}$$

By doing so, I am able to reduce the dimension of the problem from $|\mathbb{S}| \times L$ down to $(2L+1)L$.[14]

I now describe in detail the procedure I use to obtain the approximation function for the variable profit. Let $S = \{N_1, N_2, ..., N_{|S|}\}$ be a subset of $\mathbb{S}$, which is a set of all possible N. Given P^r and A, I compute the simulated variable profit $vp_l^e(N_s, P^r, A)$

[13] This approach is equivalent to assuming that agents are boundedly rational in their perception of the variable profit as has been done in the literature (Krusell and Smith, 1998; Dingel and Tintelnot, 2021).

[14] By approximating the variable profit as a second order polynomial in the number of mills in each location, I am making the following assumptions: 1) the marginal effect of n_k on vp_l^e is $\beta_{kl}^{(1)} + \beta_{kl}^{(2)} n_k$, and 2) the marginal effect of n_k is not affected by n_j, $j \neq k$.

for each $N_s \in S$. This means that I have a simulated dataset consisting of $|S|$ observations. For each $l \in L$, I obtain the approximation function (1.20) by running the following OLS regression on the simulated dataset:

$$vp^e_{ls} = \beta^{(0)}_l + \sum_{k=1}^{L} \beta^{(1)}_{kl} n_{ks} + \sum_{k=1}^{L} \beta^{(2)}_{kl} n^2_{ks} + \nu_{ls} \ . \tag{1.21}$$

Having obtained $\beta^{(0)}_l$, $\{\beta^{(1)}_{1l}, \beta^{(1)}_{2l}, ..., \beta^{(1)}_{Ll}\}$, and $\{\beta^{(2)}_{1l}, \beta^{(2)}_{2l}, ..., \beta^{(2)}_{Ll}\}$, for a given belief $\overline{\Psi}$, I can approximate for the expected variable profit as:

$$\widetilde{vp}^e_l(\overline{\Psi}) \approx \beta^{(0)}_l + \sum_{k=1}^{L} \beta^{(1)}_{kl} \mathbb{E}[n_k] + \sum_{k=1}^{L} \beta^{(2)}_{kl} \mathbb{E}[n^2_k] \ , \tag{1.22}$$

where

$$\mathbb{E}[n_k] = \overline{\psi}_k \cdot (M-1) + \mathbb{I}_{k=l} \ , \tag{1.23}$$

$$\mathbb{E}[n^2_k] = Var(n_k) + \mathbb{E}[n_k]^2 \ . \tag{1.24}$$

For a mill considering whether to enter location l, the expected number of mills at location k when $k \neq l$ is the probability that a rival would choose to enter location k, $(\overline{\psi}_k)$, multiplied by the number of potential rivals $(M-1)$. If $k = l$, then the mill includes itself into the expected number of mills, resulting in $\mathbb{E}[n_l] = \overline{\psi}_l \cdot (M-1) + 1$. The approximated Bayesian Nash equilibrium is therefore the solution to the fixed point problem:

$$\psi^*_l(\Psi^*) = \frac{exp\left\{\lambda\left(\beta^{(0)}_l + \sum_{k=1}^{L} \beta^1_{kl} \mathbb{E}[n_k] + \sum_{k=1}^{L} \beta^{(2)}_{kl} \mathbb{E}[n^2_k] - EC_l\right)\right\}}{1 + \sum_{l'=1}^{L} exp\left\{\lambda\left(\beta^{(0)}_{l'} + \sum_{k=1}^{L} \beta^1_{kl'} \mathbb{E}[n_k] + \sum_{k=1}^{L} \beta^{(2)}_{kl'} \mathbb{E}[n^2_k] - EC_{l'}\right)\right\}} \ . \tag{1.25}$$

A critical question is how well the approximated equilibrium matches up to the true equilibrium. To validate the approximation method, I apply the method to the same entry problems but with a much smaller number of locations and a much smaller number of potential entrants. I consider the case with four locations and 50 potential entrants. At this scale, the problem is small enough to compute the Bayesian Nash equilibrium using the exact expected variable profit, which is computed over all spatial configurations of N. Table 1.4 shows the resulting expected number of mills at each location. We can see that the approximated equilibrium is very similar to the exact equilibrium. I repeat the exercise with five locations. The approximation method yields a very similar equilibrium to the exact equilibrium across various specifications. The key takeaway is that the approximation method provides a reasonably good approximation to the exact solution to the Bayesian Nash equilibrium.

Table 1.4: Exact vs Approximated Bayesian Nash Equilibrium

	L = 4, M = 50		L = 5, M = 40		L = 5, M = 50	
	Exact	Approx.	Exact	Approx.	Exact	Approx.
E(N)	9.39	9.66	5.62	5.76	7.15	7.29
	11.58	11.44	8.27	8.21	9.91	9.96
	11.74	11.46	7.17	7.04	8.82	8.74
	7.62	7.72	7.89	7.90	9.57	9.57
			4.88	4.94	6.41	6.41

Notes: This table reports the equilibrium expected number of mills in three different entry games. L denotes the number of locations and M denotes the number of potential entrants. Each row shows the expected number of mills in each location. "Exact" column reports the true equilibrium. "Approx" column reports the approximated equilibrium, where the expected variable profit is approximated using equation (1.20).

1.5 Estimation

In this section, I estimate key parameters in the model. To take the model to the data, I partition Thailand into 0.5 degrees by 0.5 degrees grid, creating 180 locations where mills can choose to enter (L = 180). To represent the farmers, I divide Thailand into 0.1 degrees by 0.1 degrees grid, resulting in 1,175 farmer locations (F =

1,175). I calibrate the farmers' production function using data from the agricultural survey. I then estimate key parameters in the model in two steps. First, taking N in the data as given, I jointly estimate the bargaining power δ and the trade cost in the Nash bargaining problem using method of simulated moments. Second, using the estimated Nash-bargaining parameters and the calibrated production function, I estimate parameters in the entry problem using the nested fixed point maximum likelihood algorithm.

1.5.1 Nash-bargaining parameters: δ and τ

Equilibrium in the Nash-bargaining problem is defined by the Nash-in-Nash equilibrium equation (1.19). I assume that trade cost between m and k takes the functional form:

$$\tau_{mk} = 1 + \phi d_{mk} \ , \tag{1.26}$$

where d_{mk} is the geodesic distance between m and k calculated using m and k actual co-ordinates.[15] By definition, $\tau_{mk} = 1$ if $m = k$. Nash-in-Nash equilibrium equation (1.19) then becomes:

$$p^f_m = (1-\delta) \max_{k \in \mathcal{M}-\{m\}} \left\{ \frac{p^f_k}{1+\phi d_{mk}} \right\} + \delta p^r_m \qquad \forall m \in \mathcal{M} \ , \tag{1.27}$$

The two parameters I need to estimate for the Nash-bargaining problem are the trade cost parameter ϕ and the bargaining power parameter δ.

Given that the farmer prices across different mills are interrelated through the outside options, I estimate the Nash-bargaining parameters $\Theta^{NB} = (\delta, \phi)$ by the method of simulated moments. I use the annual average of the prices of white rice

[15] This functional form is similar to Chatterjee (2020). However, whereas Chatterjee (2020) explicitly includes an exogenous trade cost term in the functional form, in this paper, the randomness in trade cost is driven by the realization of the mill's co-ordinates.

and sticky rice between 2008-2018. I search over Θ^{NB} that minimizes the distance between the simulated moments and the data moments, achieving:

$$\hat{\Theta}^{NB} = \arg\min_{\Theta^{NB}} \left(\varphi^d - \varphi^s(\Theta^{NB})\right) W \left(\varphi^d - \varphi^s(\Theta^{NB})\right)' \ , \tag{1.28}$$

where φ^d represents the data moments, $\varphi^s(\Theta^{NB})$ represents the simulated moments, and W is the inverse of the variance-covariance matrix.[16] For each iteration of simulation at a new value of Θ^{NB}, I solve for the Nash-in-Nash equilibrium for each year and rice type between 2008-2018, taking the number of mills in the data as given.

The moments I choose to identify δ and ϕ come from an auxiliary regression and the distribution of farmer prices. First, following Chatterjee (2020), I adopt an auxiliary linear regression model that closely reflects the equilibrium equation (1.27):

$$p^f_{mt} = \beta_0 + \beta_1 \left(\max_{k \text{ s.t. } d_{mk} < 100km} p^f_{kt} \right) + \beta_2 d_{mk} + \beta_3 p^r_{mt} + \varepsilon_{mt} \tag{1.29}$$

where m indexes the mill, t indexes the year, and d_{mk} is the distance between mill m and mill k.[17] The moments I target are the coefficients β_1, β_2, and β_3. Second, I also match the distribution of farmer prices by targeting the mean, the 5th, the 25th, the 50th, the 75th, and the 95th percentile of the farmer prices. Although all parameters are jointly estimated and there is no one-to-one mapping between the parameters and the moments, some moments are more sensitive to certain parameters than others. Intuitively, δ is identified from β_1 and β_3 which capture the correlation between farmer price at mill m and farmer price at a competing mill and the correlation between farmer prices and retail prices respectively, whereas ϕ is identified through β_1 and β_2,

[16] I calculate W by bootstrapping the initial dataset. Specifically, I resample with replacement from the initial dataset 1,000 times and calculate the corresponding moments from each sample. I then calculate the covariance between the bootstrapped moments.

[17] I do not use the reduced form IV regression (1.4) as my auxiliary regression model because it does not help with identification of δ and ϕ since the reduced form regression (1.4) captures all the competition effect through the $COMP$ measure. Instead, I will use the coefficient of the $COMP$ measure as an untargeted moment to assess the goodness of fit.

which capture how distances between mills correlate with the farmer prices.

Note that to estimate the auxiliary regression (1.29), I make the following assumptions about the data. First, since I only observe the prices that farmers received and not which mills they sold the rice to in my dataset, in order to run this auxiliary linear regression, I assume that if a mill is situated in the same grid cell as the farmer, then the farmer sold rice to that mill and the reported price that the farmer received is p^f_{mt}, the price that the mill gave the farmer. Second, I only observe retail prices at the province level. Therefore, I assume that all mills located in the same province receive the same retail price. For province-year with missing retail prices, I linearly interpolate the retail prices from adjacent provinces.

Table 1.5 reports the estimated values of the parameters. The bargaining power of farmer δ is estimated to be 0.39, and the trade cost parameter ϕ is estimated to be 0.84. The estimated trade cost parameter is relatively high since it also captures elements of trade costs beyond the distance-related transport cost. For instance, in transporting rice to sell to another mill, the farmer faces the risk that they may not make it in time before the other mill closes their buying window, meaning the farmer may have to make another trip on the next day. Additionally, it is difficult for farmers to arrange transportation to another mill in practice since the agreement to transport rice from the farm to the rice mill is often done on a leg basis. Table 1.6 displays the moments from the data and simulated data. Column 1 provides the moments calculated from the data, which are the moments that I target, and column 2 displays the moments generated by the model.

I check for the goodness of fit in the following ways. Figure 1.6(a), shows the binned scatter plot of the log of the farmer prices that I observe in the data and the log of farmer prices generated in the model. The farmer prices simulated in the model strongly correlate with the data. The coefficient from a linear fit without an intercept term is 0.984. Figure 1.6(b) displays the histogram of the log of farmer

Table 1.5: Estimated Parameters from MSM

Parameter	Point Estimate	SE
δ	0.3876	0.0010
ϕ	0.8352	0.0058

Notes: This table reports the point estimates of the δ, the bargaining power of the farmer, and ϕ, the trade cost parameter using the method of simulated moments. Parameters are estimated using farmer prices between 2008-2018.

Table 1.6: MSM Targeted Moments

	Data	Model
β_1	0.840	0.889
β_2	-0.014	-0.004
β_3	0.013	0.049
Mean	10.829	10.948
25th	8.600	9.452
50th	10.750	10.825
75th	12.828	12.489

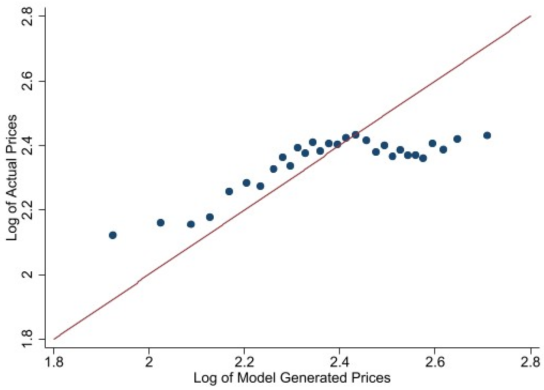
Notes: This table reports the targeted moments used in MSM to estimate parameters in the Nash bargaining problem. β_1, β_2, and β_3 are coefficients from the auxiliary regression (1.29). The last four rows show the mean, the 25th, the 50th, and the 75th percentile of farmer prices.

prices in the data and the farmer prices simulated in the model. Overall, the model is able to capture the distribution of farmer prices, although the model generates a slightly wider variation in price compared to the data.[18] I further check how well my model is able to match the empirical results I presented in Section 1.3. Since I did not use the IV specification (1.4) in my estimation, I use β_1, the coefficient that captures how local competition impacts farmer prices, from the IV regression as my untargeted moment. An equivalent IV regression using the simulated data yields a coefficient of 0.079, which is relatively close to the coefficient of 0.074 in the data.

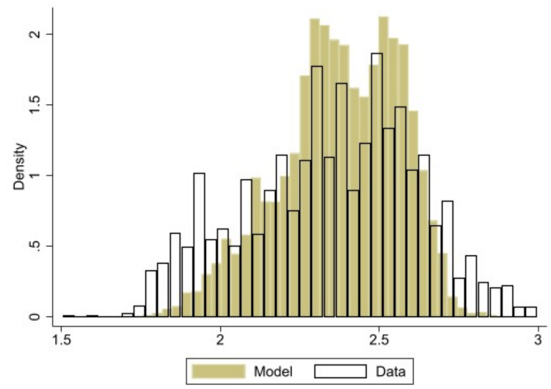
[18]Farmer prices in the data can be more compressed than the model-generated prices because of several reasons. First, farmers could have other outside options not captured by the model, such as keeping the rice at home. Likewise, mills may also have an upper bound on the prices they are willing to give to farmers, beyond which they consider to be unprofitable to buy rice from the farmers. In addition, some rice mills may choose to buy only certain rice varieties, which affects the degree of local competition in a way that is not captured in the model.

Figure 1.6: MSM Goodness of Fit

(a) Binned Scatter Plot of Farmer Prices



(b) Distribution of Farmer Prices



Notes: Panel (a) shows a binned scatter plot of the log of farmer prices observed in the data against the log of farmer prices simulated from the model using estimates from the MSM. The red line is the 45-degree line. Panel (b) shows a histogram of the log of farmer prices in the data and the log of the model generated farmer prices. Both panels use farmer prices of white and sticky rice between 2008-2018.

Table 1.7: MSM Untargeted Moment

	log(price)	
	Data	Model
COMP (std)	0.074	0.079

Notes: This table reports the coefficient for the standardized competition measure from the IV regression (1.4). The first column reports the estimated coefficient from the data and the second column reports the estimated coefficient from the model generated data. Note that because data from the model is generated at an annual frequency, I exclude the fixed effects for the month-of-highest-sales from the regression using the model simulated data.

1.5.2 Parameters in Entry Problem: λ and EC

The equilibrium in mills' entry-location problem is given by the Bayesian Nash equilibrium equation (1.16). The parameters I need to estimate are the scale parameter, λ, and the common knowledge component of entry costs, EC_l. I assume that

EC_l takes the following specification:

$$EC_l = \theta_0^{EC} + \theta_1^{EC} ruggedness_l + \theta_2^{EC} \ \% \ in \ season \ rice_l + \theta_3^{EC} population \ density_l + \gamma_r \tag{1.30}$$

where $ruggedness_l$ is the ruggedness of the location, $\% \ in \ season \ rice_l$ is the percentage of rice in the area that is grown in season, $population \ density_l$ is the population density of the location, and γ_r is the region fixed-effects.[19] Given the specification of EC_l, the set of parameters I need to estimate for the entry problem $\Theta^{EC} = \{\lambda, \theta_0^{EC}, ..., \theta_3^{EC}, \gamma_{r \in R}\}$.

Estimation of Θ^{EC} proceeds via nested fixed-point algorithm. Given $\psi_l^*\big(\Theta^{EC}, X_t\big)$, the probability that the best response of a mill is to enter location l as given by the equilibrium probability (1.16), the number of mills at a location follows a multinomial distribution. The probability that we would observe $\{n_{1t}, ..., n_{Lt}\}$ number of mills at time t is:

$$Pr\Big(n_{1t}, ..., n_{Lt} | \Psi^*\big(\Theta^{EC}, X_t\big)\Big) = \frac{M!}{n_{1t}! \cdots n_{L+1,t}!} \prod_{l=1}^{L+1} \psi_l^*\big(\Theta^{EC}, X_t\big)^{n_{lt}} \ , \tag{1.31}$$

where X_t are the variables needed to determine the expected variable profit. Assuming there is no unobserved location heterogeneity, the log-likelihood function is then given by:

$$l\left(\Psi^*\big(\Theta^{EC}, X_t\big)\right) = \sum_{t=1}^{T} \sum_{l=1}^{L+1} \left\{ n_{lt} \ln \psi_l^*\big(\Theta^{EC}, X_t\big) \right\} \ . \tag{1.32}$$

[19] I choose the variables in the specification for EC_l the following reasons. Terrain ruggedness matters for the cost of doing busing, as Nunn and Puga (2012) have stated, *"geographical ruggedness is an economic handicap,... making it more expensive to do business."* The percentage of rice grown in season likely affects the fixed operating cost of the mill since it indicates whether farmers in the area grow rice consistently throughout the year or only during certain time period. If farmers only grow rice during a specific part of the year, mills in the area will likely have to shut down during some part of the year. The percentage of rice grown in season captures the costs arising from mills' inability to conduct businesses continuously. The population density captures variations in the cost of land. The region-fixed effects captures variations in the entry cost across the regions.

The log-likelihood function is summed up to $L+1$ to account for the mills' option to not enter altogether, where $\psi^*_{L+1}\big(\Theta^{EC}, X_t\big) = 1 - \sum_{l=1}^{L} \psi^*_l\big(\Theta^{EC}, X_t\big)$ and $n_{L+1t} = M - \sum_{l=1}^{L} n_{lt}$. Calculation of log-likelihood function therefore requires knowledge of M, the number of potential entrants, which is unobserved. Following the literature, I fix the number of potential entrants, M, to be an exogenous value, setting $M = 2,000$.[20]

The nested fixed point maximum-likelihood estimation proceeds as follows. For a given set of variables X_t which determines the variable profits, I randomly sample a subset S of size $60,000$ from all possible configurations of N and compute the simulated variable profit for each $N_s \in S$.[21] I then calculate the approximation function for the variable profit according to (1.20). Having done so, or a given set of parameter values Θ^{EC} and approximated variable profit function, I solve for an approximated fixed point solution to the Bayesian Nash equilibrium (1.25). This Bayesian Nash equilibrium is then nested into the maximum-likelihood procedure to estimate the parameters Θ^{EC}.

To calculate the variable profit, I need data on the quantity of crop output. Data on the quantity of rice harvested at the district level is only available between 2012-2018. Therefore, I restrict my sample size to that time period. Additionally, I use the retail price of white rice in my estimation since white rice is more widely grown across Thailand.

Table 1.8 reports the estimated parameters. The goodness of fit can be seen in Figure 1.7. Figure 1.7(a) displays the binned scatter plot of the number of mills in each

[20] Since the number of potential entrants is unobserved, it is standard in the literature to set this to an exogenous number. For instance, one of the specifications that Seim (2006) uses is to assume that there is an entrant pool of 50 firms and the other specification is to set the number of potential entrants such that 50% of the potential entrants enter the market. since the number of mills per year I observe on average is 1,011 and the highest number of mills observed in the data is $1,084$, I set M to be $2,000$. Appendix A.3 reports results when I use a different value of M. Intuitively, as long as M is sufficiently high such that the observed number of mills is below M in any of the baseline or counterfactual scenarios, the exact value of M is not important.

[21] As a sensitivity analysis, I estimate the parameters using a subset of size $70,000$, which yields very similar results. Appendix A.3 reports the results.

location that I observe in the data and the number of mills generated in the model. The linear fit without an intercept has a coefficient of 1.02. Visual representation of the goodness of fit can be seen in Figures 1.7(b) and 1.7(c), which plot the number of mills in each location. The model does a relatively good job capturing the variation in the number of mills across Thailand.

Table 1.8: Estimated Parameters from NFP

	Point estimate	SE
λ	2.913	0.102
constant	1.790	0.047
I(east)	0.426	0.021
I(north)	-0.319	0.027
I(northeast)	0.326	0.022
I(south)	1.106	0.055
I(west)	0.180	0.032
ruggedness	0.772	0.017
% in season	-0.002	0.001
population density	0.005	0.001

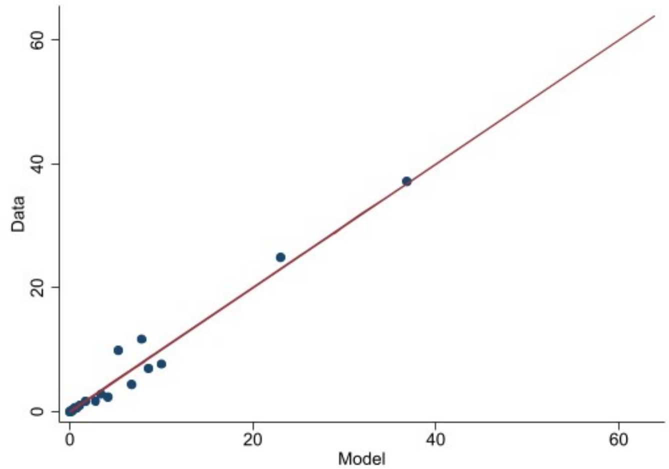
Notes: This table reports the point estimates and bootstrapped standard errors for the scale parameter, λ, and entry cost parameters using the nested fixed-point algorithm. Entry cost is assumed to be a function of the location's region, the ruggedness of the location, the percentage of rice that is grown in season at the location, and the population density. Parameters are estimated using data from 2012-2018.

1.5.3 Farmers' Production Function

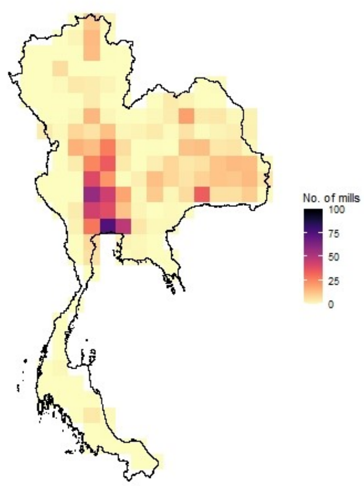
To calculate the change in the production of rice in response to a change in farmer prices, I only need to calibrate the share of intermediate input β. I calibrate the share of intermediate input using data from the socio-economic and labor survey of agricultural households, obtaining $\beta = 0.25$. Details of how I calculate changes in rice production are given in Appendix A.4.1.

Figure 1.7: NFP Goodness of Fit

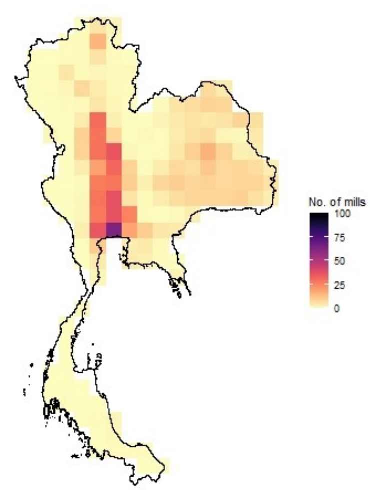
(a) Binned Scatter Plot of No. of Mills



(b) No. of Mills in Data



(c) No. of Mills in Generated from Model



Notes: Number of mills in each location between 2012-2018. Panel (a) shows a binned scatter plot of the number of mills in each location observed in the data against the number of mills generated from the model. The red line is the 45-degree line. Panels (b) and (c) show a heatmap of the average number of mills in each location in the data and the simulated data, respectively. Mill locations consist of 0.5 degrees $\times$ 0.5 degrees grid cells.

1.6 Counterfactual Analysis

Having estimated the relevant parameters, I will now examine two counterfactual scenarios, both guided by real-world policies in Thailand. In the first scenario, I study the impact of a country-wide improvement in road infrastructure. In the second scenario, I examine how intermediaries impact farmers' decisions to invest in new technology. To separately examine the role of entry-location decisions of intermediaries, I conduct two exercises for each counterfactual scenario. First, I keep the number of mills in each location the same as in the baseline scenario. Then, I allow mills to change their entry-location decisions.

Computation of equilibrium in the baseline and counterfactual scenarios requires data on retail prices and farmers' outputs, which I will use to deduce farmer's outputs in the model. I use the average retail prices for white rice and the output per district between 2012-2018 to compute equilibrium in the baseline scenario. Note that since farmer prices and the output depend on the realization of the number of mills in each location, for each scenario, I compute the equilibrium farmer prices and output across 1,000 simulations and average the farmer prices and output across the simulations. In each counterfactual scenario, I keep the retail prices the same as in the baseline scenario.[22]

1.6.1 Improvement in Road Infrastructure

In 2017, the Department of Highways released a strategic plan, setting a goal to reduce highways-related transportation cost down by 9.09%, from 4.4% of GDP to 4% of GDP. Therefore, I map this into the model as a 9.09% country-wide reduction

[22] The decision to keep the retail prices unchanged can be justified by the fact that Thailand exports a large proportion of the rice it produces. According to the USDA (2021), the percentage of rice that Thailand exported ranges from 29.7% of the rice it produced in 2020/21 and 54.5% in 2017/18. Furthermore, the total quantity of rice produced in Thailand formed a very small percentage of the global rice production, producing about 1.1% of the rice produced globally in 2020/21 (USDA, 2021).

in the iceberg trade costs.[23] To isolate the role of intermediaries' entry decisions from the rest of the channels, I first simulate a reduction in trade costs keeping the intermediaries' entry-location decisions the same as in the baseline scenario. Then, I let the rice mills change their entry-location decisions, allowing the last channel to come into play.

Shutting Off Entry Response of Rice Mills

I first study what happens when I reduce trade costs if I shut down the entry response of the mills. I do this by keeping the number of mills in each location, N, the same as the baseline scenario. The results from this exercise are presented in the first column of Table 1.9. The aggregate income of the farmers increases by 15.79%. More importantly, the gains to farmers are regressive. The second and the third rows of Table 1.9 show the percentage change in income of the farmers whose incomes in the baseline scenario are in the top and bottom decile. We can see that the top decile farmers benefit from 11% higher percent increase in income relative to the bottom decile farmers.

Table 1.9: % Change in Farmer Income following 9.09% Decrease in Trade Costs

	% Change in Income	
	Baseline N	Flexible N
Aggregate	15.79	16.75
Top 10% (avg.)	16.14	17.27
Bottom 10% (avg.)	14.54	13.84
SD	0.82	1.50

Notes: This table reports the percentage change in farmer income following a country-wide 9.09% decrease in iceberg trade costs. The first column reports the results when the number of mills in each location is the same as in the baseline scenario. The second column reports the results when mills are allowed to change their entry and location decisions. The second and thirds rows show the average percentage change in income of the farmers whose incomes in the baseline scenario are in the top and bottom decile.

To further understand the channels through which a reduction in trade costs im-

[23]Specifically, I reduce τ everywhere by 9.09%. Since the quantity of rice reaching the mill is $\frac{y_f}{\tau_{fm}}$, if τ_{fm} falls by 9.09%, farmers are going to arrive at the mill with 10% more rice than before.

pacts the farmers' income, Table 1.10 decomposes the percentage increase in farmers' incomes that arises from a decrease in trade costs into three different channels: 1) the direct reduction in transport cost, 2) the increase in prices that farmers receive, and 3) the changes in farmers' outputs. The second channel is a result of higher spatial competition among rice mills, which results from higher outside options of the farmers due to lower trade costs, and the opportunity for farmers to re-optimize which mills to sell their rice to. The third channel arises because farmers re-optimize their intermediate input usage in response to higher prices. Column 1 shows the percentage increase in income that results directly from lower transport costs paid by farmers to transport rice from their farms to the mills. When τ falls by 9.09%, farmers arrive at the mill with 10% more rice than in the baseline scenario. Therefore, if farmers had produced the same quantity of rice and sold it to the same mills at the same prices as in the baseline scenario, all farmers' incomes would have risen by 10%. The direct effect of reduction in trade cost on farmers' income is homogeneous across all farmers.

Table 1.10: Decomposition of % Change in Income following 9.09% Decrease in Trade Costs

		Baseline N		Flexible N	
	Transport	Price	Output	Price	Output
	(1)	(2)	(3)	(4)	(5)
Aggregate	10.00	1.63	4.16	2.32	4.44
Top 10% (avg.)	10.00	1.92	4.22	2.65	4.62
Bottom 10% (avg.)	10.00	0.65	3.90	0.20	3.64
SD	0.00	0.59	0.22	1.09	0.41

Notes: This table decomposes the total percentage change in farmer income into the percentage change arising from three different channels. Column 1 reports the percentage point increase in income arising directly from the reduction in transport cost. Column 2 reports the additional percentage point increase arising from the increase in prices that farmers receive, holding the number of mills and the farmers' outputs the same as in the baseline scenario. Column 3 reports the additional percentage point increase coming from changes in farmers' production decisions, holding the number of mills constant at the baseline level. Columns 4 and 5 report the equivalence of columns 2 and 3 when mills can change their entry and location decisions.

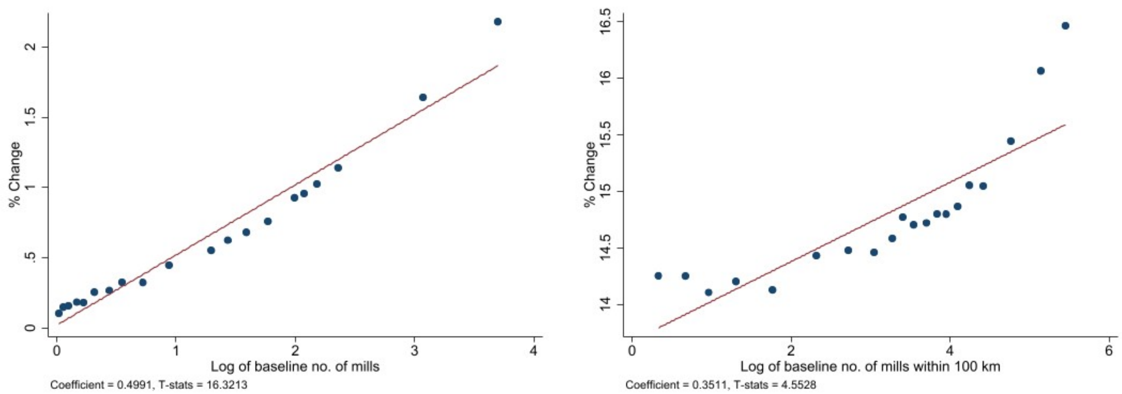
The percentage increase in income arising from further changes in the prices that farmers receive is presented in column 2 of Table 1.10. Prices that farmers receive increase because of two reasons. First, lower trade costs mean that the values of farmers' threat points in the Nash bargaining process are higher, leading to higher equilibrium farmer prices. Second, farmers reoptimize their choices of mill to trade with. Holding the quantity of rice produced by farmers the same as in the baseline scenario, the aggregate income of the farmers further increase by 1.63 percentage points as a result of changes in prices that farmers receive. Note that the gains arising through this channel are regressive. While the income of top decile farmers further rises by 1.92 percentage points from this channel, the income of the bottom decile farmers only increases by 0.65 percentage points. Likewise, the standard deviation in the percentage increase in farmers' incomes increases from 0 to 0.59 percentage points.

This regressive effect results from the uneven spatial distribution of rice mills in the baseline scenario, which arises from mills' strategic location decisions. Productive places are more profitable; therefore, in the baseline scenario, the number of mills is higher in productive areas. Since farmer prices are determined by equation (1.19), higher density of mills in productive locations means shorter distances between mills. Therefore, the threat points of productive farmers form a larger proportion of the equilibrium farmer prices. Since lower trade cost impacts farmers' outside options, the reduction in trade costs has larger impacts on farmer prices at productive locations. This is illustrated through the positive correlation between the percentage change in farmer prices and the baseline number of mills in Figure 1.8(a).

Subsequent changes in farmers' production decisions further widen the gap between the percentage increase in income of the top and bottom decile farmers. In response to price changes, farmers reoptimize their use of intermediate inputs in their rice production, increasing the quantity of rice that they produce. In particular, for farmer f, the ratio of the new output (y'_f) to the baseline output (y_f) is a function of

Figure 1.8: Impacts of Improvement in Road Infrastructure: Baseline N

(a) % Change in farmer prices (b) % Change in income



Notes: Counterfactual results from 9.09% reduction in the iceberg trade costs when the number of mills in each location, N, is fixed at the baseline level. Panel (a) shows a binned scatter plot of the average percentage increase in farmer prices in each location against the log of the number of mills in the location in the baseline scenario. Panel (b) shows a binned scatter plot of the percentage change in farmer income against farmer access to rice mills, measured using the log of the number of mills within 100 km from the farmer in the baseline scenario.

the ratio of the new farmer price and iceberg trade cost $\left(\frac{p_{m'}^{f\prime}}{\tau_{fm'}^{\prime}}\right)$ to the baseline farmer price and iceberg trade cost $\left(\frac{p_m^f}{\tau_{fm}}\right)$:[24]

$$\frac{y_f'}{y_f} = \left(\frac{p_{m'}^{f\prime}/\tau_{fm'}^{\prime}}{p_m^f/\tau_{fm}}\right)^{\frac{\beta}{1-\beta}}. \tag{1.33}$$

Column 3 of Table 1.10 reports the further increase in income once farmers reoptimize their production decisions. Productive farmers who benefit from a larger increase in prices increase their output by more than the unproductive ones, thus widening the gap between the top and bottom decile farmers. The top decile farmers experience a further 4.22 percentage points increase in income after we account for changes in farmers' production decisions. In contrast, the bottom decile only experience an

[24]See Appendix A.4.1 for details.

additional 3.90 percentage points increase.

The heterogeneity in the changes in prices that farmers receive and changes in farmers' production decisions lead to the overall regressive effects on the gains to the farmers. Productive farmers, surrounded by a larger number of mills, experience a larger percentage increase in income relative to the unproductive ones. This is reflected in Figure 1.8(b), which shows the percentage change in farmers' incomes against the number of mills within 100 km from the farmer. Because productive areas have a higher density of mills, mills in productive areas face a greater reduction in market power following a reduction in trade costs, causing productive farmers to experience larger gains.

Allowing for Entry Response of Rice Mills

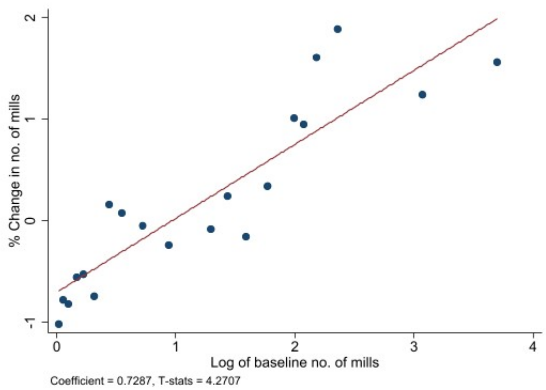
In this exercise, I incorporate the entry response of rice mills into the counterfactual simulation. The second column of Table 1.9 shows the percentage change in farmer income once mills are able to change their entry-location decisions. Entry responses of rice mills have important implications on the gains to farmers. The first row of Table 1.9 shows that after accounting for the entry responses of rice mills, the percentage change in the aggregate income of the farmers increases from 15.79% to 16.75%. Hence, if we had ignored the changes in entry decisions of rice mills, we would have underestimated the percentage increase in aggregate farmer income by 5.7%. More importantly, the entry responses of intermediaries have important distributional consequences. Changes in the entry decisions of the rice mills exacerbate the regressive nature of the gains to the farmer. The gap between the percentage change in income of the top and bottom decile farmers increases by 2.1 times as a result of the entry response of mills.

To shed light on why the intermediaries' entry responses are regressive, let us consider how intermediaries change their entry-location decisions following a reduction in trade costs. Ex-ante, it is unclear how a decrease in trade costs will impact the entry decisions of the rice mills. When trade costs fall, there are three competing forces at play. First, lower trade costs increase the value of the farmer's threat point in the Nash bargaining problem, putting upward pressure on farmer prices and subsequently lowering per-unit profit, making mills less likely to enter. Second, lower trade costs and higher farmer prices mean farmers increase their output, leading to higher total profit for mills. The increased profitability makes mills more likely to enter. Third, lower trade costs mean that farmers are more likely to travel further to places with higher farmer prices, increasing the profitability in places with high farmer prices and vice versa.

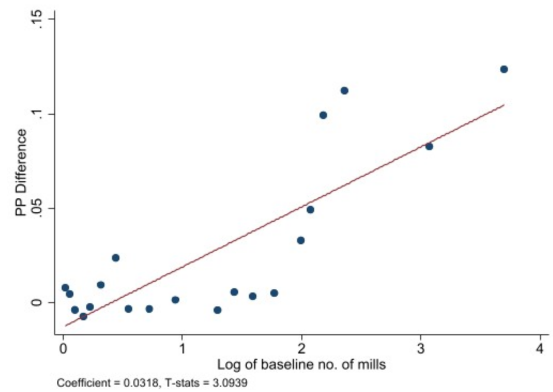
Simulations indicate that the second and the third channels dominate in productive locations, resulting in higher overall profitability. As a result, productive farmers experience a larger increase in income, as shown in Figure 1.9. In Figure 1.9(a), we can see the positive correlation between the percentage change in N and baseline N. Since in the baseline scenario, the number of mills positively correlates with the productivity of the location, this means that entry following a decrease in trade costs is regressive; productive locations experience an increase in the number of mills while unproductive locations experience a decrease in the number of mills on average. As a result, locations with higher baseline number of mills experience a larger percentage increase in farmer prices following a decrease in trade costs, as shown in Figure 1.9(b). This causes a chained response in rice production; farmers in productive locations increase their output by a larger percentage than the unproductive ones, further amplifying the distributional consequences. Figure 1.9(c) and 1.9(d) illustrate this regressive effect. After we account for changes in entry-location decisions of rice mills, productive farmers who have higher baseline income and are located in areas with higher mill density experience a larger percentage increase in income relative to when we do not account for entry response of mills. In comparison, unproductive farmers experience a smaller percentage increase in income.

Figure 1.9: Impacts of Improvement in Road Infrastructure: Flexible N

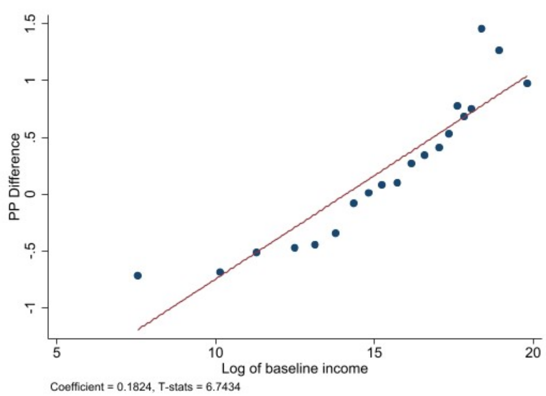
(a) % Change in N vs Baseline N



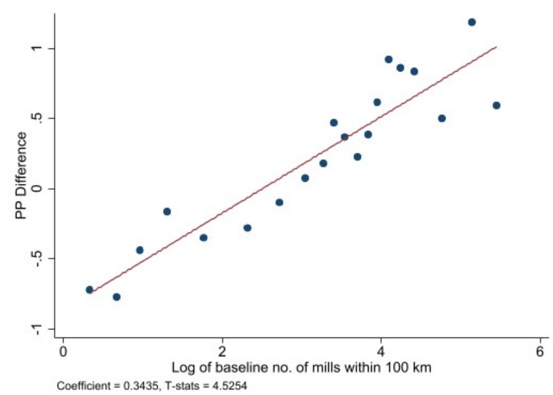
(b) Percentage Point Change in $\%\Delta p_l^f$ after Allowing N to Change vs Baseline N



(c) Percentage Point Change in $\%\Delta$ Income after Allowing N to Change vs Baseline Income



(d) Percentage Point Change in $\%\Delta$ Income After Allowing N to Change vs No. of Mills within 100 km in Baseline Scenario



Notes: Counterfactual results from 9.09% reduction in the iceberg trade costs after allowing mills to change their entry-location decisions. Panel (a) shows a binned scatter plot of the percentage change in the number of mills against the baseline number of mills in each location. Panel (b) shows binned scatterplot of the percentage point difference in the percentage change in farmer price before and after the entry response of mills against the baseline number of mills in each location. Panels (c) and (d) show the percentage point difference in the percentage change in farmer income before and after the entry response of mills. A positive percentage point difference means that the percentage increase in farmer income (farmer price) is larger after accounting for mills' entry response.

Overall, this counterfactual scenario indicates that intermediaries' entry decisions and market power have important distributional consequences. Entry is regressive.

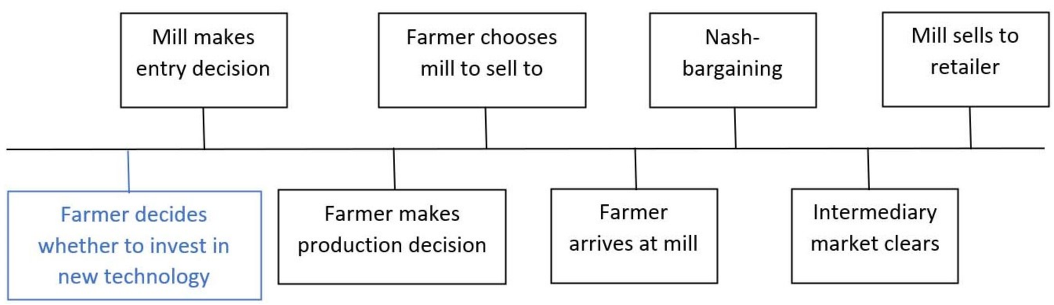
Intermediaries' strategic entry decisions lead to higher density of rice mills in productive areas, resulting in lower market power of rice mills in productive areas. As a result, farmers in productive areas experience a larger percentage increase in income relative to those in unproductive areas. Entry decisions of rice mills following the shock further exacerbate the gap in the gains between the productive and unproductive farmers. Country-wide reduction in trade costs causes productive areas to become relatively more profitable than the unproductive ones, leading to a higher number of mills in productive areas and vice versa. Therefore, entry responses of intermediaries further widen the gap in the percentage increase in farmer prices between the productive and unproductive farmers. Ignoring the entry response of rice mills would cause us to underestimate the gap in the percentage change in income between the top and bottom decile farmers by 53%.

1.6.2 Opportunity for Farmers to Invest in New Technology

In the second counterfactual, I consider the role of spatial market power and strategic entry in shaping farmers' decisions to invest in new farming technology. In Thailand, there are many ongoing efforts to encourage farmers to adopt new farming practices or technology. For instance, in 2018, the Thai Rice Department budgeted over 60 million USD for projects aimed to develop the production potential of the agricultural sector (Rice Department, 2018). A significant factor determining the success of these projects is the farmers' uptake of the technology. In what follows, I show that the entry response of intermediaries impacts farmers' decisions to invest in the new technology, resulting in multiple equilibria.

I build this counterfactual scenario on one of the ongoing projects, the Thai Rice NAMA, which encourages farmers to adopt low-carbon emission technology and practices. Mapping this into the model, I allow farmers in the six targeted provinces in the central plains to decide whether to invest in the new technology at the beginning of the period, as shown in Figure 1.10. The publicly available information on the project suggests that the new technology will increase farmers' productivity by 30% and that farmers will break even at the current prices (NAMA Facility, n.d.). I implement this into the model by setting the investment costs such that farmers will break even at the baseline prices.[25] I assume that farmers will only invest if the return on investment is strictly positive.

Figure 1.10: Timeline with Opportunity to Invest in New Technology



Because farmers are small, they do not consider how their individual investment decisions impact the aggregate output in the area and subsequently the number of mills in each location. Farmers' investment decisions are determined solely from the expected return from the investment given the expected farmer prices. Since rice mills' density impacts farmer prices and thus the return from investment, farmers' investment decisions are affected by their beliefs on whether other farmers will invest and what the subsequent mill density will be. Multiple equilibria arise, depending on the farmers' beliefs about others' decisions. In the non-socially optimal equilibrium, farmers believe that no one else will invest. They believe that the number of mills and subsequently the farmer prices will be the same as in baseline scenario. Therefore, there will be no positive gains to farmers from investing in the technology. As a result, no investment is made.[26]

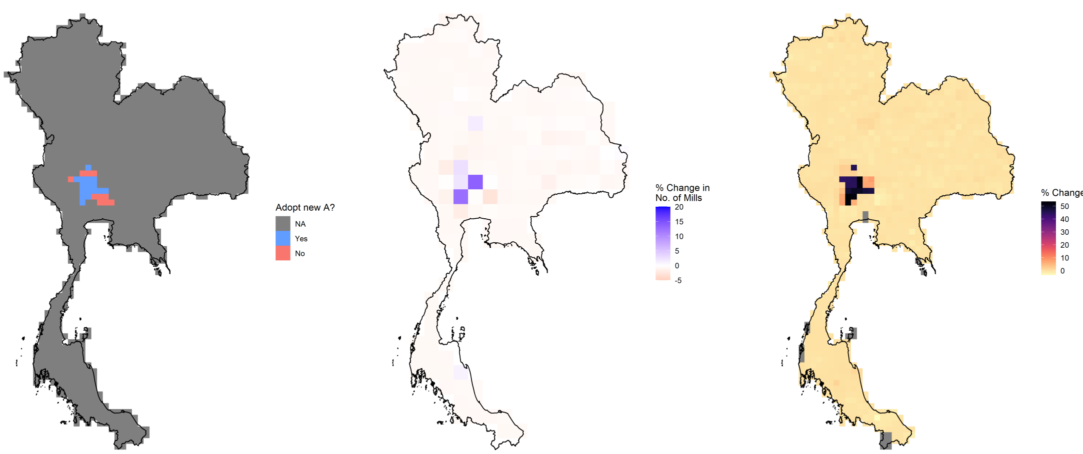
[25]See Appendix A.4.3 for further details on the project and how I map the project to the model.

[26]This equilibrium would also be achieved if farmers are myopic and do not realize that mills' entry decisions are affected by the quantity of rice harvested.

However, such equilibrium is not socially optimal. If farmers collectively invest in the new technology, the increase in output would result in a higher number of mills. Higher number of mills means higher farmer prices. As such, ex-post, the majority of farmers would be willing to invest in new technology. Such equilibrium is shown in Figure 1.11. If 62% of the targeted farming locations adopt the new technology as shown in Figure 1.11(a), a higher number of mills will enter those corresponding areas as depicted in Figure 1.11(b). Subsequently, farmer prices in those areas rise; this increases the return to investment for those farmers such that it is worthwhile for that same 62% of the farming areas to invest in the new technology. As a result, the farmer income rises, as displayed in Figure 1.11(c).

Figure 1.11: Technology Adoption in a Socially Optimal Equilibrium

(a) Investment made (b) $\%\Delta N$ (c) $\%\Delta Income$



Notes: This figure shows a socially optimal equilibrium when farmers are presented with an opportunity to invest in new technology. N/A denotes that farmers are not in the provinces targeted by the project and are not offered an opportunity to invest. Panel (a) shows the investment decisions of the farmers. Panel (b) shows the percentage change in the number of mills. Panel (c) shows the percentage change in farmer income.

This counterfactual analysis shows the importance of the entry response of intermediaries in shaping the farmers' investment decisions. Because farmers do not internalize the strategic complementarity arising from endogenous strategic decisions, it is possible to be in an equilibrium in which the level of investment in technology is lower than the socially optimal level.

1.7 Conclusion

The key message in this paper is that strategic entry decisions of intermediaries matter in the presence of trade frictions. Even in the absence of regulatory barriers to entry, due to the existence of fixed costs of entry and trade costs, intermediaries strategically choose their locations. This results in an uneven spatial distribution of intermediaries, with higher density of intermediaries in productive areas. The presence of trade costs means that intermediaries situated in areas with low density of intermediaries enjoy higher spatial market power. Therefore, farmers situated in productive areas, surrounded by a larger number of intermediaries, receive higher prices relative to those in unproductive areas.

While a country-wide infrastructure policy, which reduces trade costs, increases the income of the farmers, the gains from the policy are regressive. Because intermediaries in productive areas have lower market power, farmers in these areas benefit from higher percentage increase in prices relative to those in unproductive areas. The entry response of intermediaries following the policy further exacerbate this regressive effect. Counterfactual simulation indicates that in Thailand, the percentage increase in income of the top decile farmers is on average 25% larger than that of the bottom decile farmers. Ignoring changes in entry decisions of rice mills would lead us to underestimate the gap in gains to the top and bottom decile by 53%.

In addition, the strategic entry decisions and the market power of intermediaries have important implications for farmers' technology adoption. Since farmers may not internalize the strategic complementarity between farmers' adoption of technology and the endogenous entry decisions of intermediaries, farmers can be stuck in a non-socially optimal equilibrium in which there is under-investment in new technology relative to the socially optimal level. I demonstrate the existence of such equilibrium in the context of Thailand. To encourage farmers to adopt new technology, it may not be sufficient for policymakers to simply present the new technology know-how to farmers and expect farmers to invest in the new technology themselves. Since farmers' investment decisions are influenced by the behaviors of their peers, policymakers may need to provide additional incentives, for instance in the form of subsidies, to overcome the initial inertia among the farmers.

Chapter II

The Impact of Trade on Development: Evidence from Pastoralist Practices on the Ancient Silk Road

Joint with Michelle Lam

2.1 Introduction

What is the long-term impact of historical trade on modern development? We approach this question in the context of the overland ancient Silk Road, the ancient trade route across Eurasia. Although the development of long-distance maritime technology in the sixteenth century has rendered the overland Silk Road trade route obsolete, path dependence could result in a persistent effect on economic activity along the ancient Silk Road trade route. Therefore, we seek to examine whether, five centuries after the decline of the overland ancient Silk Road trade, places in close proximity to the ancient Silk Road continue to be more developed relative to places that were not on the Silk Road. In particular, we focus on the long-term impact of the ancient Silk Road in the Inner Asia Mountain Corridor (IAMC), which spans modern-day Afghanistan, China, India, Kyrgyzstan, Kazakhstan, Pakistan, Tajikistan, and Uzbekistan.[1]

[1] We choose to study the IAMC as it contains unique conditions for the existence of nomadic pastoralism, which are keys to our identification strategy. We explain further details about the

Studying the impact of the ancient Silk Road trade on modern development along the IAMC is challenging because of the limited data availability. We overcome the data constraints by utilizing high-resolution satellite imagery. Our main analysis uses the intensity of night lights to proxy for the level of modern development. Remote sensing of nighttime light emissions from the Earth's surface has been widely used as a proxy for economic activity and economic development where conventional measures such as GDP are not available. In addition to its availability on a high spatial resolution, the night lights data allow researchers to circumvent concerns about the manipulation, censoring, and measurement errors in official statistics, which may be non-trivial issues in the context of the geographical area we study. Nevertheless, acknowledging the limitations of night lights data, we also use population density and data on urbanized lands as alternative measures of modern development in our supplement analysis.

To provide evidence of the causal relationship between proximity to the Silk Road and modern development level, we adopt a novel instrument for the locations of the Silk Road. We take advantage of the characteristics of the IAMC and its inhabitants to construct an instrument that provides exogenous variation in the locations of the Silk Road sites. Due to the harsh geographical conditions and the strong pastoralist tradition along the IAMC, highland Silk Road networks emerged in relation to seasonal mobility patterns of the nomadic herders (Frachetti et al., 2017). We use the simulated mobility patterns of the nomadic herders, which are generated based solely on the seasonal pasture quality, to provide variations in the placement of the Silk Road sites that do not arise from ease of travel. Conditional on the location's suitability for growing crops, our instrument only affects modern development level through the ancient Silk Road trade.

We conduct the main analysis in this paper using a grid of 0.167 degrees by

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instrument in Section 2.4. Nomadism refers to not having a fixed place of abode, and pastoralism refers to people making their livelihood by herding animals.

0.167 degrees grid cells covering the highland region of the Silk Road. We find a negative and significant relationship between distance to the Silk Road and modern development level; as distance to the Silk Road increases by one standard deviation, the night lights intensity decreases by 10.0%. Based on the elasticity of night lights with respect to GDP in the literature, a 10.0% decrease in night lights intensity corresponds to a decrease in GDP of about 4.1%-9.7%.[2] Our results are robust across different measures of modern development, with a one standard deviation increase in distance to the Silk Road resulting in a 85.5% decrease in population density, and a 12.3% decrease in the percentage of land covered by cultivated land or artificial surfaces.

This paper makes three main contributions to the economics literature. The first contribution of this paper is adding to the sparse literature on how trade routes may have a persistent effect on development, even when the trade routes are no longer relevant to trade patterns in the period of development that is of interest. To do this, this paper also draws on the literature studying path dependence and the impact of durable built infrastructure, such as Rauch (1993), Bleakley and Lin (2012), Jedwab and Moradi (2015), Duranton et al. (2014), and Baum-Snow et al. (2017).

Second, this paper is one of the first studies on the ancient Silk Road using modern econometric techniques and detailed satellite data. Our paper adds to the small but growing economics literature that studies ancient civilizations using limited archaeological records: Garcia-López et al. (2015) study Ancient Roman roads, Dalgaard et al. (2018) also study Ancient Roman roads, Michaels and Rauch (2018) study British and French urbanization from 117 to 2012, Bakker et al. (2019) study the Ancient Phoenicians around ninth century BCE, and Barjamovic et al. (2019) study Assyrian merchants in nineteenth century BCE. Of particular interest is Ahmad and Chicoine (2021), who also study the persistence along the ancient Silk Road. To study the

[2]Literature has found the elasticity of night lights with respect to GDP to be around 0.41-0.97 (Henderson et al., 2012; Hu and Yao, 2021).

long-term consequences of the ancient Silk Road on economic activities, they regress the night lights intensity outcome variable per grid on the presence of the Silk Road in four bins: 0-50km away, 50-100km away, 100-150km away, and 150-200km away, and find there is a persistent and positive association in areas that are within 50km to the ancient Silk Road. While they have conducted exercises to provide suggestive evidence about the long-term impact of the ancient Silk Road on modern economic activities, the nature of the specification in their paper does not allow them to establish a causal relationship. Our study differs from theirs in two main respects: 1) our perspective that the Silk Road is a dynamic network of paths, leading us to avoid using static routes generated from least-cost paths calculation like those in Williams (2014); because of this, 2) we introduce a unique simulated instrument for distance to Silk Road sites to establish a causal link.

This paper is part of a strand of research that uses detailed satellite data, including papers such as Bleakley and Lin (2012), Michalopoulos and Papaioannou (2013), and Dingel et al. (2019) that use night light data to study development intensity. More recent papers have begun to use daytime imagery, often alongside machine learning, to extract features such as farmed land, building density, vegetation type, transportation, and roof types to study the economic development of areas that may otherwise have sparse data or data that is not easily comparable across borders. Such papers include Engstrom et al. (2017) Baragwanath et al. (2019), and Ahmad and Chicoine (2021).

The third contribution of this paper is introducing novel-to-economics mapping simulation techniques to generate a valid instrument for the impact of ancient trade routes on modern development. Lack of direct and accurate information is a major challenge when studying events from antiquity, but depending on the right conditions, a study may be able to use modern simulation techniques to generate patterns of movement that we can plausibly argue to be similar to those experienced in antiquity.

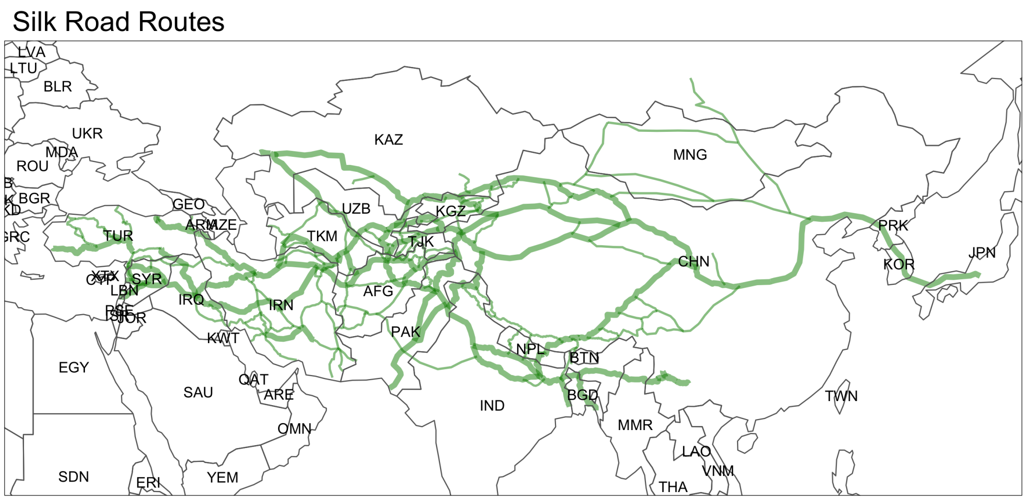
In this paper, we take advantage of the importance of the highlands area to the overland Silk Road trade and the highlands' continuing primary usage by herders and their flocks. Because of this, we are able to use modern satellite imagery to produce herding movement simulations comparable to those experienced in the ancient Silk Road heyday, and then use these calculated flows to instrument for the locations of the Silk Road sites.

Section 2.2 of the paper introduces the relevance to the background of the ancient Silk Road. Section 2.3 describes the data and how we construct data for each unit of observation. Section 2.4 details the empirical strategy, describing the instrument that we use and the various robustness checks we perform. Section 2.5 discusses possible mechanisms through which the ancient Silk Road impacts modern development. Section 2.6 concludes.

2.2 Background

Despite its name, the "ancient Silk Road" does not refer to a physical road, nor is there an unambiguous route that researchers agree to be definitively used during the centuries of overland Silk Road trade. Maps of the ancient Silk Road, such as Figure 2.1 pick important nodes at the researcher's discretion and often deploy least-cost methods based on terrain and elevation to determine where a likely path would lie. More accurately, one may think of the Silk Road as "skein of routes linking many entrepots" connecting East Asia to the Mediterranean and a phrase that represents the dynamic cultural phenomenon that connected Eurasia's people, ideas, and goods together Millward (2013); Spengler III (2019). Thus, when this paper mentions the ancient Silk Road, we are not referring to a physical road in particular, but to the dynamic network of paths identified through known historical sites.

Figure 2.1: Silk Road Routes



Notes: This figure presents hypothetical Silk Road routes compiled in Williams (2014). The thicker lines denote the main corridors; the thinner lines denote the sub-corridors. Williams first chose important nodes such as prominent cities and mountain passes, and then chose pathways considering smaller-scale sites and the ease of travel between segments. The scope of the routes spans from central China to the eastern Mediterranean, but does not address Mongolia and the routes between East Asia (China, Japan, Korea). The routes are also sparse in South Asia.

2.2.1 Definitions

The term Silk Road (in German, "Seidenstrasse") was coined in 1877 by a German geographer, Ferdinand Freiherr von Richthofen. At the time, this term narrowly referred to routes under the Han Empire (206 BCE to 220 CE) which commonly traded Chinese silk (Millward, 2013). However, since this initial usage, the Silk Road has evolved to describe diverse goods and ideas exchanges ranging over diverse geographies and long stretches of time–thousands of years and tens of thousands of kilometers. Travelers on the ancient Silk Road carried precious goods such as textiles, metals, stone, ceramics, perfumes, and horses, disseminated religious beliefs like Buddhism, Islam, Christianity, and technological advancements like paper, gunpowder, calendrical sciences, and medicine. As such, although the ancient Silk Road is often represented as a set of unchanging least-cost paths through important nodes as in Figure 2.1, the ancient Silk Road is more accurately thought of as a dynamic network that connected various geopolitical concerns at different settings in time (Williams, 2014). Therefore, in this paper, unless otherwise stated, the terms "road", "path" and "route" do not refer to an explicit, physical set of roads. Rather, we acknowledge the Silk Road dynamically evolved and shifted with the populations that inhabited the region, a trait that we use in this paper to arrive at an instrument.

This study exploits the mobility patterns of pastoral nomads to form an instrument. Following Wendrich and Barnard (2008) *The Archaeology of Mobility: Definitions and Research Approaches*, "pastoral nomadism" is the "general term for mobility centered on maintenance and welfare of flocks or herds." The word "pastoral" describes the herding, and the word "nomadism" describes the high mobility and impermanence of settlements. It is useful to make the distinction between pastoral nomads and hunter-gatherers, who are often thought to be similar but are distinct (Cribb, 2004). First, hunter-gatherers move towards resources for humans, whereas pastoral nomads move towards resources for flocks, independent of human resources.

Second, hunter-gatherers have typically varied mobility to secure different resources, whereas pastoral nomads are only interested in grazing resources. As such, the former's migration patterns are more complex compared to the latter's, which tend to be more predictable and can be simulated with greater confidence.

Seasonal migration, also referred to as transhumance, has two differentiating terms (Wendrich and Barnard, 2008). Vertical transhumance describes seasonal movements in mountainous areas where the snow in the winter forces the flock to move to the lowlands meadows, but in the warmer weather, the flocks move back to the highland pastures. Horizontal transhumance describes movement at around the same elevation even despite untoward weather. In this paper, following Frachetti et al. (2017), we define highland to be between 750m and 4,000m in elevation.

The area that we study in this paper is referred to as the Inner Asia Mountain Corridor (IAMC). The wide-ranging IAMC stretches from the Hindu Kush mountain range in present-day Afghanistan and Pakistan to the Altai Mountains in Siberia. The IAMC also spans the modern-day countries of China, India, Kyrgyzstan, Kazakhstan, Tajikistan, and Uzbekistan. Before the development of reliable, long-distance maritime routes in the sixteenth century, any trade between East Asia and the Mediterranean had to pass through the long overland routes in the IAMC. The IAMC's varied geography of deserts, steppes, and tall mountain ranges coupled with fertile valleys, oases, and inland deltas gave rise to both vibrant nomadic pastoralist and sedentary agricultural traditions (Frachetti et al., 2017). In the IAMC, vertical transhumance is the dominant seasonal migration pattern and, thus, the main focus of this paper. We use the small-scale, dynamic vertical transhumance routes of nomadic pastoralists on the highland steppes to study the impact of the ancient Silk Road on modern development.

In summary, using terms as developed by previous scholars across varied disciplines, we use the pastoral nomads' patterns of vertical transhumance in the Inner

Asia Mountain Corridor to establish a causal relationship between the ancient Silk Road and modern development.

2.2.2 History

Silk Road in Six Periods

Evidence of long-distance trade in Eurasia stretches as far back as the fourth millennium BCE, the period which ushered in the Bronze Age and in which writing was invented. One can divide the ancient Silk Road's history into roughly six periods (Millward, 2013). The first period, which spans from c. 3000 BCE to c. 300 BCE, is characterized by the expansion of farmers and herders out onto the steppe geographies in Central Asia by taking advantage of the new wheel and wagon technologies discovered c. 3500 BCE. These populations became the first nomadic pastoralists on the steppe.

The second period, lasting from c. 300 BCE to 300 CE, may be thought of as the "Classical Silk Road" period in which the broad area between the Mediterranean and China fell under the centralized control of a few empires. Zhang Qian, a government minister, was dispatched by the Han dynasty in 139 BCE to serve as an imperial envoy to Central Asia. Qian's trip has often been credited with stimulating the opening of different empires and Central Asia to transcontinental trade.

The third to fifth centuries CE was a "dark age" in some sense with the collapse of the western Roman Empire and the fall of the Han empire. However, the Silk Road trade still flourished, with Persians and other Central Asians taking control of the flows.

The fourth and fifth periods of the Silk Road occurred from the sixth to fifteenth centuries CE. They are characterized by the continued expansion of Persians and Arabs in Central Asia and the reunification of China again by the Sui and Tang dynasties and their cosmopolitan tastes. This is then followed by the domination of the Mongol empire over Eurasia.

The last period began in the sixteenth century CE. This period had two major developments: improvement in long-distance maritime technology such that ships were more efficient than overland caravans, and increased security of traveling via the Black Sea. These two developments led to the decline of the overland Silk Road, leading to a simultaneous decline of nomad-steppe culture in Central Asia (Williams, 2014; Millward, 2013).

Nomadic Pastoralists on the Silk Road

Early scholarship on the ancient Silk Road in Central Asia focused on lowland oases where the agricultural tradition is strongest, because they are still heavily populated today and more easily accessible to study. However, with more archaeological work in more remote locations, historians in the past decades have identified more Silk Road sites in the highland mountains. In doing so, they continue to reaffirm the hypothesis that the nomadic pastoralists contributed significantly to the development of the highland Silk Road geography (Millward, 2013). Generally, pastoralists in the IAMC would herd their livestock in the mountainous regions to feast on the productive grassland in the summer months and retreat to the lowland oases to weather the winter months. As the grazing herd moved to the productive grassland through the mountainous regions, mobile pastoralists followed. Evidence suggests that these small-scale mobility patterns and subsequent paths formed influenced the formation of the macro-scale Silk Road network (Frachetti et al., 2017). Trade was most likely conducted in short stages: sold at one node, transported to the next node by following the paths influenced by the nomadic pastoralists, resold at that node, and so forth (Gorbunova, 1993).

2.3 Data

2.3.1 Data Sources

Examining the relationship between the ancient Silk Road trade and modern level of development requires data on the locations of the Silk Road and fine-level geospatial data on modern development and other characteristics of the areas. We outline below the primary datasets that we use.

Silk Road Sites: Data on locations of Silk Road sites come from Old World Trade Routes (OWTRAD) Project (Ciolek, 2014), a public-access aggregator of geo-referenced and/or chrono-referenced data of nodes between Eurasia and Africa ranging from 4,000 BCE to 1820 CE, and from Williams (2014), a study of the Silk Road sites done on behalf of International Council of Monuments and Sites. Compiled by historians and archaeologists, the OWTRAD Gazetteer and the ICOMOS study include locations such as current and past settlements, oases, temples, rest houses, markets, forts, river and mountain crossings. As of writing, these databases combined had over 16,000 entries. We follow Frachetti et al. (2017) and extract 258 sites by choosing only sites that are on the IAMC, collapsing duplicate observations which differ only in name, and removing sites that were entered solely to facilitate the generation of a Silk Road path. We further subset to include only the 254 sites situated between 750m and 4,000m in elevation.

Table 2.1 summarizes the final count of the Silk Road sites by country and node types. Figure 2.2 maps the locations of the Silk Road sites in the IAMC highlands.

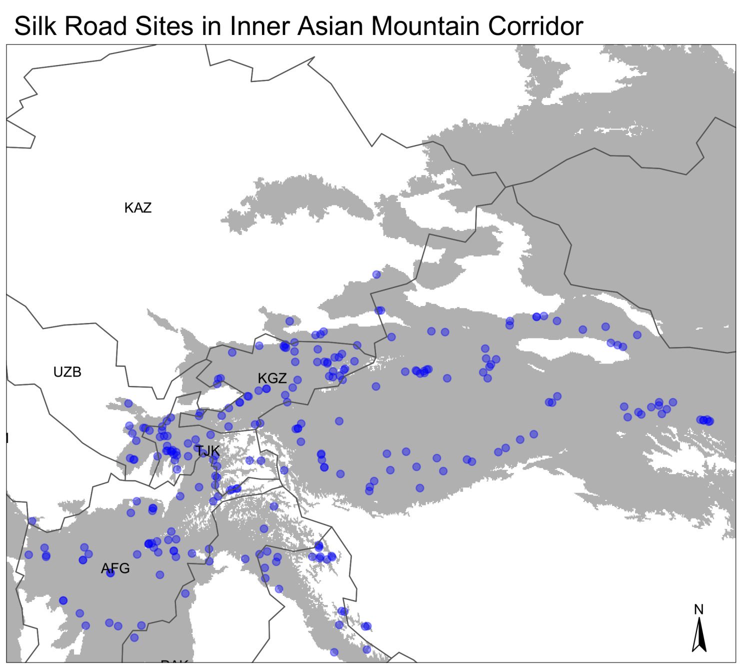
Nighttime Lights: Measuring development at fine spatial scales and across countries using existing surveys is a challenging task. Thus, we use high-resolution satellite imagery instead to proxy economic development. First, we use nighttime lights data from two sources: 1) the Version 1 Nighttime VIIRS Day/Night Band (VIIRS-DNB) Composites for the year 2016 from the Earth Observation Group (EOG) at

Table 2.1: Count of Silk Road Sites by Country and Node Types

	AF	AF/CN	AM	CN	IN	KG	KG/CN	KZ	PK	TJ	TR	UZ	Total
Current Settlement	18	0	1	41	7	17	0	3	0	29	2	0	118
Former Settlement	0	0	0	7	0	1	0	0	0	1	0	0	9
Gorge	0	0	0	1	0	1	0	0	0	0	0	0	2
Halting Place	1	0	0	0	7	0	0	0	0	0	0	0	8
Land Waypoint	0	0	0	0	0	1	0	0	0	0	0	0	1
NA	21	0	0	33	8	15	0	4	6	11	1	6	105
Pass	1	1	0	1	0	2	1	1	1	1	0	0	9
Stream	0	0	0	0	0	1	0	0	0	1	0	0	2
Total	41	1	1	83	22	38	1	8	7	43	3	6	254

Notes: This table summarizes the final count of the Silk Road sites by country and node types. Data is from ICOMOS/OWTRAD and Frachetti et al. (2017).

Figure 2.2: Silk Road Sites in Inner Asia Mountain Corridor



Notes: This figure presents Silk Road sites in the Inner Asia Mountain Corridor, as compiled by Old World Trade Routes (OWTRAD) Project (Ciolek, 2014) and Frachetti et al. (2017). The gray area represents the area of interest, i.e., the landmass of the IAMC that falls between 750m and 4,000m in elevation.

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NOAA/NCEI, and 2) the Satellite 18 Year 2013 Version 4 DMSP-OLS Nighttime Lights Time Series.

The DMSP-OLS dataset provides the annual cloud-free composites of the night lights intensity, available in 30 arc-second geographic grid cells. We use the "stable_lights.avg_vis" product, which filters out ephemeral events, such as fires. The data values range from 0 to 63. Meanwhile, the VIIRS-DNB dataset provides the annual composites of the night lights intensity, produced in 15 arc-second geographic grids. We use the "vcm-orm-ntl" product, which measures the cloud-free average radiance values, removing outliers to filter out the fire and ephemeral lights. The data contains the radiance values with units in nano Watts per square centimeter per steradian ($nanoWatts/cm^2/sr$). The VIIRS-DNB is considered to be superior to its predecessor DMSP-OLS, both in terms of spatial precision and low-light detection capabilities. We therefore consider the VIIRS-DNB dataset to be our preferred measurement.

The limitations with night lights data are well-known (Lowe, 2014). Light spills over into adjacent grid cells, some lights are a result of gas flares instead of economic activity, and the light measurements are usually not sensitive enough to pick up on less dense activities, such as agriculture. Because of the limitation of night lights data, we supplement our measure of modern-day development with two additional measures of development, as detailed below.

Other Development Measures: We first supplement our measure of modern-day development with data on population density, which we obtain from the Gridded Population of the World (GPWv4) provided by the NASA Socioeconomic Data and Applications Center (SEDAC). GPWv4 uses data from the 2010 round of Population and Housing Census to model the distribution of the human population at a spatial resolution of 30 arc-seconds. We use the estimate of the population density for the year 2015, which provides the number of persons per square kilometer.

In addition to nighttime lights and population density data, we use land cover data from GlobeLand30-2020 as an alternative measure of modern development. GlobeLand30's classification system consists of ten land cover types, namely cultivated land, forest, grassland, shrubland, wetland, water bodies, tundra, artificial surfaces, bareland, and permanent snow and ice. Data is available at 30-m resolution.

Other Datasets: We supplement our data with other high-spatial-resolution data for our instrument and controls. We adopt the normalized difference vegetation index (NDVI) and the algorithm to simulate the seasonal mobility pattern of nomadic herders, both of which will be used for the construction of our instrumental variable, from (Frachetti et al., 2017). The NDVI data used is the 7-day average NDVI values in the month of August from eMODIS. We provide further details about the instrument in Section 2.4.3.

The data for the controls are standard in the literature. We use the caloric suitability index from Galor and Özak (2016), which calculates the potential agricultural output based on crops that were available for cultivation in the time before 1500 CE. We also use the terrain ruggedness measure developed by Nunn and Puga (2012) as well since terrain ruggedness could affect how suitable an area is for settlement. Lastly, we use AquaMaps for yearly precipitation and shapefiles of major rivers. We also add a selection of variables from the Global Agro-ecological Zones v3.0 (IIASA/FAO, 2012), such as the crop suitability index and total production capacity in terms of tons per hectares for barley, flax, foxtail-millet, pearl-millet, rice and wheat.

Finally, we have a few other spatial datasets that we use to test for mechanisms. We use the Global Map of Irrigation Areas from FAO's AQUASTAT, which reports the percentage of irrigated land per cell size of 5 minutes worldwide as of 2005. Additionally, we use the 2015 Global Exposure Database for GAR provided by the United Nations Office for the Coordination of Humanitarian Affairs. This dataset is primarily used to assess damage from disasters and includes estimates of various exposed capital stock worldwide at 1km spatial resolution. It includes the value of the capital stock, separated into categories such as housing, education, and health.

2.3.2 Data Construction

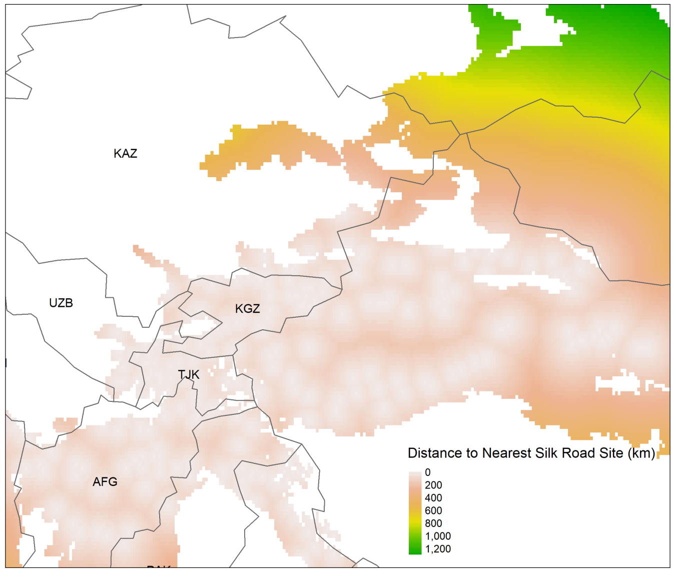
Since we are interested in the highland Silk Road along the Inner Asian Mountain Corridor, we limit the geographic extent of the study zone to 30 degrees to 55 degrees latitude and 60 degrees to 100 degrees longitude.[3] Additionally, we follow Frachetti et al. (2017) in limiting the study zone between the elevations of 750 m and 4,000 m. Within the region of interest, we construct a regular 0.167×0.167 degrees grid, which corresponds to approximately 19×19 kilometers. We treat each grid cell as an observation. We construct the variables as follows.

Shortest Distance to Silk Road Site: We define a cell as a Silk Road cell if it contains at least one Silk Road site. We capture the distance from each grid cell to the Silk Road sites by measuring the distance[4] between the cell's centroid to the centroid of the nearest Silk Road cell. We call this the shortest distance from the cell to the Silk Road site.[5] Figure 2.3 plots the shortest distance measure that we construct.

Our choice to define the Silk Road based on the Silk Road sites rather than the Silk Road routes as established by historians is intentional. Despite the name "Silk Road," there were no physical roads that dictated specific routes of the Silk Road. Traditionally, historians established Silk Road routes by calculating the least-cost paths between pre-identified historical Silk Road sites. By construction, the Silk Road routes as established by historians are inherently dictated by ease of travel, which is endogenous to modern development. In this respect, defining the Silk Road based on the Silk Road routes is problematic for the purpose of this paper. Therefore,

[3]The range of interest for our study area is dictated by our instrument.
[4]We use the shortest distance along the earth's surface, also known as"as the crow flies" distance.
[5]We also construct an alternative measure as a robustness check. See Appendix B.2 for details.

Figure 2.3: Shortest Distance to Silk Road site



Notes: This figure displays the shortest distance between the centroid of each grid cell to the centroid of the nearest Silk Road cell.

we define the Silk Road locations based on the Silk Road sites without imposing any routes between them.

Measure of Modern Level of Development: Nighttime lights data and population density data consist of continuous values. As such, we compute the variable value from those datasets by averaging the values across all pixels in a grid cell. The land cover dataset consists of categorical values and cannot be treated in the same manner. For each grid cell, we compute the percentage of the area that is classified as artificial surfaces, which are defined as "lands modified by human activities, including all kinds of habitation, industrial and mining area, transportation facilities, and interior urban green zones and water bodies, etc." A higher percentage of artificial surfaces signifies a higher level of urbanization and thus a higher level of development. Additionally, to account for the possibility that human activities in the region may consist primarily of agriculture, we construct an alternative variable that measures the percentage of the area classified as cultivated land or artificial surfaces.

Table 2.2 presents the summary statistics of the development measures at the 0.167×0.167 degrees grid cells level. Given the presence of grid cells with zero value, we use the inverse-hyperbolic-sine (IHS) transformation before taking log in our subsequent analyses. This approach is consistent with what has been adopted in the literature (Gibson et al., 2021; Bruederle and Hodler, 2018).

Other Variables: All other non-distance variables are computed by averaging the values across all pixels in each grid cell. We construct all distance-related variables in the same manner as how we measure the shortest distance to the Silk Road. Variables containing zero are transformed using IHS transformation before taking log in the subsequent analyses.

2.4 Specification and Results

The relationship between ancient Silk Road trade and modern development can be represented by the following regression:

$$Y_i = \beta_0 + \beta_1 DistancetoSilkRoad_i + \beta_2' Z_i + \gamma_i + \varepsilon_i \tag{2.1}$$

where Y_i is a measure of modern development of grid cell i, $DistancetoSilkRoad_i$ is the shortest distance from grid cell i to the ancient Silk Road site, Z_i represents other control variables, and γ_i represents the country fixed effects. We control for the geographical features that can influence both the placement of Silk Road sites and modern development. Specifically, we control for the potential agricultural output, terrain ruggedness, distance to the nearest river, and elevation.

Analyzing the standard errors of the coefficients from our regressions is particularly important given that we are working with spatial data. Below, we first describe how we calculate the standard errors before presenting the results from our OLS regressions

Table 2.2: Summary Statistics of Development Measures

	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
VIIRS	0.04	0.57	0.00	40.10	46.95	2,703.67
DMPS	0.38	2.04	0.00	62.92	13.03	262.54
Population Density	27.76	134.70	0.00	7,423.69	25.13	980.31
Land cover (artificial surfaces)	0.00	0.02	0.00	0.92	19.58	565.77
Land cover (both)	0.06	0.15	0.00	1.00	3.71	17.56

Notes: This table reports the summary statistics of measures of development measures. One unit of observation is a 0.167 degrees by 0.167 degrees grid cell. Population density refers to the number of persons per square kilometer. Land cover (artificial surfaces) refers to the percentage of a grid cell that is covered by lands modified by human activities. Land cover (both) refers to the percentage of a grid cell that is classified as cultivated land or artificial surfaces.

and introducing our instrumental variable approach.

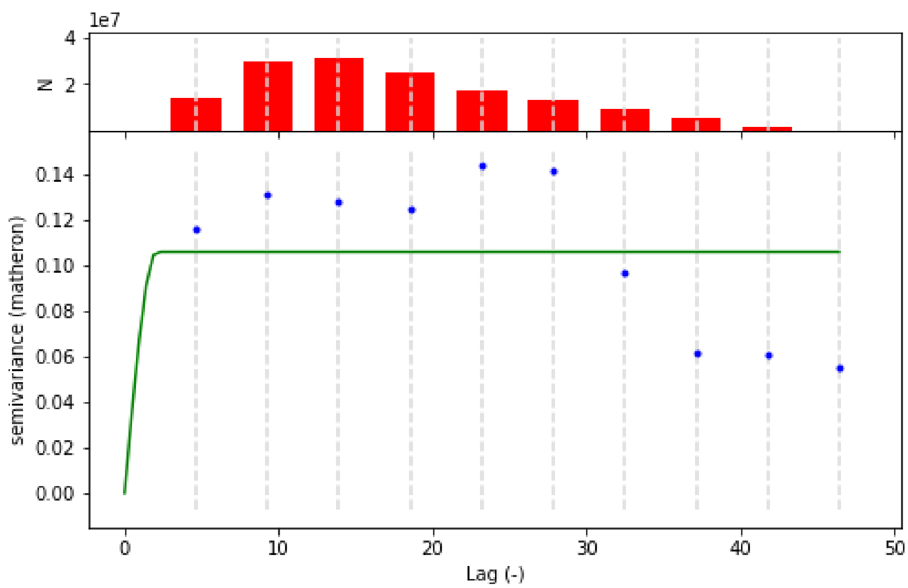
2.4.1 Standard Errors

The First Law of Geography, written by Tobler (1970), states that “everything is related to everything else, but near things are more related than distant things.” Spatial data is autocorrelated and thus must be taken into account in the empirical strategy. Unlike the literature that addresses standard errors and autocorrelation through time, the literature that addresses standard errors in the context of spatial autocorrelation has less consensus on what methods are best to minimize the influence of correlated noise on the results.

The common starting point is Conley (1999)’s paper, which outlines a process for generating spatial Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors. Conley (1999)’s method is successful in curbing estimated t statistics, relative to robust standard errors, but is sensitive to the choice of kernel, bandwidth, and the unique spatial pattern of the data (Kelly, 2019). Related research has shown that the choice of kernel is less important relative to the choice of bandwidth. This is because asymptotically, different kernel densities tend to converge to similar results (Cameron and Trivedi, 2005). Thus, we focus on choosing a correct bandwidth, and then perform robustness checks on our regressions to confirm that the standard errors are of the correct magnitude.

There are three methods we consider to choose an optimal bandwidth. The first method is a simple rule-of-thumb proposed by (Kelejian and Prucha, 2007). They suggest choosing a bandwidth b based on the following formula $b = n^{2\tau}$ where n is the number of observations, and $\tau \leq 1/3$. In our study, an observation is a grid cell, the size of which may be adjusted. Next, Lambert et al. (2008) suggest a data-driven cross-validation method performing the following minimization: $\min_b \sum_{i=1}^{n}(y_i - \hat{y}_{-i}(b))^2$ where $\hat{y}_i$ is the fitted value of y_i with location i omitted during the fitting process. Lambert et al. (2008) also suggest another data-driven approach of fitting a variogram to the data and setting the bandwidth as the generated range r, which is when the distance at which points are not significantly spatially correlated. Due to its straightforwardness and ease of interpretation, we use the last approach and fit a variogram (Figure 2.4), leading us to choose a bandwidth of 2 degrees.

Figure 2.4: Variogram



Notes: This figure presents the variogram that we generate to determine the bandwidth used to calculate spatial HAC standard errors. A variogram is a function that describes the degree of spatial dependence (y-axis) of a spatial field as the distance between two spatial units increases (x-axis). A variogram has three important parameters: the nugget n, the height of the variogram at the origin; the sill s (0), the spatial dependence value at which the curve begins to flatten (0.11); and the range r, the distance at which the curve begins to flatten (2.07). The range determines the bandwidth we will use when calculating the spatial HAC errors.

2.4.2 OLS Approach

Preliminary results from the OLS regressions are shown in Table 2.3 and Table 2.4. Table 2.3 shows the results when we use the VIIRS night lights as a proxy for modern level of development. Distance to Silk Road site is standardized and all other variables are log-transformed. The first column shows the relationship between night lights and distance to the nearest Silk Road site, controlling for only the country fixed effects and no additional control variables. There is a significant and negative relationship; as we increase the distance to the Silk Road site by one standard deviation, the night lights level falls by 2.3% on average.

Table 2.3: OLS Results

	(1)	(2)	(3)	(4)
	Night lights (VIIRS)			
Distance to Silk Road site	-0.023***	-0.036***	-0.034***	-0.032***
	(0.006)	(0.008)	(0.008)	(0.008)
Caloric suitability index		-0.001	-0.001	-0.001
		(0.001)	(0.002)	(0.002)
Ruggedness		-0.010***	-0.015***	-0.013***
		(0.004)	(0.003)	(0.003)
Precipitation		0.040***	0.011	0.016*
		(0.008)	(0.008)	(0.009)
Distance to river		-0.007***	-0.005**	-0.004**
		(0.002)	(0.002)	(0.002)
Elevation		-0.051***	-0.029**	-0.042***
		(0.012)	(0.011)	(0.014)
Crop-Suitability-Indices	No	No	Yes	Yes
NDVI	No	No	Yes	Yes
Latitude and longitude	No	No	No	Yes
Country FE	Yes	Yes	Yes	Yes
N	17,675	17,675	17,125	17,125

Notes: This table reports results from the OLS regression following equation (2.1). Distance to Silk Road site is standardized. All other variables are log-transformed. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 2 degrees using Bartlett kernel. Crop-suitability-indices include indices for wheat, rice, barley, flax, and millet. All regressions include a constant. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The second column shows the relationship when we control for other factors that may affect modern level of development. We control the caloric suitability index, the ruggedness of the terrain, the amount of precipitation, the distance to the nearest river, and the elevation. In the third column, we control for land fertility more directly using the crop-suitability-index of major crops from the FAO GAEZ dataset. Specifically, we control for the crop-suitability-index of wheat, rice, barley, flax, and foxtail millet. Additionally, we control for the NDVI value of each grid cell. The controls used in this column constitute our baseline specification. Kelly (2020) recommends accounting for the geographical location of the observations when studying the relationship between modern outcomes and the historical characteristics of the places in the past. In the fourth column, we control for the latitude and the longitude of our observation in addition to the controls in our baseline specification. Generally, we can see that adding in controls does not significantly affect our coefficient of interest; the relationship between the night lights and the distance to the Silk Road sites is always negative and significant at 1%.

The majority of existing literature estimates the elasticity between night lights and GDP using the DMSP-OLS data. Henderson et al. (2012) estimate the elasticity using country-level data and find that the structural effect of true income growth on lights growth varies between 1.03-1.72, implying the elasticity of GDP with respect to night lights between 0.58-0.97. Similarly, Hu and Yao (2021) find the cross-country estimate to be 0.76.[6] Among the limited literature that studies the VIIRS-DNB data, Chor and Li (2021) estimate the elasticity of GDP per capita with respect to night lights intensity using prefecture-level in China. They find that a 1% increase in night lights intensity corresponds to a 0.41-0.47% increase in GDP per capita.

Table 2.4 shows the results when we use alternative measures of modern development under our baseline specification. The negative relationship between distance to the Silk Road sites and modern level of development is significant across all mea-

[6] The paper finds that a one percentage point increase in GDP growth increases night lights growth by 1.317 percentage points, which implies an inverse elasticity of $1/1.317 = 0.76$.

Table 2.4: OLS with Alternative Measures of Development

	(1)	(2)	(3)	(4)
	Night lights (DMPS)	Population density	Land cover (artificial surfaces)	Land cover (both)
Distance to Silk Road site	-0.157***	-0.689***	-0.004***	-0.064***
	(0.028)	(0.099)	(0.001)	(0.008)
Caloric suitability index	-0.013*	0.055**	-0.000	-0.007***
	(0.007)	(0.027)	(0.000)	(0.002)
Ruggedness	-0.068***	-0.048	-0.002***	-0.043***
	(0.011)	(0.047)	(0.000)	(0.005)
Precipitation	0.042	0.420***	0.001	0.019**
	(0.029)	(0.112)	(0.001)	(0.008)
Distance to river	-0.028***	-0.009	-0.000	-0.005***
	(0.006)	(0.018)	(0.000)	(0.002)
Elevation	-0.142***	-0.522***	-0.002	-0.017*
	(0.041)	(0.136)	(0.001)	(0.009)
Crop-Suitability-Index	Yes	Yes	Yes	Yes
NDVI	Yes	Yes	Yes	Yes
Latitude and longitude	No	No	No	No
Country FE	Yes	Yes	Yes	Yes
N	17,125	17,125	17,125	17,125

Notes: This table reports results from the OLS regression following equation (2.1) with alternative development measures as dependent variable. Distance to Silk Road site is standardized. All other variables are log-transformed. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 2 degrees using Bartlett kernel. Crop-suitability-indices include indices for wheat, rice, barley, flax, and millet. All regressions include a constant. $^{*}p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

sures. The first column shows that the coefficient of the distance to the Silk Road site is larger in magnitude when we use the DMSP night lights measure instead of the VIIRS night lights data. This is somewhat expected since the DMSP data has limited capability to detect lights at low radiance levels; therefore, the DMSP may have underestimated the level of night lights in areas with a lower level of economic activity, leading to an upward bias in the estimate. The second column shows the result when we use modern level of population to measure modern outcome. On average, a one standard deviation increase in distance to the Silk Road sites corresponds to a 49.8% decrease in population density.[7] The third and the fourth columns show the results when using data from the land cover data set as our dependent variable. In column 3, modern development is measured by the percentage of land that is covered by artificial surfaces, which are defined as areas that have artificial cover resulting from human activities such as construction. In column 4, the dependent variable is the percentage of land classified as artificial surfaces or cultivated land. On average, as the distance to the nearest Silk Road site increases by one standard deviation, the percentage of area covered by artificial surfaces decreases by 0.4%, and the percentage of area covered by artificial surfaces or cultivated land decreases by 6.2%.

2.4.3 Instrumental Variable Approach

Although regression (2.1) shows that proximity to Silk Road site corresponds to a higher level of modern development, one can still be concerned about other unobserved heterogeneity. To establish a causal relationship between the ancient Silk Road trade and modern development, we adopt an instrumental variable strategy. A valid instrument is a variable that, after controlling for other controls in the regression, i) strongly correlates with the proximity to the Silk Road sites, and ii) only affects

[7]We find a stronger effect when we proxy for development using population density, which is in line with what has been found in the literature. For example, Bleakley and Lin (2012) found that a 10% increase in distance away from a portage predicts a 6% lower population density and 2% lower night lights intensity.

modern development level through the Silk Road.

2.4.3.1 Instrument: Seasonal Mobility Patterns of Nomadic Herders

To provide exogenous variation for the location of the Silk Road sites, we use two unique features of the Inner Asia Mountain Corridor and its inhabitants. First, ancient Silk Road traders wishing to travel between East Asia and the Mediterranean were obligated to use the overland routes in the IAMC. In the lowland regions, which were flatter and fertile with strong agricultural traditions, trading routes were generally selected based on ease of travel for traders. In the highland regions, because of the sparsely populated and often barren terrain in the highland area, the group of people who had generally traversed the area was the nomadic herders; subsequently, traders crossing the highland region followed the paths taken by the nomadic herders.

Second, unlike the traders, the nomadic herders' objective for moving overland was not to find the least-cost path of traversing the highland region to get to the lowland destination, but to exploit variation in the pasture quality as they traversed the highlands. The quality of pastures in the lowland and highland regions changes substantially over the seasons. In the summer months, lowland pastures become too arid while highland pastures become more productive. For over 4,500 years, nomadic herders have exploited these seasonal variations in pasture quality, moving from the lowland areas to the highland areas in the summer and returning to the lowland regions in the winter. Frachetti et al. (2017) find that the seasonal mobility patterns of nomadic herders shaped the highland Silk Road networks. By following the footsteps of the nomadic herders, the traders were not taking the optimal path they should have taken if they simply wanted to cross the highland region to get to the lowland destinations.

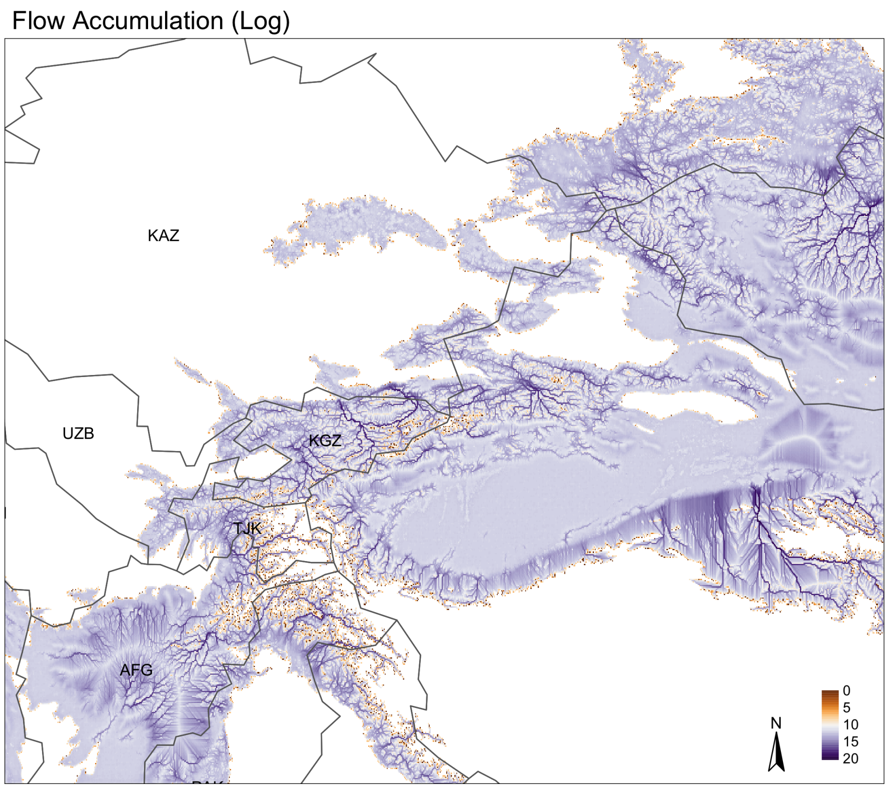
Given that the highland Silk Road networks are shaped by the nomadic herders' seasonal mobility patterns and that the nomadic herders' movements are not dictated by the least-cost path of traversing the IAMC, the seasonal mobility patterns of the nomadic pastoralist provide variations in the locations of the highland Silk Road that are not dictated by the ease of travel. We therefore instrument for the locations of the Silk Road sites using the seasonal herding patterns. The exclusion restriction is that after controlling for the suitability of the area for growing agricultural crops, the seasonal herding patterns of the nomadic pastoralist only affect modern development through the Silk Road trade.

Actual historical herding patterns of nomadic pastoralists are unrecorded. We therefore proxy for the nomadic herders' herding paths using the simulated seasonal herding patterns from Frachetti et al. (2017). Frachetti et al. (2017) uses flow accumulation modelling[8] to simulate the aggregated seasonal movements of herd animals across the IAMC using classified grass fodder quality as the input. The model simulates a figurative count of 'animals' flowing from one cell to another across the IAMC based on the pasture quality, which is categorized based on the NDVI values, over 20 human generations. The result is a flow accumulation measure that represents the simulated herding patterns. For more detail about its construction, please refer to Appendix B.1.1 or Frachetti et al. (2017) directly. Figure 2.5 provides a visual representation of the distribution of simulated flow accumulation values across the IAMC. The resulting paths from these simulated flow accumulation values can be thought of the herding pattern of the nomads.

The map of flow accumulation values is continuous. For computational feasibility, we must choose a cutoff for flow accumulation to isolate a pathway before constructing a distance to the flow accumulation path. We choose 1.5 million as a cutoff. Figure 2.6 shows the path generated. We later vary this cutoff to check the robustness of our results. After implementing this cutoff, the method to calculate the distance to the flow accumulation path is identical to the previous calculation of the distance to Silk

[8]Named the 'pastoralist participation' model.

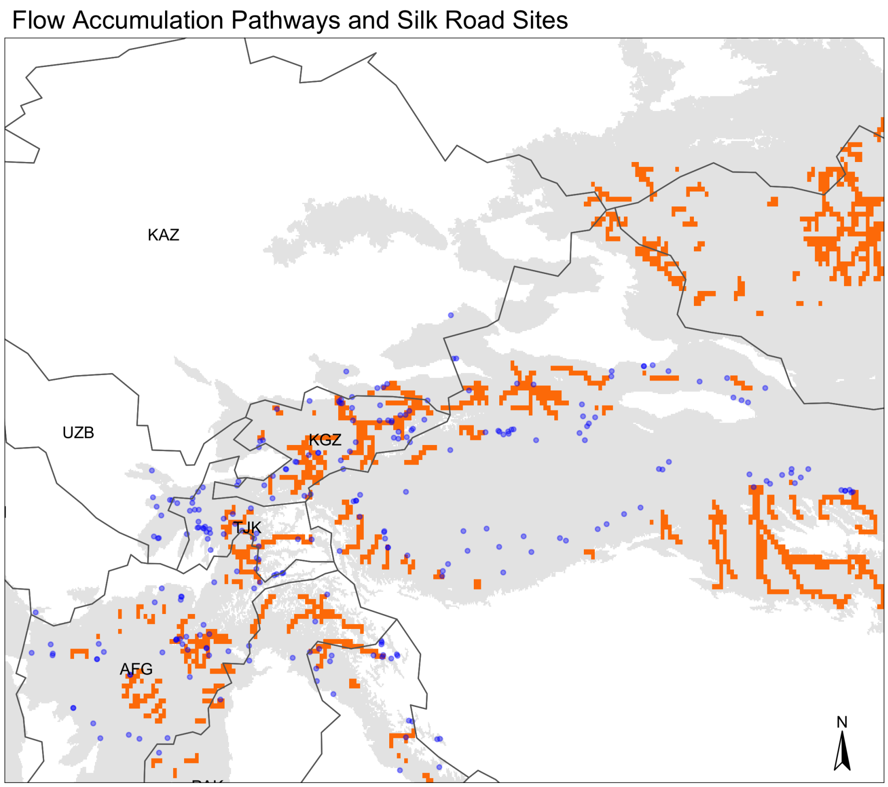
Figure 2.5: Simulated Herding Path



Notes: This figure presents the log flow accumulation values from the simulated season mobility pattern of nomadic herders in the Inner Asia Mountain Corridor as initially introduced and calculated by Frachetti et al. (2017).

Road site.

Figure 2.6: Simulated Herding Path and Silk Road Sites



Notes: This figure presents the simulated herding paths generated using flow accumulation values of 1.5 million as a cutoff. The gray area represents the area of interest, i.e., landmass of the IAMC that falls between 750m and 4,000m in elevation.

We argue that the simulated seasonal nomadic herding patterns satisfy the exclusion for the following reasons. First of all, nomadic mobility in the highland regions is primarily dicated by seasonal pasture quality rather than the ‘ease of travel’ (Frachetti et al., 2017). In fact, by construction, the simulated seasonal nomadic mobility is dictated by pasture quality and is not affected by typical factors that affect the ease of travel, such as slope. Secondly, the seasonal quality of pasture for grazing, which matters for the herders, does not translate to the productivity of land for farming, which is what matters for settlements. The highland region we are interested in is generally very rugged, making the entire area unsuitable for cultivation. As noted by Nunn and Puga (2012), cultivation becomes impossible when slopes are greater than 6; out of 36,000 cells in our region of interest, only 14 cells have a slope measure of less than 6. Therefore, the seasonal pasture quality that drives the nomadic herding patterns does not dictate the modern level of development of a certain location. Likewise, to further address concerns that pasture quality may correlate with the suitability of land for cultivation, we directly control for the suitability of land for various staple crops in our regressions using the FAO crop-suitability-indices. We also further directly control for the NDVI values in each grid cell. Thirdly, although nomadic herders move between lowland to highland areas over the year, they do not 'settle' permanently. Settlements, which matter for modern level of development, only took place as a result of trade through the Silk Road.

2.4.3.2 Instrumental Variable Results

Using the constructed distance to the flow pathways measure as an instrument, we run the following first-stage regression:

$$SilkRoad_i = \alpha_0 + \alpha_1 Flow_i + \alpha_2' Z_i + \lambda_i + \eta_i \tag{2.2}$$

where $Flow_i$ is the distance to the flow pathways measure that we constructed. We then use the predicted value $\widehat{SilkRoad}_i$ in the second-stage regression:

$$Y_i = \beta_0 + \beta_1 \widehat{SilkRoad}_i + \beta_2' Z_i + \gamma_i + \varepsilon_i \tag{2.3}$$

Table 2.5 shows the results from our IV specification. The first column shows the first stage result. The distance to the herding path positively correlates with the distance to the Silk Road sites, which is what we expect given Frachetti et al. (2017)'s finding that the seasonal mobility patterns of nomadic herders shape the highland Silk

Road networks. The F-statistic from our first stage is around 31.6, which is in the acceptable range for a strong instrument.

Columns (2)-(6) in Table 2.5 present the second stage results. The IV estimates are larger in magnitude than the OLS estimates, which can be explained by measurement errors in the locations of the Silk Road sites. From the IV regression, a one standard deviation increase in distance from the Silk Road site results in a 10.0% decrease in night lights intensity using the VIIRS-DNB data and 38.4% decrease in night lights intensity using the DMSP-OLS data.[9] Columns (4)-(6) present the IV results when we use alternative measures of modern development. The population density decreases by 85.5% with a one standard deviation increase in distance to the Silk Road site, while the percentage of area covered by artificial surfaces and the percentage of area covered by both artificial surfaces and cultivated land decrease by 1.4% and 12.3% respectively.

2.4.3.3 Robustness Checks

Random Sites: One could be concerned that the results in our analyses are driven by spatial noises. To ensure that this is not the case, we repeat our analyses using random sites instead of the Silk Road sites. Specifically, we generate the same number of random points in our region of interest as the number of Silk Road cells to represent random sites. We then calculate the shortest distance between the centroid of each grid cell to the centroids of the cells containing those random points, as illustrated in Figure 2.7.

We then reestimate the OLS equation (2.1) using the shortest distance to a random site instead of the shortest distance to a Silk Road site. The results are shown in the

[9] Our result is smaller than that in Ahmad and Chicoine (2021), who found that night lights intensity is about 80% higher in cells within 50 km of the Silk Roads relative to cells that are 200-500 km away from the Silk Roads using DMSP-OLS data. This difference is somewhat expected since the area of study in Ahmad and Chicoine (2021) covers the lowland region of the Silk Road, where the routes are believed to be dictated by ease of travel and pass through big cities. Therefore, one would expect to see larger variations in night lights intensity in their paper.

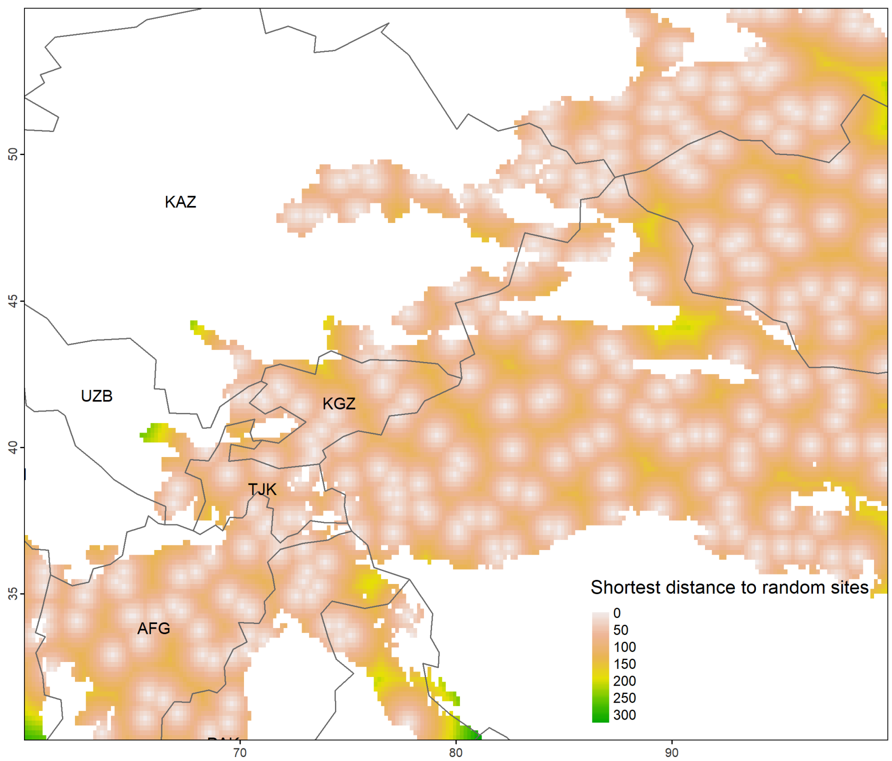
Table 2.5: IV Results

	(1)	(2)	(3)	(4)	(5)	(6)
	First stage	Second stage				
	Distance to Silk Road site	Night lights (VIIRS)	Night lights (DMPS)	Population density	Land cover (artificial surfaces)	Land cover (both)
Distance to Silk Road site		-0.105***	-0.485***	-1.930***	-0.014***	-0.131***
		(0.029)	(0.107)	(0.365)	(0.004)	(0.025)
Distance to herding path	0.190***					
	(0.034)					
Caloric suitability index	-0.041***	-0.004**	-0.028***	-0.003	-0.001**	-0.010***
	(0.014)	(0.002)	(0.009)	(0.034)	(0.000)	(0.003)
Ruggedness	-0.048*	-0.018***	-0.083***	-0.103*	-0.003***	-0.046***
	(0.026)	(0.004)	(0.015)	(0.060)	(0.001)	(0.005)
Precipitation	0.255***	0.029**	0.125***	0.737***	0.003**	0.036***
	(0.047)	(0.011)	(0.040)	(0.138)	(0.001)	(0.010)
Distance to river	-0.026***	-0.005***	-0.031***	-0.020	-0.000*	-0.006***
	(0.007)	(0.002)	(0.007)	(0.020)	(0.000)	(0.002)
Elevation	0.021	-0.042***	-0.199***	-0.737***	-0.004*	-0.028**
	(0.106)	(0.016)	(0.060)	(0.213)	(0.002)	(0.012)
Crop-Suitability-Indices	Yes	Yes	Yes	Yes	Yes	Yes
NDVI	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	31.590					
N	17,125	17,125	17,125	17,125	17,125	17,125

Notes: This table reports results from the IV regressions. Distance to Silk Road site and distance to herding path are standardized. All other variables are log-transformed. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 2 degrees using Bartlett kernel. Crop-suitability-indices include indices for wheat, rice, barley, flax, and millet. All regressions include a constant. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

first column of Table 2.6. We do not observe a statistically significant relationship between the shortest distance to a randomly generated site and the intensity of night lights.

Figure 2.7: Shortest Distance to Random Points



Notes: Shortest distance between the centroid of each grid cell and the centroid of the nearest cell with a randomly generated site. The number of randomly generated sites is the same as the number of the Silk Road cells present in the dataset.

Least-cost mobility patterns of nomadic herders: Although our simulated herding patterns use pasture quality as the cost raster in the flow accumulation modeling, one could still be concerned that pasture quality may correlate with elevation, which would violate the exclusion restriction. To address this concern, we simulate the least-cost paths of the nomadic herders. Specifically, we generate new mobility patterns of the nomadic herders using the same flow accumulation modeling algorithm, but with the slope of the terrain as a cost raster in the model instead of

Table 2.6: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Night lights (VIIRS)	Distance to herding path	Night lights (VIIRS)	Distance to herding path	Night lights (VIIRS)	Night lights (VIIRS)
Distance to Silk Road site			-0.087**		-0.131***	
			(0.036)		(0.033)	
Distance to herding path		0.204***		0.199***		-0.001
		(0.054)		(0.034)		(0.001)
Distance to random site	-0.011					
	(0.013)					
Caloric suitability index	0.001	-0.041***	-0.003*	-0.023**	-0.003*	-0.000
	(0.002)	(0.014)	(0.002)	(0.011)	(0.002)	(0.000)
Ruggedness	-0.013***	-0.045*	-0.017***	-0.045**	-0.014***	-0.001
	(0.003)	(0.027)	(0.004)	(0.022)	(0.005)	(0.001)
Precipitation	0.002	0.266***	0.025**	0.294***	0.064***	-0.003
	(0.008)	(0.051)	(0.012)	(0.052)	(0.012)	(0.003)
Distance to river	-0.004**	-0.022***	-0.004**	-0.032***	-0.008***	-0.001*
	(0.002)	(0.007)	(0.002)	(0.008)	(0.002)	(0.001)
Elevation	-0.023**	-0.029	-0.047***	0.075	-0.060***	0.002
	(0.011)	(0.116)	(0.015)	(0.085)	(0.016)	(0.004)
Distance to herder's least-cost path		-0.000	-0.000			
		(0.000)	(0.000)			
Crop-Suitability-Indices	Yes	Yes	Yes	No	No	Yes
NDVI	Yes	Yes	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat		14.278		34.271		
N	17,125	17,125	17,125	17,675	17,676	7,467

Notes: This table reports results from the robustness check exercises. Distance to Silk Road site, distance to herding path, and distance to random site are standardized. All other variables are log-transformed. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 2 degrees using Bartlett kernel. Crop-suitability-indices include indices for wheat, rice, barley, flax, and millet. All regressions include a constant. Column 1 shows the OLS results when we replace distance to Silk Road site with distance to randomly generated sites. Columns 2 and 3 show the IV results when we control for distance to herder's least-cost path. Columns 4 and 5 show the IV results when we exclude crop-suitability-indices and NDVI from the control variables. Column 6 shows the relationship between distance to herding path and night lights intensity when we only consider locations that are at least 150km away from the nearest Silk Road site. $*p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

pasture quality. Intuitively, this new generated path represents the hypothetical path we would expect 'animals' to take with a preference for a flatter slope. In the same manner as the construction of our instrument, we choose a cutoff of 1.5 million flow values for ease of computation. We then compute the shortest distance between each grid cell and the simulated least-cost paths of the herders.

Column 3 of Table 2.6 present the second-stage IV results after controlling for the shortest distance to the simulated least-cost paths of the herders. We can see that controlling for the least-cost paths of the herders does not significantly impact our IV estimate. Once we take into account the herders' least-cost paths, a one standard deviation increase in distance to Silk Road site corresponds to a 8.3% decrease in the night lights intensity, which is relatively similar to our baseline estimate of 10.0%.

Excluding crop-suitability-indices and NDVI from control variables: Given that nomadic herders' mobility pattern is simulated using pasture quality as the input, one may be concerned that the variation in our instrument is all driven by agriculture-related factors. To verify that this is not the case, we exclude crop-suitability-indices and NDVI from our IV regressions. The fourth and fifth columns of Table 2.6 present the results. When we do not control for crop-suitability-indices and NDVI, a one standard deviation increase in distance to the nearest Silk Road site is associated with a 12.3% decrease in night lights, which is relatively close to our baseline estimate of 10.0%. The exclusion of crop-suitability-indices and NDVI does not significantly affect our results. Although the simulated herding path uses pasture quality as the input data, the actual simulation of the flow of animal stocks depends on the direction and the relative pasture quality. Nomadic herders move from locations with low pasture quality to locations with relatively higher pasture quality. The simulated herding path tracks their mobility pattern, crossing both places with low and high pasture quality. Our instrument is therefore not solely driven by agriculture-related factors.

Testing correlation between proximity herding path and development: We conduct an additional exercise to verify that proximity to herding path only affects modern development through the Silk Road. If herding path of the nomads only affects modern development through the Silk Road, we would expect to see no correlation between proximity to herding path and modern development in places where the Silk Roads are absent. We test this by only considering observations that are at least 150 km away from the nearest Silk Road site and run the OLS regression (2.1), replacing distance to Silk Road site with distance to herding path. The last column of Table 2.6 present the results. We can see that there is no significant relationship between proximity to herding path and night lights intensity in areas that are not in close proximity to the Silk Road. The result supports that proximity to herding path only affects modern development through the Silk Road.

Other robustness checks: We perform additional robustness checks, including using an alternative measure for proximity to Silk Road sites, excluding outliers, using different grid sizes, and using different cutoffs to construct our instrument. The results are reported and discussed in Appendix B.2.

2.5 Mechanisms

The results in the previous section indicate that the persistent impact of the ancient Silk Roads on modern development four centuries after the decline of the overland Silk Roads. However, what are the mechanisms through which the ancient trade routes impact the level of development in modern day? Night lights intensity itself is an indicator of economic activity. It does not answer why the ancient Silk Road's effects are persistent over time. In this section, we discuss two possible mechanisms: connectivity and capital investment.

Connectivity refers to the "connections" made between different places, which have endured over time. The ancient Silk Road both fostered new connections and strengthened existing connections across Eurasia. These connections may have persisted over time, even after the decline of the overland Silk Roads. Therefore, places that developed these connections as a result could remain more connected to markets today, and subsequently may be more developed and able to share new technologies more quickly. As time passes, this connectivity could manifest itself through stronger transportation network.

To explore the connectivity mechanism, we substitute distance to major roads in place of the nighttime lights intensity as a dependent variable. The first column of Table 2.7 presents the second stage results from the IV regression, using the shortest distance to a major road as a dependent variable. On average, as the distance to Silk Road increases by one standard deviation, the distance to a major road increases by 1.1 standard deviations. The result provides some evidence of the persistent effect of the Silk Roads arising from the connectivity mechanism.

Additionally, the persistent effect of the ancient Silk Roads may be a result of capital investment. Capital investment may refer to physical capital such as irrigation and urban development. As trade activity grew, investment in infrastructure in areas along the ancient Silk Road arose to service the traders. Even after the decline of the overland Silk Road trade, such infrastructure continued to be a source of agglomeration for subsequent economic activity and infrastructure investment. As a result, places along the ancient Silk Road could benefit from better irrigation and a higher density of health services.

To explore the investment mechanism, we substitute irrigation and building stock measures as a dependent variable in place of the nighttime intensity. Columns 2-6 of Table 2.7 report the results from the second stage IV regressions. The second column uses the (log) percentage of land equipped for irrigation as the dependent variable. Columns 3-6 use the (log) value of building stock used for housing, healthcare, edu-

Table 2.7: Mechanisms

	Distance to road	Irrigation	Building stock used for			
			Housing	Health	Education	All purposes
Distance to Silk Road site	1.087***	-1.252***	-1.656***	-0.192***	-1.236***	-2.141***
	(0.359)	(0.257)	(0.313)	(0.045)	(0.250)	(0.416)
Caloric suitability index	-0.008	-0.041	-0.072**	-0.012***	-0.039*	-0.084**
	(0.038)	(0.025)	(0.030)	(0.003)	(0.023)	(0.039)
Ruggedness	0.191***	-0.202***	-0.269***	-0.019***	-0.215***	-0.378***
	(0.053)	(0.038)	(0.047)	(0.006)	(0.037)	(0.062)
Precipitation	-0.594***	0.256***	0.484***	0.044***	0.361***	0.713***
	(0.168)	(0.093)	(0.115)	(0.014)	(0.090)	(0.156)
Distance to river	0.019	-0.105***	-0.146***	-0.011***	-0.112***	-0.197***
	(0.018)	(0.018)	(0.018)	(0.002)	(0.014)	(0.023)
Elevation	-0.217	-0.314**	-0.287*	-0.053**	-0.214*	-0.273
	(0.164)	(0.130)	(0.165)	(0.021)	(0.127)	(0.213)
Crop-Suitability-Indices	Yes	Yes	Yes	Yes	Yes	Yes
NDVI	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	17,125	17,125	17,125	17,125	17,125	17,125

Notes: This table reports results from the second-stage IV regressions. Distance to Silk Road site and distance to road are standardized. All other variables are log-transformed. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 2 degrees using Bartlett kernel. Crop-suitability-indices include indices for wheat, rice, barley, flax, and millet. All regressions include a constant. $*p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

cation, and any purposes in that order. We consistently see a negative and significant relationship between distance to Silk Road site and measures of capital stock, indicating that capital investment and agglomeration could be one of the mechanisms through which the ancient Silk Roads affect modern development.

Our results in this section have shown a higher level of connectivity and capital investment in areas closer to the Silk Road. Note that both types of mechanisms may be acting in complementarity with each other, i.e., capital investment enhances connectivity, and connectivity enhances investment. Because of this, due to our current empirical strategy, we do not aim to disentangle one category of mechanism from each other, but provide suggestive evidence of their functioning.

2.6 Conclusion

The paper studies the long-term effect of trade routes on development. Using a novel instrument constructed from herding flows in the Inner Asia Mountain Corridor, this paper finds that locations along the highland Silk Road continue to be more developed centuries after the decline in the importance of ancient Silk Road overland trade corridors. The results are robust across different measures of modern development and different specifications.

Future work in this area may include studying further which types of Silk Road sites continue to have persistent effects on modern development over time and what mechanisms seem to be the most important. Another direction for work includes developing a theoretical model, including mechanisms, to explain the empirical link between the ancient Silk Road and modern development.

Simply, this study seeks to understand the effects of the past on the present and demonstrates that even choices made in antiquity, which dwindled in importance by the sixteenth century, still have enduring persistent effects on modern development today. Policymakers may consider that not only does the choice of a trade route or improvement in transportation have effects a decade later, but centuries later. Today, the ancient Silk Road is being revitalized in China's Belt and Road Initiative, which was introduced in 2013. Along with concentrating on maritime shipping lanes ("roads"), the Chinese government has identified several overland corridors ("belts") that they will target for development. One of these overland corridors is called the China-Central Asia–West Asia Economic Corridor (CCWAEC), a geographic area that encompasses the Inner Asia Mountain Corridor. Our study could have important implications for such an initiative.

Chapter III

Dynamics of Export Entry and Exit Under Uncertainty

3.1 Introduction

Data from disaggregated international trade transactions reveal a high degree of turnover among exporters. For instance, in any given year in Colombia, about a third of the exporters are new entrants and about a third of the exporters would stop exporting by the end of the year (Fernandes et al., 2015). In particular, as shown in this paper, a significant portion of the exporter turnover is accounted for by exporters that start to export and do not export beyond one year. This observation is puzzling; from a standard trade model with sunk cost of entry into the export market, one would expect most of the exporter turnover to result from newer, more productive exporters replacing older, less productive ones. In other words, one would expect to see a very small proportion of firms that export for only one year. This contradiction motivates a question: what accounts for the high exporter turnover and the high proportion of one-year exporters that we observe in the data?

This paper studies the dynamics of export entry and exit using plant-level data from the Chilean manufacturing census. I first show that about 34 percent of the exporter turnover among Chilean plants arises from plants that export for only one year. I verify that this high proportion of one-year exporters is present across all industries and is therefore not driven by industry-specific characteristics. Next, I show that there are differences in characteristics among plants with different export statuses. In addition to the differences in size and productivity among exporters and non-exporters, there exist some differences among the exporting plants. Incumbent exporters are on average larger and more productive than plants that are entering or exiting the export market. Among plants that are entering or exiting the export market, plants that enter and export for only one year are on average smaller and less productive than those that enter and export for two years or longer. However, there is no significant difference in terms of productivity between one-year exporters and plants that exit the export market after having exported for longer than one year.

These findings are at odds with the models typically used in the literature such as Melitz (2003). These models typically consist of heterogeneous plants that face a sunk cost of entry into the export market. In a standard sunk-cost model, all costs of exporting are known by plants prior to entering the export market. The presence of sunk cost of entry means that a plant's decision to enter the export market depends not only on its current profitability, but also on its expectation of future profitability. Plants only choose to enter the export market when their productivity is high enough that they expect to continue to export in the following periods in order to recover the sunk cost of entry. This results in two implications. First, the proportion of plants that export for only one year should be low. Second, plants should start to export when their productivity is sufficiently high; therefore, entrants into the export market should be, on average, the most productive group of plants. Neither of these implications is consistent with the cross-sectional features I observe in the data.

I propose an alternative model of entry and exit that captures the cross-sectional features observed in the data. My model consists of two features that are different from a standard sunk-cost model: 1) uncertainty in the cost of exporting, and

2) heterogeneity in the productivity process across plants. First, to address the high proportion of one-year exporters observed in the data, I introduce uncertainty into the export decision; the cost of exporting is heterogeneous across plants, and plants can only learn about the actual value of the cost once they have started exporting. Given their productivity, plants each have their own cutoff for the cost of exporting. If they draw a cost lower than their cutoff, they continue to export in the following periods; if the cost drawn is higher than their cutoff, they stop exporting after exporting for only one year. This leads to a higher proportion of one-year exporters than that in a standard sunk-cost model. In addition, the lower the plant's productivity, the higher the probability of the plant drawing a cost above the cutoff and subsequently exiting the export market. Therefore, on average, the productivity of plants that export for only one year in this model will be lower than that of plants that export for two years or longer. Second, to address the observation that incumbent exporters are, on average, the most productive group, I introduce heterogeneity in the productivity process across plants. Specifically, in my model, different plants face stochastic productivity processes with different productivity means, implying that certain plants are inherently more productive than others. Therefore, incumbent exporters consist of plants with higher productivity mean on average.

Having described the model, I calibrate the model to match some key moments in the data. I verify that my proposed model is consistent with the cross-sectional features in the data while a standard sunk-cost model fails to match those features. I then run two counterfactual analyses to show that the aggregate response in my proposed model is significantly smaller than that in a standard sunk-cost model. Uncertainty in the cost of exporting lowers the expected gain from entry into the export market, leading to an attenuated export entry response after a shock. On impact, the change in the export participation rate from a temporary 10% depreciation in my proposed model is three times smaller than that in the canonical model. Likewise, the hysteresis in my proposed model is significantly more attenuated. Similarly, in response to a 5% permanent increase in foreign demand, the change in the export participation rate in my proposed model is seven times smaller than that in the canonical model.

This paper connects with existing literature in several dimensions. First is a large body of works that speaks to the differences in characteristics across different groups of firms. Bernard et al. (1995) and Bernard and Jensen (2004) examine the differences between exporting and non-exporting firms, establishing that exporters tend to be larger and more productive. Building on these empirical findings, a large body of theoretical literature has been developed (Melitz, 2003; Chaney, 2008). Models in this literature typically feature heterogeneous plants that face sunk cost of export entry. These standard sunk-cost models have successfully captured the differences in productivity and size between exporting and non-exporting firms. Empirically, I contribute to this literature by documenting the high proportion of one-year exporters and the differences in characteristics across different groups of exporting plants, a feature that standard sunk-cost models cannot explain.

Additionally, this paper speaks to the body of works that study the dynamics of exporters. Over the past several years, the increased availability of disaggregated trade data has led to an increased interest in the exporter dynamics. However, the majority of the literature in this area focuses on understanding the behaviors of firms once they start exporting rather than the turnover of the exporters (Fitzgerald et al., 2019; Das et al., 2007; Berman et al., 2015). Although some papers (Apaitan et al., 2016; Martha et al., 2013) note empirical evidence of the high exporter turnover and the low survival rate among export entrants, there has been limited work that provides a theoretical framework to understand the high proportion of one-year exporters that I observe in the data.

Among the limited literature on one-year exporters, Ruhl and Willis (2017) document the low survival rate of export entrants and model the high proportion of one-year exporters by randomly allowing some plants to face zero export cost for one period. In doing so, they can replicate the high proportion of one-year exporters in the data. Nevertheless, their model implies that the average productivity of plants that export for one year should be the same as that of non-exporting plants, which is not consistent with the stylized fact that I find in the Chilean data. Another branch of the literature shows the interdependencies between domestic and foreign markets. in the presence of increasing marginal costs (Almunia et al., 2021; Soderbery, 2014; Vannoorenberghe, 2012; Blum et al., 2013). Blum et al. (2013) propose a story about stochastic demand shock to account for plants that export for less than one year. In this story, plants have to make capital investment decisions before realizing domestic demand; if the domestic industry experiences a negative demand shock, plants export in that period to compensate for the low domestic industry demand. This story is consistent with the productivity pattern and the fraction of one-year exporters I observe in the data. Nonetheless, as Blum et al. (2013) themselves have acknowledged in their paper, the story is not able to explain why a large number of firms that export for less than one year only export once and never export again.

This paper contributes to the literature on export entry and exit dynamics by providing a framework that can account for why a group of firms only export for one year and never export again. I build on the idea of informational uncertainty in the cost of exporting as proposed by Segura-Cayuela and Vilarrubia (2008) and extend it to make the cost of exporting heterogeneous across firms. In addition, I document the differences in productivity across different groups of exporting firms and propose a model that is consistent with this observation.

The rest of the paper proceeds as follows. Section 3.2 describes the data and establishes five stylized facts about the dynamics of export entry and exit that motivate my model. Section 3.3 and 3.4 describe the model and the estimation results.

Section 3.5 presents results from two counterfactuals and illustrates the aggregate implications of the uncertainty in the cost of exporting. Section 3.6 concludes.

3.2 Data

I use Chilean plant-level data from the Encuestra Industrial Anual (ENIA). ENIA is an annual survey covering all registered manufacturing plants with more than ten employees in Chile. It is an unbalanced panel from 1995 to 2007, consisting of around 5,400 plants per year on average. The survey contains data on plants' gross value of production, cost of raw materials, wage bills, nominal value of fixed capital, value of sales coming from export, and 4-digit ISIC code. The details on how the sample is constructed can be found in the Appendix.

3.2.1 Exporter dynamics

I characterize plants' export status as follows. A plant is classified as an exporter in year t if its value of sales from export is positive. An export entrant in year t is a plant that was not exporting in year $t-1$ and is exporting in year t. An export exiter in year t is a plant that is an exporter in year t but will not be an exporter in year $t+1$. Note that the terms entry and exit in this paper refer to entry into and exit out of the export market; plants may have been operating before they start to export, and plants may still be operating after they stop exporting.

The descriptive statistics of the data are shown in Table 3.1. The table only shows descriptive statistics for 1996-2006 since export entrants cannot be identified in the first year of the data and export exiters cannot be identified in the last year of the data. On average, about 20 percent of plants export each year, and exporters export about 25 percent of their total output on average. Even though only a small fraction of plants exports, there is a significant amount of exporter turnover; in any given year, about 19 percent of exporting plants are new exporters, and about 19 percent will stop exporting by the end of the year.

Table 3.1: Descriptive Statistics

Total	Number	
Plants	7,584	
Plants that export at some point	1,886	
Average	Mean	Std. Dev
Plants per year	5,400	222
Exporters per year	1,080	80
Export entrants per year	183	41
Export exiters per year	191	20
Export entry rate	18.8%	3.6%
Export exit rate	19.1%	1.8%
Average annual value per exporting plant	Mean	Std. Dev
Export value (deflated)	$6,543,597.00	$41,500,000.00
Percentage of sales exported	24.7%	29.4%

Notes: This table reports the descriptive statistics of plants present in the data. Since export entrants cannot be identified in the first year in the data (year 1995) and export exiters cannot be identified in the last year of the data (year 2007), this table shows the descriptive statistics for year 1996-2006.

To further understand the dynamics of export entry and exit, I further classify exporting plants based on their export duration. I define export spell as the number of consecutive years that a plant has been exporting. An illustration of how I classify export spells can be found in Table 3.2. Figure 3.1 shows the percentage of export exiters by their export spell in the year that they stop exporting.[1] A significant portion of the exporter turnover that I observe arises from plants that export for only one year. About 34 percent of exiting exporters have an export spell of one year on average. Figure 3.2 shows that the high proportion of one-year exporters can be observed in all industries with an average of 15 or more exporters, indicating that

[1]To address the truncated spells issue, I only consider data between 1999-2000. Given that my sample starts in 1995, from 1999 onwards, I can identify all exporters with an export spell with less than five years. By definition, all exporters who exported continuously from 1995 to 1999 have an export spell of 5 years or longer.

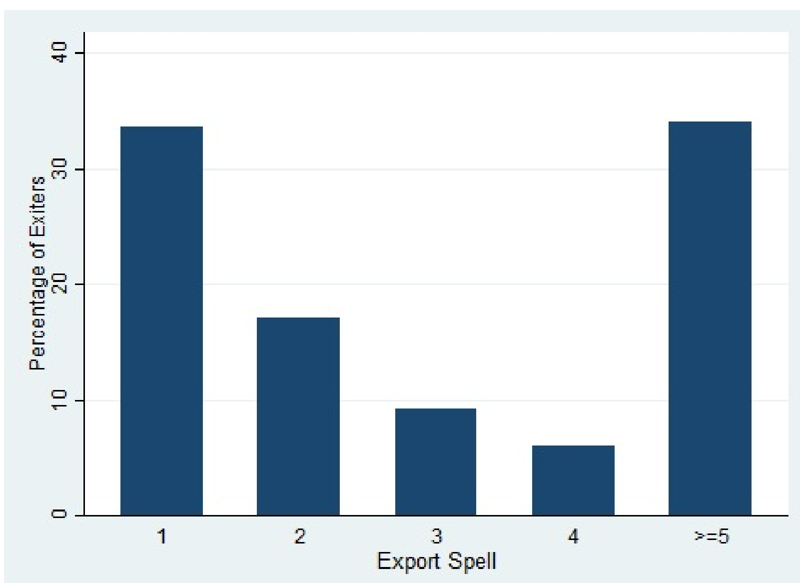
this observation is not driven by industry-specific characteristics of certain, special industries.[2] Breakdown of number of exiters by export spell for all industries can be found in the Appendix.

Table 3.2: Illustration of Export Spell Classification for a Plant

Year	Export Dummy	Export Spell
1	0	0
2	1	1
3	1	2
4	1	3
5	0	0
6	1	1
7	1	2

Notes: This paper provides an illustration of how export spell is classified for a plant. Export dummy = 1 if plant exports in that year. Data in this table is hypothetical.

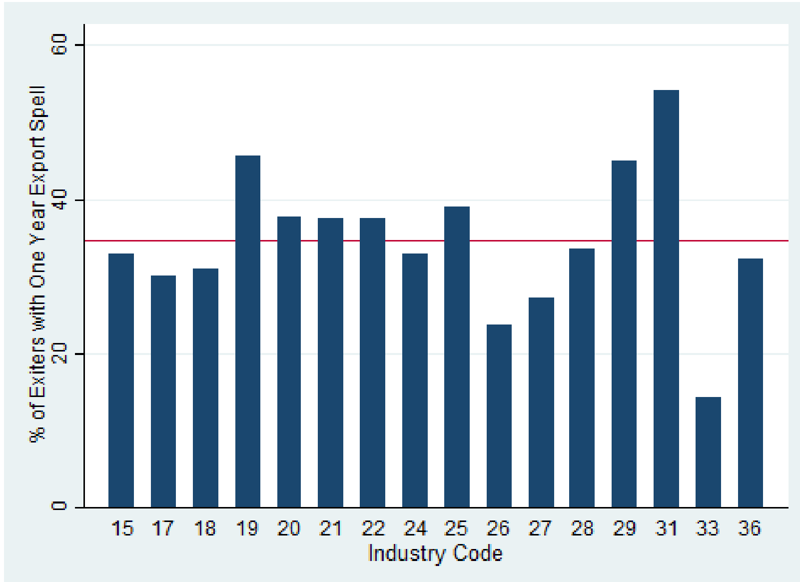
Figure 3.1: Percentage of Exiters by Export Spell



Notes: This figure presents the average percentage of exiters by export spell between 1999-2006.

[2]There are only seven industries with less than 15 exporters.

Figure 3.2: Percentage of Exiters with One Year Export Spell by Industry



Notes: This figure presents the percentage of exiters who export for only one year in each industry. This figure only includes industries with more than 15 exporters. Details of exiters by export spell for all industries can be found in the Appendix.

3.2.2 One-year exporters

The large proportion of one-year exporters among exiting exporters observed in the data is rather puzzling. In a standard trade model with sunk cost of entry and persistent productivity, plants that enter the export market are expected to be profitable and to continue to export in subsequent periods. This implies that plants that start to export should export for several periods and that the proportion of one-year exporters among plants that stop exporting should be low. However, this is not the case observed in the data.

<u>General characteristics</u>

To better understand plants' export behaviors, I examine the characteristics of plants based on their export status. Plants are divided into five groups based on their export status across three consecutive years ($t = -1, t = 0, t = 1$). These five groups are surviving entrants, old exiters, one-year exporters, incumbent exporters, and nonexporters. Surviving entrants are plants that start to export at $t = 0$ and continue to export at $t = 1$. Old exiters are plants that export at $t = -1$ and stop exporting by the end of $t = 0$. One-year exporters are plants that start exporting at $t = 0$ and do not continue to export beyond that. Incumbent exporters are plants that export across all three periods, and nonexporters are plants that do not export across all three periods. I drop plants that do not fit into these categories, for instance those that exported at $t = -1$ but not at $t = 0$ and $t = 1$. Table 3.3 illustrates how plants are classified based on their export status.

Table 3.3: Illustration of Group Classification Based on Export Status across Three Consecutive Years

Plant ID	Export Status at time t			Group
	$t=-1$	$t=0$	$t=1$	
1	0	1	1	Surviving entrant
2	1	1	0	Old exiter
3	0	1	0	One-year exporter
4	1	1	1	Incumbent exporter
5	0	0	0	Nonexporter
6	1	0	0	Dropped
7	1	0	1	Dropped
8	0	0	1	Dropped

Notes: This table illustrates how exporters are grouped based on their export status across three consecutive years. Dropped indicates that the observation is excluded from the sample. Data used in this table is hypothetical.

Table 3.4 compares the characteristics across the five groups after controlling for the industry and year fixed effects. I compute the estimates by running the following regression:

$$\begin{aligned} y_{st} =& \beta_0 + \beta_1 I(IncumbentExporter_s) + \beta_2 I(SurvivingEntrant_s) + \beta_3 I(OldExiter_s) \\ &+ \beta_4 I(Nonexporter_s) + industry_s + year_t + \mu_{st} \end{aligned} \tag{3.1}$$

the variable $I(group)$ is an indicator that is equal to one if a plant belongs to the group. The constant shows the characteristics of one-year exporters. From Table 3.4, I can see significant differences across plants' characteristics in different groups. Firstly, on average, incumbent exporters have higher sales and employ higher capital and labor than plants in any other group. Secondly, there are differences in characteristics between one-year exporters and other entering and exiting plants. One-year exporters tend to have lower total sales, employ less labor, and have less capital compared to surviving entrants and old exiters, though their export-sales ratios are not significantly different. Nevertheless, one-year exporters are still on average larger than non-exporters in terms of total sales, labor employed, and capital employed.

Productivity

I have so far established that one-year exporters tend to be smaller than other exporting plants. However, what is the relative productivity of the plants? I estimate plants' productivity following the method proposed by Levinsohn and Petrin (2003).[3] I use raw materials and electricity as proxies for unobserved productivity shocks in order to address the simultaneity problem, namely that levels of labor and capital adopted by the firm could be correlated to the unobserved productivity shock and that production function estimated using OLS could be biased.

All variables are measured as follows. Value added is measured as the difference between the value of gross output and the cost of all inputs. Labor input, l_{sit}, is measured using wage bill to account for quality differences among labor. All these variables are deflated using GDP deflator. Capital input k_{sit} is measured by the book value of capital deflated by the country-specific price of investment goods provided by the World Development Indicator. Plants are grouped using 2-digit ISIC industry. Any industries with less than 100 observations are not used in this estimation.

[3] As robustness checks, I also estimate the productivity using the methods proposed by Ackerberg et al. (2015) and Wooldridge (2009). Results are presented in Appendix C.2. Overall, the results are robust to different productivity estimation methods.

Table 3.4: Plants' Characteristics by Export Status

	Total sales	Domestic sales	Export value	Export/Total Sales	Wage bill	Capital
I(incumbent exporter)	1.060***	0.688***	2.820***	0.169***	1.016***	1.298***
	(0.080)	(0.082)	(0.124)	(0.010)	(0.068)	(0.104)
I(surviving entrant)	0.427***	0.385***	0.851***	0.020	0.422***	0.606***
	(0.096)	(0.098)	(0.151)	(0.012)	(0.084)	(0.122)
I(old exiter)	0.313**	0.267**	0.467**	0.018	0.348***	0.499***
	(0.097)	(0.099)	(0.153)	(0.011)	(0.085)	(0.123)
I(nonexporter)	-0.964***	-0.903***	-	-	-0.836***	-1.233***
	(0.077)	(0.079)	-	-	(0.067)	(0.101)
Constant	15.095***	14.738***	11.904***	0.372***	12.728***	13.250***
	(0.086)	(0.089)	(0.156)	(0.015)	(0.075)	(0.114)
ISIC 3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	32,291	32,268	7,003	7,003	32,291	32,291

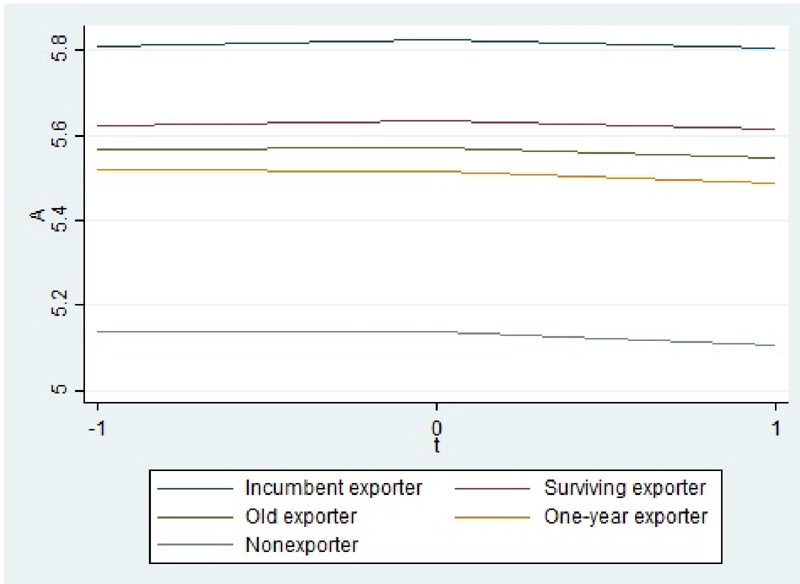
Notes: This table reports regression results from equation 3.1. I(group) is an indicator for each group based on export statistics. The baseline is the characteristic of plants that are one-year exporters. Total Sales, domestic sales, export value, and wage bill are deflated by GDP deflator; capital is deflated by Chilean price of investment goods proved by the World Development Indicator. Total sales, domestic sales, export value, wage bill, and capital are in log. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.3 and Table 3.5 show the average productivity of plants based on their export status after controlling for industry and year fixed effects. Following the definitions for each export status defined earlier, $t = 0$ denotes the year of entry/exit. Consistent with my earlier findings regarding plants' general characteristics, exporters are more productive than nonexporters on average; this finding is consistent with the prediction made by a standard-sunk cost trade model. However, among exporting plants, incumbent exporters are the most productive group. This finding is at odds with the implications of a standard sunk-cost model, which predicts that entrants into the export market should be, on average, the most productive group. Furthermore, Table 3.5 shows that comparing among entering and exiting plants, surviving entrants are on average more productive than one-year exporters. The productivity difference between surviving entrants and one-year exporters exists since the year $t = -1$ before they begin to export and persists till year $t+1$ after they have exported; the difference in productivity shown here appears to be an inherent characteristic of plants. This rules out the explanation than one-year exporters are plants that are productive enough to export ex-ante but are hit by a large negative productivity shock the year they start to export and are therefore forced to stop exporting in the next year. Nevertheless, there is no statistically significant evidence that one-year exporters are less productive than old exiters.

Domestic industry demand channel

Why do plants export for only one year? One possible explanation is the domestic industry demand shock as proposed by Blum et al. (2013). According to the domestic industry demand shock story, firms temporarily export when domestic industry is hit by a negative demand shock in order to smooth out their total sales. However, my data suggest that the stochastic domestic industry demand story cannot fully account for the observed pattern of one-year exporters. I proceed in two steps. First, I argue that the pattern of one-year exporters in the data is not consistent with the

Figure 3.3: Productivity by Export Status



Notes: This figure presents the estimated productivity across different groups of plants at $t = -1, t = 0$, and $t = 1$ after controlling for industry and year fixed effects.

Table 3.5: Productivity by Export Status

	$t = -1$	$t = 0$	$t = 1$
I(incumbent exporter)	0.292***	0.310***	0.319***
	(0.043)	(0.048)	(0.043)
I(surviving entrant)	0.104*	0.119*	0.127*
	(0.052)	(0.055)	(0.051)
I(old exiter)	0.048	0.055	0.061
	(0.053)	(0.056)	(0.054)
I(nonexporter)	-0.381***	-0.380***	-0.380***
	(0.042)	(0.046)	(0.042)
Constant	5.518***	5.516***	5.486***
	(0.047)	(0.051)	(0.048)
ISIC 3 FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	32,291	32,291	32,291

Notes: This table reports regression results from equation (3.1). Dependent variable is the productivity estimated following Levinsohn and Petrin (2003). I(group) is an indicator for each group based on export statistics. The baseline is the characteristic of plants that are one-year exporters. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

story about industry-wide shocks and needs to be explained by firm-specific shocks or firm-specific factors. Next, I argue that the stochastic domestic demand story is inconsistent with the data even when I allow the demand shocks to be firm-specific.

Industry-wide shock vs. firm-specific factors

I first examine whether an industry-wide domestic demand shock can explain the occurrences of one-year exporters observed in the data. To examine this, I consider the correlation between the number of one-year exporters in the industry and the industry's domestic sales growth. If the occurrences of one-year exporters can be primarily accounted for by industry-wide domestic demand shock, one would expect to see a negative correlation between the number of one-year exporters in the industry and the industry's domestic demand growth. I run a regression with the number of one-year exporters in the industry on the left-hand side and the industry's domestic sales growth on the right-hand side, controlling for the industry fixed effects. The first column of Table 3.6 reports the result when industries are defined at the 3-digit ISIC level. The correlation between domestic sales growth of the industry and the number of one-year exporters in the industry are neither economically nor statistically significant. The second column of Table 3.6 shows that this result holds true even when we define industries at 4-digit ISIC level, which is a finer classification of industries. Again, there is no significant relationship between domestic sales growth and the number of one-year exporters in the industry, even when we classify the industries on a finer scale. These results indicate that industry-wide domestic demand shock cannot fully explain the occurrences of one-year exporters in the data.

Possibility of firm-specific demand shock?

Although I have presented evidence that the industry-wide demand shock cannot fully account for the occurrences of one-year exporters in the data, one may argue that different plants within an industry are not perfectly identical; therefore, the demand

Table 3.6: Correlation between Domestic Sales Growth and Number of One-Year Exporters

.	Number of one-year exporters in an industry	
	3-digit ISIC level	4-digit ISIC level
Domestic sales growth	1.26×10^{-10}	1.09×10^{-10}
	(7.67×10^{-11})	(7.97×10^{-11})
Constant	5.565***	0.888**
	(1.014)	(0.307)
Industry fixed effects	Yes	Yes
N	391	634

Notes: This table reports the OLS regression with the number of one-year exporters in the industry on the left-hand side and the industry's domestic sales growth on the right-hand side. The first column reports results when industries classified at 3-digit ISIC level, and the second column reports results at 4-digit ISIC level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

shock may be firm-specific. I present here evidence that the stochastic domestic demand channel cannot fully account for the occurrences of one-year exporters, even when I allow for the demand to be firm-specific.

To illustrate this, I categorize plants that have been one-year exporters at least once into two groups. The first group consists of plants that have always been one-year exporters. In other words, this group consists of plants that never export continuously for longer than one year; I further break this group down by the number of times these one-year exporters enter the export market. The second group consists of plants that were once one-year exporters but became surviving entrants later on (i.e., they re-enter the export market and export continuously for two years or longer). Table 3.7 presents the percentage of plants that have been one-year exporters at least once in each group. If occurrences of one-year exporters are mainly driven by stochastic domestic demand, one would expect the majority of one-year exporters to enter the export market multiple times and export for only one year each time since one would expect plants to be hit by negative demand shock more than once throughout the sample period. However, Table 3.7 shows that out of all the plants that have been exported for one year at least once, only about 6 percent are one-year exporters that enter the export market multiple times and export for one year each time. In contrast, 63 percent are plants that export only once and never export again, and 31 percent are plants that were once one-year exporters and later became surviving entrants. The low proportion of one-year exporters that enter the export market more than once suggests that the stochastic domestic demand channel cannot fully account for the occurrences of one-year exporters.

Table 3.7: Breakdown of One-Year Exporters

	Number of times entering the export market	Percentage of one-year exporters
One-year exporters only	1	62.98%
	2	5.43%
	3	0.60%
	4	0.20%
One-year exporters, then become surviving entrants	N/A	30.78%

Notes: This table presents the proportion of one-year exporters based on the number of times they enter the export market. The first four rows show plants that never export beyond one year. The last row consists of plants that used to be one-year exporters and later became surviving entrants. The sample for this table consists of all plants that have at some point entered the export market and exported for only one year between 1996-2006.

I further examine whether the stochastic domestic demand channel can account for the occurrences of one-year exporters by comparing domestic sales growth across plants based on their export status. If one-year exporters enter the export market because they are hit by a negative domestic demand shock, we should expect to see that their domestic sales fall by a larger magnitude than other groups of plants when they enter the export market. Table 3.8 compares the domestic sales growth across different groups of plants. The baseline is the sales growth of one-year exporters, and period $t = 0$ is the year in which plants enter/exit the export market. If the entry of a one-year exporter is driven by stochastic demand shock, the domestic sales growth of one-year exporter at $t = 0$ should be significantly lower than that of surviving entrants and nonexporters. However, from the second column of the table, we can see that the domestic sales growth of one-year exporters at $t = 0$ is not significantly different from that of one-year exporters and non-exporters. In addition, old exiters do experience higher domestic sales growth the year they exit the export market. Again, there is no significant relationship between domestic sales growth and the number of one-year exporters in the industry, even when we classify the industries on a finer scale. The change in domestic sales growth observed here appears to result from input adjustment frictions rather than evidence that one-year exporters' behavior is driven by stochastic domestic demand.

Table 3.8: Domestic Sales Growth of Exporters

	$t = -1$	$t = 0$	$t = 1$
I(incumbent exporter)	-0.016	0.041*	-0.049*
	(0.015)	(0.019)	(0.020)
I(surviving entrant)	0.039	-0.032	-0.061*
	(0.020)	(0.025)	(0.026)
I(old exiter)	-0.048*	0.063*	0.021
	(0.022)	(0.025)	(0.028)
I(nonexporter)	-0.027*	0.025	-0.077***
	(0.013)	(0.018)	(0.019)
Constant	0.072***	0.009	0.083***
	(0.019)	(0.022)	(0.023)
ISIC 3 FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	26,344	32,265	32,260

Notes: This table compares the domestic sales growth across different groups of plants. Dependent variable is the domestic sales growth. $t = -1$ is the year before entry/exit; $t = 0$ is the year of entry/exit; $t = 1$ is the year after entry/exit. I(group) is an indicator for each group based on export status. The baseline is the domestic sales growth of one-year exporters. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To summarize, I have so far established the following stylized facts using the data on Chilean manufacturing plants:

1. There is significant turnover among Chilean manufacturing exporters. About

19 percent of the exporters enter, and 19 percent of the exporters exit each year.

2. One-year exporters account for about 34 percent of the turnover I observe.

3. Incumbent exporters are on average more productive than entering and exiting plants.

4. One-year exporters tend to be smaller and have lower productivity than export entrants who export beyond one-year. Nevertheless, one-year exporters are not significantly different from exiting plants that have exported for longer than one year. Furthermore, one-year exporters are still, on average, larger and more productive than nonexporters.

5. The occurrences of one-year exporters in the data appear to be driven by firm-specific factors rather than industry-wide shocks. However, they are not driven by productivity shocks that happen during the period that plants start exporting. In addition, stochastic domestic demand cannot fully account for the occurrences of one-year exporters.

In the next section, I propose a model that captures the stylized facts discussed above.

3.3 Model

This section presents a partial equilibrium model that is in the spirit of Melitz (2003) and Hopenhayn (1992). The purpose of this model is to explain the stylized facts from the Chilean data discussed above, with a focus on the high proportion of one-year exporters among entering and exiting plants, and the productivity differences among different groups of firms based on their export status. I introduce uncertainty in the cost of exporting to explain the high proportion of one-year exporters in the data. In addition, in my model, plants are heterogeneous and face productivity process with a different mean but with the same persistence and variance. As a result, some firms are inherently more productive than others.

3.3.1 Demand

The domestic economy consists of a representative consumer with preferences over a CES aggregate consumption good C defined by

$$C = \left[\int_i c_i^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}} \tag{3.2}$$

where i indexes the variety of differentiated goods and σ is the elasticity of substitution across varieties. I assume that $\sigma > 1$. The representative consumer maximizes consumption of aggregate good subject to the budget constraint

$$\int_i p_i c_i \, di = E \tag{3.3}$$

where E denotes total domestic expenditure. Optimal consumption for each variety can be shown by

$$c_i = \left(\frac{p_i}{P} \right)^{-\sigma} \frac{E}{P} \tag{3.4}$$

where P is the CES price index defined by

$$P = \left[\int_i p_i^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} \tag{3.5}$$

Note that by definition, $C = \frac{E}{P}$.

The rest of the world is represented by a representative consumer with preferences and budget constraint identical to the domestic consumer. Optimal consumption for the foreign consumer is given by

$$c_i^* = \left(\frac{p_i^*}{P^*}\right)^{-\sigma} \frac{E^*}{P^*} \tag{3.6}$$

where $*$ denotes a foreign variable. I assume the σ is the same for both domestic and foreign consumers, but that expenditure and price level (E, E^*, P and P) are allowed to differ.

3.3.2 Plant

Plants are heterogeneous and are faced with stochastic productivity A_{it}. Productivity is assumed to follow an AR1 process

$$A_{it} = \rho_{0i} + \rho_1 A_{it-1} + \varepsilon_{it}, \;\; \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \tag{3.7}$$

Although ρ_1 and the distribution of ε_{it} are the same for all plants, ρ_{0i} are heterogeneous across plants. Before plants begin to operate, they draw the value of ρ_{0i} which pins down the mean of their productivity $(\frac{\rho_{0i}}{1-\rho_1})$ and decide whether to operate. If they decide to operate, their productivity then evolves according to the AR1 process described in (3.7).

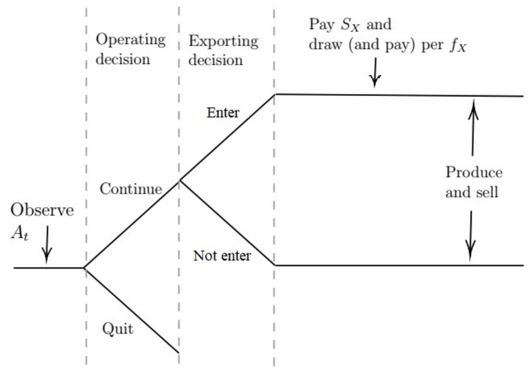
Plants face monopolistic competition, and each plant produces a differentiated variety of the good indexed by i. Plants use labor and capital as their inputs and have Cobb-Douglas production function

$$y_i = A_{it} L_{it}^{\alpha_L} K_{it}^{\alpha_K} \tag{3.8}$$

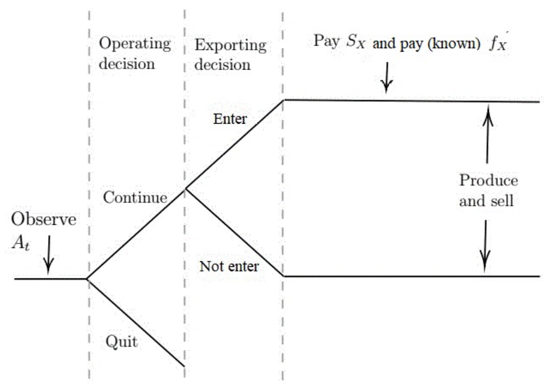
Plants can choose to export. Exporting involves a one-time sunk cost of entry S_x, a per period fixed cost f_x that needs to be paid in every period, and an iceberg trade cost τ. However, $f_x \sim [\underline{f}_x, \bar{f}_x]$ is different for every plant and while its distribution is known, plants do not know its actual value until they have exported at least once. The timing in each period is shown in Figure 3.4. The dynamic and static problems faced by plants are described below.

Figure 3.4: Firm Decision in Each Period

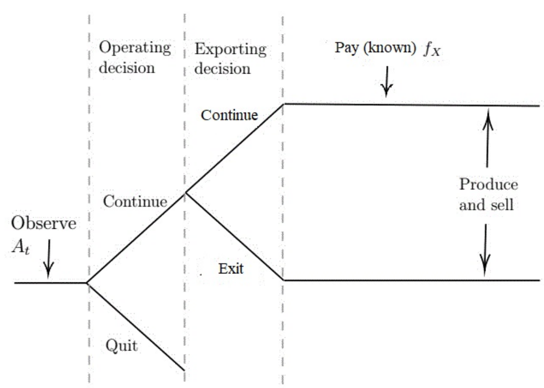
a) Firm that has never exported



b) Firm that exported before but is currently not exporting



c) Firm that is currently exporting



Notes: This figure illustrates the timing in the model.

Plant's dynamic problem

A plant's dynamic problem consists of plant's decision on its export status. Plant's export status is denoted by X_i, where $X_i' = 1$ if plant exports in the current period and $X_i' = 0$ if plant does not export in the current period. Plant chooses its export status to maximize its current value function. The problem can be summarized by the Bellman equation

$$\begin{aligned} V(A_i, X_i, f_{xi}) &= \max_{X_i'}\{E[\pi(A_i, X_i', f_{xi})] - \mathbb{I}_{Ei}S_x + \\ &\quad \beta(1-\delta)E[V(A_i', X_i', f_{xi}')|A_i, X_i, f_{xi}]\} \end{aligned} \tag{3.9}$$

where

$$f_{xi} = \begin{cases} E[f_x], & \text{if plant has never exported} \\ f_{xi}, & \text{otherwise} \end{cases} \tag{3.10}$$

$$\pi(A_i, X_i, f_{xi}) = \begin{cases} \pi^D(A_i), & \text{if } X_i = 0 \\ \pi^X(A_i, f_{xi}), & \text{if } X_i = 1 \end{cases} \tag{3.11}$$

$$\mathbb{I}_{Ei} = \begin{cases} 1, & \text{if } X_i = 0, X_i' = 1 \\ 0, & \text{otherwise} \end{cases} \tag{3.12}$$

Plant's state variables consist of its productivity in the current period A_i, its export status in the previous period X_i, and its knowledge of its own per period fixed cost of exporting f_{xi}, which is equal to the expected value of f_x if a plant has never exported before. The first term in (3.9) is the plant's current period profit, which is equal to its domestic profit if it does not export and equal to the sum of domestic and foreign profit after accounting for the per period fixed cost of exporting if it exports. The profit is the expected profit if plant exports for the first time since the per period fixed cost of exporting is still unknown to plant. The second term S_x is the one-time sunk cost the plant pays if it switches its status from not exporting to exporting. β is the discount rate, and δ is the probability that plant will be hit by a death shock.

Plant's static problem[4]

Within each period, plant solves a static problem by choosing K and L to maximize its current period profit given its export status. Plant's static problem is summarized by

$$\begin{aligned}
\max_{K,L} \; p_i y_i + \mathbb{I}_{xi} e p_i^* y_i^* &- wL - RK - f_d - \mathbb{I}_{xi} f_{xi} && (3.13)\\
s.t.\; \bar{y}_i &= A_i L_i^{\alpha_L} K_i^{\alpha_K} && (3.14)\\
\bar{y}_i &= y_i + \mathbb{I}_{xi} \tau y_i^* && (3.15)\\
y_i &= \left(\frac{p_i}{P}\right)^{-\sigma} \frac{E}{P} && (3.16)\\
y_i^* &= \left(\frac{p_i^*}{P^*}\right)^{-\sigma} \frac{E^*}{P^*} && (3.17)
\end{aligned}$$

where e is the nominal exchange rate, expressed as domestic currency/foreign currency, and $\mathbb{I}_{xi}$ is an indicator that equals 1 if a plant exports. Equations (3.16) and (3.17) come from the assumption that market clear and equations (3.4) and (3.6).

Cost minimization means that plant's variable cost and marginal cost are given by

$$\begin{aligned}
VC(\bar{y}) &= \phi \bar{y}^{\frac{1}{\alpha_L + \alpha_K}} && (3.18)\\
MC(\bar{y}) &= \frac{\phi}{\alpha_L + \alpha_K} \bar{y}^{\frac{1}{\alpha_L + \alpha_K} - 1} && (3.19)
\end{aligned}$$

where $\phi = \frac{1}{A}^{\frac{1}{\alpha_L + \alpha_K}} \left[w \left(\frac{\alpha_L}{\alpha_K} \frac{R}{w}\right)^{\frac{\alpha_K}{\alpha_L + \alpha_K}} + R \left(\frac{\alpha_K}{\alpha_L} \frac{w}{R}\right)^{\frac{\alpha_L}{\alpha_L + \alpha_K}} \right]$. Monopolistic firm sets price

[4] I suppress the time subscript in this section.

equal to mark up over marginal cost; therefore, prices are given by

$$p(\bar{y}) = \frac{\sigma}{\sigma-1}MC(\bar{y}) \tag{3.20}$$

$$p^*(\bar{y}) = \frac{\tau}{e}\frac{\sigma}{\sigma-1}MC(\bar{y}) \tag{3.21}$$

This allows me to solve for the closed form solution for price, which is given by

$$p = \left(\frac{\sigma}{\sigma-1}\frac{\phi}{\alpha_L+\alpha_K}\right)^{\frac{\alpha_L+\alpha_K}{(1-\sigma)(\alpha_L+\alpha_K)+\sigma}}\left(P^{\sigma-1}E + \mathbb{I}_{xi}\tau^{1-\sigma}e^{\sigma}P^{*\sigma-1}E^*\right)^{\frac{1-\alpha_L-\alpha_K}{(1-\sigma)(\alpha_L+\alpha_K)+\sigma}} \tag{3.22}$$

Furthermore, the share of plant's total sales coming from domestic sales and export are given by

$$\frac{py}{py+\mathbb{I}_{xi}p^*y^*} = \frac{C}{C+\mathbb{I}_{xi}\frac{\tau^{1-\sigma}}{e}Q^{\sigma}C^*} \tag{3.23}$$

$$\frac{p^*y^*}{py+p^*y^*} = \frac{\frac{\tau^{1-\sigma}}{e}Q^{\sigma}C^*}{C+\frac{\tau^{1-\sigma}}{e}Q^{\sigma}C^*} \tag{3.24}$$

where $Q = eP^*/P$ is the real exchange rate. In this model, because there is no input adjustment cost, plants always choose the optimal level of labor and capital given their productivity and export status. Subsequently, the share of export sales as a percentage of total sales is determined by the relative size of export and domestic market, weighted by the exchange rate and trade cost; productivity affects the volume of sales from export but not the fraction of sales from export.

3.4 Estimation

I calibrate parameters in the model to replicate the cross-sectional facts from the Chilean manufacturing survey. My parameters can be grouped into two categories: 1) the predetermined parameters that are used in the literature or can be inferred from the data, and 2) parameters that are estimated to make key moments in the simulated data match with those in the empirical data.

3.4.1 Predetermined Parameters

I describe here the parameters that are set or estimated without having to solve for the dynamic equilibrium. Table 3.9 summarizes all predetermined parameters. For parameters on the demand side, the elasticity of substitution σ is set to be 3, a value within the range that has been used in the literature (Costantini and Melitz, 2008; Ruhl and Willis, 2017). Domestic expenditure E and domestic aggregate price level P are normalized to one. Foreign total expenditure E^* is calibrated such that the share of sales from export for an exporting plant in the simulation is equal to the average share of sales from export of long-term exporters in the Chilean data; this is pinned down by equation (3.24). I assume that foreign price level P^* and nominal exchange rate are all equal to 1.[5]

For parameters on the supply side, labor share of income α_L and capital share of the income α_K are estimated from the data under the constant returns to scale assumption. Productivity process is estimated from the Chilean data; I remove the industry and year fixed effects from the estimated productivity presented in the data section and estimate the coefficient of the lagged variable ρ_1 and the variance of the shock σ_ε^2. The mean of the productivity process is assumed to be across the range observed in the data. User cost of capital R is calculated from Jorgenson's formula $R = r + d - \Delta p_k$ when r is taken from the average real lending rate in Chile across the sample period provided by the World Bank, d is the average capital depreciation in Chile across the sample period provided by the Penn World Table, and Δp_k is the average change in the price of investment goods provided by the WDI. Wage w is calibrated to make the number of workers employed by the median plant in the simulation, which is a non-exporting plant, match that of a median plant in the data,

[5]Assuming different values for P^* and e will not impact my cross-sectional results as long as I calibrate P^*, e and E^* such that the share of export matches that from the data.

Table 3.9: Predetermined Parameters

Parameter	Value	Explanation
Demand		
σ	3	
E	1	Normalized C_h to 1
P, P^*, e	1	
E^*	0.425	Solved to make average domestic sales/total sales for exporters equal to that if continuous exporters from the data
Plant		
α_L	0.65	Estimated from data; CRS is assumed
α_K	0.35	
ρ_{0i}	0.194 - 1.746	Estimated from range of mean productivity of plants in the data
ρ_1	0.806	Estimated from data
σ_f	0.497	Estimated from data
w	0.242	Solve to make L equal to that of median firm
r	0.065	Real lending rate (source: World Bank)
d	0.041	Capital depreciation rate (source: Penn World Table)
Δp_k	0.007	Percentage change in price of capital (source: WDI)
R	0.100	Jorgenson's formula
Others		
τ	1.1	
f_d	1.0	Firm would exit if productivity fall below 1
β	0.939	$1/(1+r)$
δ	0.100	Make fraction of firms that stop operating equal to that in the data

Notes: This paper reports the values of the predetermined parameters in the model. In the simulation with homogeneous productivity process, ρ_0 is set to 1.028.

which is also a non-exporting plant. The probability of a death shock δ is set to make the fraction of plants that stop operating, in addition to those that stop exporting when their productivity fall below certain threshold, in each period matches what I observe in the data.

3.4.2 Estimated Parameters

The remaining parameters are estimated to make the key moments in the simulation match what I observe in the data. The parameters that need to be estimated are the one-time sunk cost of exporting S_x and the distribution of the per period fixed cost of exporting f_x. I assume that f_x has a uniform distribution and estimate for the mean $E[f_x]$ and the variance σ_f^2 of the distribution.

The three moments I choose to identify the three parameters are 1) fraction of plants that export (export participation rate), 2) fraction of plants that start exporting out of all exporting plants (export entry rate) and 3) fraction of one-year exporters among exiting plants. The three parameters I am interested in affect these moments through equation (3.9). In my model, there is no one-to-one mapping between the parameters and the moments. For instance, a higher value of S_x lowers the expected present value of entry into export and increases the productivity cutoff for entering plants, which lowers the entry rate and the fraction of one-year exporters. However, higher S_x also raises the opportunity cost of exit from the export market for exporting plants; therefore, its effect on export participation rate is ambiguous.

I solve for the three parameters computationally. For a given set of parameters $\theta = (S_x, E[f_x], \sigma_f^2)$, I solve the plant's dynamic programming problem in (3.9) and use the corresponding policy functions to simulate data for 4,000 plants across 20 periods. I discard the first nine periods of the simulated data and calculate the interested moments from the remaining eleven periods, which is equal to the number of years I use from the Chilean data. I then search for the parameters to minimize

$$\min_{\theta} (m(\theta) - m_d)' W (m(\theta) - m_d) \tag{3.25}$$

where $m(\theta)$ is a vector of moments calculated using the simulated data when the parameters are set to θ, m_d is a vector of moments from the Chilean data, and W is a weighing matrix. Column 3 of Table 3.10 shows the estimated values of my parameters.

Table 3.10: Estimated Parameters

	Model 1: known f_x, homogeneous productivity mean	Model 2: uncertain f_x, homogeneous productivity mean	Model 3: uncertain f_x, heterogeneous productivity mean
S_x	2.5	5.05	1.35
$E[f_x]$	4.2	4.38	5.2
σ_f^2	N/A	3.33	0.96

Notes: This table reports parameters estimated using the simulated method of moments.

3.4.3 Estimation Results

Table 3.11 displays the important moments from the Chilean data and the simulated data. The first column of the table provides the moments calculated from the Chilean plant survey, which are the moments that I target. Similarly, Table 3.12 shows the productivity comparison across plants by their export status in the Chilean data and the simulated data; specifically, I run regression (3.1) on the Chilean data and the simulated data with productivity as the dependent variable. The constant term represents the average productivity of one-year exporters. The first column of Table 3.12 shows the results from the Chilean data.[6] Since the productivity differences among different groups are not targeted, I use them as a benchmark to evaluate

[6]The results in this column are the same as those in the second column of Table 3.5.

whether the model I propose is consistent with the empirical facts observed. To illustrate why uncertainty and heterogeneous productivity mean are important for the model, I also present here the simulated results from two other variants of the model presented in the earlier section. I estimate each model separately to match the key data moments. The simulated results that I present are therefore from the following three models:

- *Model 1: A standard sunk cost model with no uncertainty and homogeneous productivity mean.*

  Specifically, in this variant of the model, ρ_0 is set to 1.028 for all plants, and all plants face the same f_x, a value that is known by all plants. Subsequently, there is no uncertainty in the cost of exporting. The corresponding estimated parameters are shown in the first column of Table 3.10.

- *Model 2: A model with uncertainty and homogeneous productivity mean.*

  Specifically, ρ_0 is set to 1.028 for all plants but f_x is heterogeneous across plants and is unknown to plants before they start exporting. The corresponding estimated parameters are shown in the second column of Table 3.10.

- *Model 3: A model with uncertainty and heterogeneous productivity mean.*

  This is the model that I presented in the earlier section and is the focus of this paper. The corresponding estimated parameters are shown in the third column of Table 3.10.

Model 1: Known f_x and homogeneous productivity mean

The second column of Table 3.11 reports the simulated moments from Model 1 – a standard sunk cost model in the literature in which all plants face the same productivity process, as well as the same per period fixed cost of exporting. In this case, S_x and f_x are the only two parameters that need to be estimated. Consequently,

Table 3.11: Moments in Chilean Data and Simulated Data

	Data	Model 1: known f_x, homogeneous productivity mean	Model 2: uncertain f_x, homogeneous productivity mean	Model 3: uncertain f_x, heterogeneous productivity mean
Export participation rate	0.20	0.21	0.19	0.20
Export entry rate	0.19	0.19	0.18	0.20
Fraction of one-year exporter	0.34	0.11	0.34	0.34
Export exit rate (untargeted)	0.19	0.19	0.17	0.20

Notes: This table presents the moments in the Chilean data and the simulated data. Export participation rate, export entry rate, and fraction of one-year exporter are the targeted moments. Note that fraction of one-year exporter is an untargeted moment in the model with known f_x (second column).

Table 3.12: Productivity Comparison: Chilean Data and Simulated Data

	Data	Model 1; known f_x, homogeneous productivity mean	Model 2: uncertain f_x, homogeneous productivity mean	Model 3: uncertain f_x, heterogeneous productivity mean
I(incumbent exporters)	0.292***	-0.352***	-0.702***	0.385***
	(0.043)	(0.0483)	(0.033)	(0.034)
I(surviving entrants)	0.104*	0.014	0.071	0.227***
	(0.052)	(0.050)	(0.039)	(0.039)
I(old exiters)	0.048	-0.726***	-0.704***	0.071
	(0.053)	(0.050)	(0.039)	(0.039)
I(nonexporters)	-0.381***	-1.597***	-1.490***	-1.676***
	(0.042)	(0.048)	(0.032)	(0.032)
Constant	5.518***	6.476***	6.450***	6.490***
	(0.047)	(0.048)	(0.032)	(0.032)
N	32,291	44,000	44,000	44,000

Notes: This table reports the regression results from equation (3.1) using Chilean data and simulated data. Productivity is the dependent variable. $t = -1$ is the year before entry/exit; $t = 0$ is the year of entry/exit; $t = 1$ is the year after entry/exit. I(group) is an indicator for each group based on export status. The baseline is the characteristic of plants that are one-year exporters. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I only need two target moments. In this case, I target the export participation rate and export entry rate. From the second column of Table 3.11, I can see that the standard sunk cost model with no uncertainty implies a fraction of one-year exporters that is much lower than what I see in the data. In the simulated results, one-year exporters only form about 11 percent of the export exiters; this is roughly the same as the percentage of plants that stop operating in each period and is much lower than the 34 percent that I observe in the data.

In addition, the second column of Table 3.12 shows that a standard sunk cost model with no uncertainty and homogeneous productivity mean leads to a productivity pattern across plants that is not consistent with the data. Looking at the productivity across plants grouped by their export status, in the Chilean data, incumbent exporters are the most productive group, followed by the surviving entrants; one-year exporters and old exiters are less productive than surviving entrants. However, in the model with no uncertainty and homogeneous productivity mean, surviving entrants are not significantly more productive than one-year exporters. Moreover, both one-year exporters and surviving entrants are significantly more productive than incumbent exporters and old exiters.

The discrepancy arises from the following reasons. Firstly, since there is no uncertainty in the cost of exporting, plants only exit after exporting for one year if they are hit by a death shock or a large negative productivity shock. Subsequently, the productivity of one-year exporters is not significantly different from that of surviving entrants. Secondly, because of the one-time sunk cost of entry into the export market, plants only start to export when their productivity is higher than average in order that they have a higher chance of exporting for several periods. Likewise, once plants are already exporters, the existence of the sunk cost deters plants from exiting the export market since they would need to pay for the sunk cost again if they re-enter the export market. In other words, the sunk cost of entry lowers the productivity threshold for plants to exit the export market. As a result, the productivity of entering plants, including one-year exporters, is higher than the incumbent exporters and the old exiters. In this respect, a standard sunk cost model with no uncertainty and homogeneous productivity mean is inconsistent with the stylized facts from the data.

Model 2: Uncertain f_x and homogeneous productivity mean

The third columns of Table 3.11 and 3.12 show the results from Model 2, in which I introduce uncertainty in the cost of exporting but still assume that all plants face the same productivity process. Introducing uncertainty in the per period fixed cost allows me to match the fraction of one-year exporters in the simulated data to that in the Chilean data. However, the productivity pattern across different groups of plants based on their export status are still inconsistent with the stylized facts. The productivity of surviving entrants is still not significantly different from that of one-year exporters. Additionally, incumbent exporters are still significantly less productive than surviving entrants and one-year exporters.

The mismatch in productivity pattern arises because the mechanisms outlined in Model 1 are still present here. The productivity cutoff for entering plants is higher than the productivity threshold for exiting plants in the presence of the sunk cost of entry into the export market. If anything, allowing f_x to vary over a range of values while maintaining the homogeneous productivity process assumption means that more firms are going to be allowed to export. Subsequently, the sunk cost S_x needs to be calibrated to a higher value to make the export participation rate match what I observe in the data. This, in turn, makes the productivity gap between one-year exporters and incumbent exporters larger than that in Model 1. In this respect, a model with uncertainty in the cost of exporting and homogeneous productivity mean is not consistent with the stylized facts observed in the Chilean data.

Model 3: Uncertain f_x and heterogeneous productivity mean

The third column of Table 3.11 and 3.12 report the results from Model 3, which is the full version of the model outlined in the Section 3.3. This model includes both uncertainty in the cost of exporting and heterogeneous productivity mean across plants. Uncertainty allows for the proportion of one-year exporters to match what I observe in the Chilean data, while heterogeneous productivity mean across plants generates the productivity pattern that is consistent with the stylized facts. The fourth column of Table 3.12 shows that in this model, the average productivity of incumbent exporters is significantly higher than the productivity of all the other groups. Furthermore, surviving entrants are significantly more productive than one-year exporters, while there is no significant difference between the productivity of one-year exporters and that of old exiters.[7]

Introducing heterogeneous productivity mean implies that some plants are inherently more productive than others. It is unlikely for the productivity of plants with very high productivity mean to reach the exiting threshold. This affects the productivity pattern in two ways. Firstly, the existence of plants with high productivity mean raises the average productivity of incumbent exporters. Secondly, the productivity cutoff relative to the productivity mean is lower for plants with higher productivity mean, which brings down the average productivity of the entrants. This is combined with the fact that plants that enter and exit the export market are generally plants with lower productivity mean compared to the incumbent exporters, which further bring down the average productivity of the surviving entrants and one-year exporters.

[7]Nevertheless, it should be noted that although my proposed model has successfully matched the productivity pattern in the data in terms of direction and statistical significance, my proposed model still performs quite poorly in terms of matching the magnitude of the productivity differences across groups. This is partly because the productivity distribution within each group in my model is still smaller than that in the data. For instance, the lowest productivity of an exporting plant in the data is still lower than that in my model.

3.5 Aggregate Implications

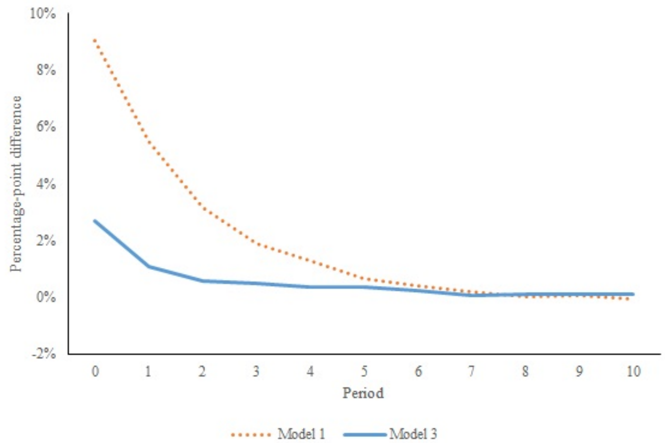
I consider the implications of my model for the aggregate response of the economy. The two counterfactuals I consider are a temporary exchange rate depreciation and a permanent increase in foreign demand. I use Model 1, which is a standard sunk cost model with homogeneous productivity mean and no uncertainty in the cost of exporting, as my benchmark. Note that the response considered here is from a partial equilibrium model; therefore, general equilibrium effects from changes in factor input prices have not been taken into account.

Figure 3.5 shows the response of export participation rate and export entry rate to a temporary 10% depreciation in domestic currency. Figure 3.5(a) presents the percentage-point deviation of export participation rate from the steady state level following a temporary depreciation of 10% at $t = 0$. In both models, the presence of the sunk cost of entry into the export market induces hysteresis in export decisions; even though the exchange rate has already returned to its original value at $t = 1$, some plants that entered at $t = 0$ continue to export since they have already paid for the sunk cost. However, the response is significantly attenuated in Model 3, which features uncertainty in the cost of exporting.

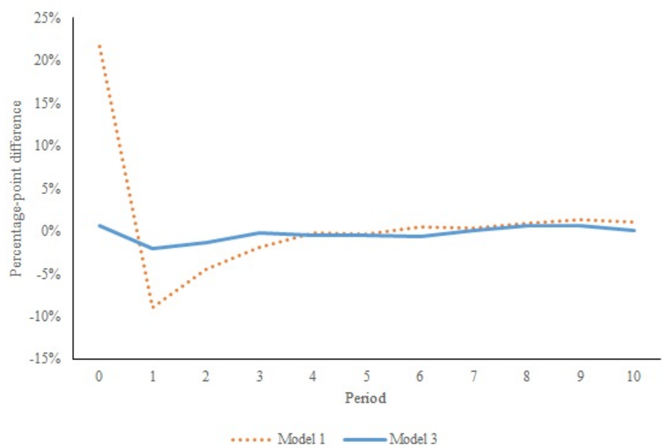
The response in Model 3 is attenuated in two ways. Firstly, the response on impact (i.e. at $t = 0$) is smaller in Model 3. Secondly, the hysteresis is less prolonged in Model 3. There are two factors at play here. The first factor is the sunk cost; the sunk cost in Model 1 is higher, leading to greater hysteresis. The second factor is the uncertainty. Uncertainty in the cost of exporting lowers the expected gain from a temporary entry into the export market. Subsequently, the entry rate in Model 3 only rises by 1 percentage point, while the entry rate in Model 1 rises by more than 20 percentage point in the period when the depreciation happens, as shown in Figure 3.5(b). The increase in the export participation rate in Model 3 is mostly driven by the fall in the exit rate; plants that would have stopped exporting in $t = 0$

Figure 3.5: Aggregate Response to Temporary 10% Depreciation

a) Export Participation Rate



b) Entry Rate



Notes: This figure presents the aggregate response to a 10% temporary depreciation in the exchange rate. Figure 3.5 (a) presents the response of the export participation rate and Figure 3.5 (b) presents the response of the entry rate.

had there been no depreciation decided to stay in the export market one period longer and exit once the exchange rate returns to the original value. As a result, the participation rate in this model returns to the steady state level relatively quickly. On the other hand, the export participation rate in Model 1, which does not feature uncertainty in the cost of exporting, is driven by both increase in export entry rate and export exit rate. The model with uncertainty has smaller response, both in terms of the initial change in export participation rate when the depreciation occurs and the hysteresis following the temporary depreciation. The attenuated response of export participation rate implied by Model 3 is in line with the empirical evidence that suggests a small response in trade volume to currency depreciation (Bussière et al., 2020).

I then consider the aggregate response of the economy to a permanent change in demand for export. Table 3.13 reports the aggregate response of the economy to a 5 percent permanent increase in foreign demand. In both models, a permanent increase in foreign demand leads to a higher steady state level of aggregate export-sales ratio. Consistent with my results in the temporary shock case, the response is significantly weaker in the presence of uncertainty in the fixed cost of exporting. In Model 1 – one that does not feature uncertainty – the export-sales ratio is 3.9 percentage-point above the steady state before the increase in demand, while the ratio in Model 3 – one that features uncertainty – only rises by 1 percentage point. This difference is driven by the difference in the extensive margin of trade. The plant-level export-sales ratio increases by the same amounts in the two models; however, the export participation rate in the model without uncertainty rises by 8.3 percentage points more than that in the model with uncertainty. In addition, a permanent change in foreign demand has a very small impact on the steady state fraction of one-year exporters in Model 1, but it reduces the fraction of one-year exporter by 3.8 percentage points (about 11 percent of the original steady state level) in the Model 3.

Table 3.13: Aggregate Response to 5% Permanent Increase in Foreign Demand

	Percentage-point difference	
	Model 1	**Model 3**
	Known f_x, homogeneous productivity mean	Uncertain f_x, heterogeneous productivity mean
Export participation	9.6%	1.3%
Entry rate	-1.2%	-1.3%
Exit rate	-1.4%	-1.5%
One-year exporter	0.5%	-3.8%
Plant-level export-sales ratio	0.9%	0.9%
Aggregate export-sales ratio	3.9%	1.0%

Notes: This table reports the aggregate response to a 5% increase in foreign demand using Model 1 and Model 3.

3.6 Conclusion

In this paper, I document a large proportion of one-year exporters among export entrants and export exiters in the Chilean data. In particular, I document the differences in productivity across different groups of exporting plants; incumbent exporters tend to be the most productive group, followed by surviving entrants. One-year exporters and old exiters are, on average, the least productive groups among the exporting plants. I then propose a model with uncertainty in the cost of exporting and heterogeneous productivity mean across plants to capture the five stylized facts from the Chilean data.

In my current model, I assume that there is no adjustment cost for both capital and labor. As a result, all exporting plants export the same fraction of their output. However, it would be interesting to examine how a combination of adjustment cost and uncertainty in the cost of export could jointly affect exporter dynamics as well as its implication on aggregate productivity. I leave this for future research.

APPENDIX A

Appendix for Chapter I

A.1 Empirics: Robustness

A.1.1 OLS

In this section, I present robustness checks for the OLS regression results. To further address concerns about location-specific unobserved heterogeneity, I use the average province-level farmer prices between 2016-2018 as an additional control variable. These are the years that do not contain data on the month-of-highest-sales and are therefore excluded from the regressions. I average the prices at the province level because the districts and sub-districts in the sample do not always overlap across the years. Table A.1 reports the results. For ease of comparison, the first column contains the results from the baseline specification, which are taken from column 2 of Table 1.2. Column 2 presents results once I control for the average farmer prices between 2016-2018.

Additionally, I check for the sensitivity of the competition measure to different distance cutoffs. I construct competition measures analogous to equation (1.1) using 75 km and 125 km as distance cutoffs instead of the original 100 km cutoff. Column

Table A.1: OLS Robustness Checks

	log(farmer price)			
	$r = 100$ km		$r = 75$ km	$r = 125$ km
	(1)	(2)	(3)	(4)
COMP (std)	0.023***	0.019**	0.019***	0.024***
	(0.008)	(0.008)	(0.007)	(0.008)
log(crop sold)	-0.006	-0.003	-0.006	-0.006
	(0.005)	(0.004)	(0.005)	(0.005)
log(province-level output)	-0.012	0.001	-0.012	-0.012
	(0.008)	(0.008)	(0.008)	(0.008)
Crop-suitability-index	0.010*	0.006	0.011*	0.010*
	(0.006)	(0.005)	(0.006)	(0.006)
log(distance to BKK)	0.024	0.016	0.020	0.026
	(0.017)	(0.018)	(0.016)	(0.017)
Average farmers' price in 2016-2018		0.025***		
		(0.007)		
Year FE	Yes	Yes	Yes	Yes
Month-of-highest-sales FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Crop-type FE	Yes	Yes	Yes	Yes
N	54,252	54,252	54,252	54,252
R^2	0.511	0.520	0.511	0.511

Notes: This table reports the OLS estimates of equation (1.2). COMP (std) is the standardized competition measure constructed using equation (1.1). r specifies the distance cutoff that is used to construct the competition measure. All regressions use farmer prices between 2008-2015 as the dependent variable. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwith of 1.5 degrees using Bartlett kernel. $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3 and 4 of Table A.1 report the results. The positive and significant relationship between local competition level and farmer prices is robust to different distance cutoffs in the competition measure.

A.1.2 IV

I check the validity of the instrument in several ways. First, I test the sensitivity of the instrument to the distance cutoffs. I use alternative distance cutoffs for the neighbor's productivity and the farmer's own productivity. I define neighbor's productivity as the productivity of land between 75 km - 100 km from the farmer and the farmer's own productivity as the productivity of the land within 25 km from the farmer. Table A.2 reports the results. The results are robust to alternative distance specifications.

Table A.2: IV Results Using Alternative Distance Cutoffs

	COMP (std)	log(price)	No. of mills (std)	log(price)
COMP (std)		0.071***		
		(0.019)		
No. of mills (std)				0.070***
				(0.023)
$Suit^{75-100}$ (std)	0.285***		0.214***	
	(0.036)		(0.050)	
$Suit^{75-100} \times Irri^{75-100}$ (std)	0.159***		0.082**	
	(0.034)		(0.038)	
$Irri^{75-100}$ (std)	0.244***		0.338***	
	(0.059)		(0.117)	
$Suit^{0-25}$ (std)	0.097*	0.015**	0.121***	0.013
	(0.055)	(0.007)	(0.034)	(0.008)
$Suit^{0-25} \times Irri^{0-25}$ (std)	0.060	0.011	0.067**	0.011
	(0.049)	(0.007)	(0.033)	(0.008)
$Irri^{0-25}$ (std)	0.281***	-0.038***	0.181***	-0.030***
	(0.100)	(0.010)	(0.057)	(0.009)
First-stage F-stats	47.952		47.667	
Hansen's p-value		0.862		0.417

Notes: This table reports the IV estimates analogous to those from equations (1.3) and (1.4) using alternative distance cutoffs: neighbor's productivity is defined as the productivity between 75 km - 100 km from the farmer and farmer's own productivity is defined as the productivity within 25km from the farmer. COMP (std) is the standardized competition measure constructed using equation (1.1). No. of mills (std) is the standardized number of mills within 100 km from the farmer. All regressions include controls for the log of quantity of crop sold, province-level output, distance to Bangkok, and fixed effects for the year, the month-of-highest-sales, the region, and the crop-type. All regressions use data from 2008 to 2015. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 1.5 degrees using Bartlett kernel. $^{*}p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

There may be a concern that neighbors' productivity may be correlated with provisions of public goods such as roads, which can affect farmer prices. To address this, I use ruggedness as an additional control variable in the IV regression since ruggedness hinders the provision of public goods. Results are reported in Table A.3. Overall, IV estimates are robust to the inclusion of additional control variables.

I further conduct falsification exercises to test the validity of the instrument. I run IV regressions like (1.3) and (1.4), but use farmer prices for other crops as the

Table A.3: IV Results Controlling for Ruggedness

	COMP (std)	log(price)	COMP (std)	log(price)
COMP (std)		**0.087***** **(0.026)**		**0.094***** **(0.025)**
$Suit^{50-100}$ (std)	0.307*** (0.049)		0.301*** (0.048)	
$Suit^{50-100} \times Irri^{50-100}$ (std)	0.183*** (0.037)		0.184*** (0.037)	
$Irri^{50-100}$ (std)	0.231*** (0.062)		0.229*** (0.061)	
$Suit^{0-50}$ (std)	0.070 (0.063)	0.014* (0.009)	0.067 (0.063)	0.017** (0.009)
$Suit^{0-50} \times Irri^{0-50}$ (std)	0.067 (0.050)	0.006 (0.008)	0.067 (0.051)	0.005 (0.008)
$Irri^{0-50}$ (std)	0.405*** (0.123)	-0.054*** (0.018)	0.404*** (0.123)	-0.055*** (0.016)
$Rugged^{0-100}$			-0.026 (0.057)	0.034 (0.022)
$Rugged^{50-100}$	(0.004) (0.061)	0.018 (0.019)		
First-stage F-stats	19.123		20.643	
Hansen's p-value		0.898		0.876

Notes: This table reports the IV estimates analogous to those from equations (1.3) and (1.4). COMP (std) is the standardized competition measure constructed using equation (1.1). No. of mills (std) is the standardized number of mills within 100 km from the farmer. All regressions include controls for log of quantity of crop sold, province-level output, distance to Bangkok, and fixed effects for year, month-of-highest-sales, region, and crop-type. All regressions use data from 2008 to 2015. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 1.5 degrees using Bartlett kernel. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

dependent variable instead of the farmer prices for rice. If unobserved factors such as the provision of public goods correlate with the instrument, one would expect the coefficient of the competition measure, instrumented using neighbor's productivity, to be positive and significant. Table A.4 shows that this is not the case.

Table A.4: Falsification Exercises

	Maize	Cassava	Longan	Rubber	Vegetables
COMP (std)	-0.074	0.092	0.102	0.297	-0.136
	(0.080)	(0.093)	(0.344)	(0.196)	(0.177)
N	4,211	5,697	926	1,769	1,209

Notes: This table reports the IV estimates analogous to those from equations (1.3) and (1.4). COMP (std) is the standardized competition measure constructed using equation (1.1). All regressions use the same instrument and control variables as the main IV regression. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 1.5 degrees using Bartlett kernel. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

A.2 Show that Solution to the Nash Bargaining Problem is a Contraction Mapping

The equilibrium farmer price is given by the a system of equations (1.19). Define $f : [0, \max_m p^r_m]^{|\mathcal{M}|} \to [0, \max_m p^r_m]^{|\mathcal{M}|}$ where

$$f(m) = (1-\delta) \max_{k \in \mathcal{M}-\{m\}} \left\{ \frac{f(k)}{\tau_{mk}} \right\} + \delta p^r_m \tag{A.1}$$

and $\tau_{mk} \in [1, \infty]$, $\delta \in (0,1)$, $p^m \in \mathbb{R}$.

The max function is continuous. Therefore, f is a continuous function. By Brouwer's Theorem, a fixed point exists. Chatterjee (2020) shows that f satisfies Blackwell's sufficient condition and is, therefore, a contraction mapping.

A.3 Estimation

A.3.1 How important are the threat points to farmer prices?

Given the estimated bargaining power parameter, δ, and the trade cost parameter, ϕ, in section 1.5, how important are the threat points in the Nash bargaining problem? Table the size of the threat point as a percentage of the equilibrium farmer prices. On average, the sizes of farmers' threat points are about 20.13% of the equilibrium farmer prices. However, there is substantial heterogeneity. Farmer's threat points can be as high as 88.62% and as low as 0.54% of the equilibrium farmer prices.

Table A.1: Size of Threat Points

	Threat point as % of farmer price
Average	20.13%
Max	88.62%
Min	0.54%
SD	13.13%

Notes: This table shows the size of farmers' threat points, $\max_{k \in \mathcal{M}-\{m\}} \left\{ \frac{p_k^f}{\tau_{mk}} \right\}$, as a percentage of equilibrium farmer prices. Results are simulated using estimates presented in Table 1.5.

A.3.2 Sensitivity Analysis on the Choice of $|S|$ and M

In this section, I check for the sensitivity of the estimated parameters to the specified number of potential entrants, M, and the size of the subset S that I use to approximate the variable profit, as described in section 1.4.3.1. Table A.2 reports the estimated parameters when I set $M = 3,000$. Table A.3 reports the point estimates for different sizes of S. The alternatives I consider are a subset of size $55,000$, $65,000$, and $70,000$. Overall, the estimated parameters are not sensitive to the choice of $|S|$ and M.

Table A.2: Entry Parameters Estimates Using Different M

	M = 2,000		M = 3,000	
	Point estimate	SE	Point estimate	SE
lambda	2.913	0.102	2.890	0.105
constant	1.790	0.047	2.048	0.048
I(east)	0.426	0.021	0.429	0.021
I(north)	-0.319	0.027	-0.322	0.027
I(northeast)	0.326	0.022	0.327	0.022
I(south)	1.106	0.055	1.114	0.055
I(west)	0.180	0.032	0.182	0.030
ruggedness	0.772	0.017	0.778	0.017
% in season	-0.002	0.001	-0.002	0.001
population density	0.005	0.001	0.005	0.001

Notes: This table reports the point estimates and bootstrapped standard errors for the scale parameter, λ, and entry cost parameters using the nested fixed-point algorithm. Entry cost is assumed to be a function of the location's region, the ruggedness of the location, the percentage of rice that is grown in season at the location, and the population density. Parameters are estimated using data from 2012-2018. $M = 2,000$ is the baseline specification; the estimates in the first two columns are the same as those in Table 1.8 and are provided here for ease of comparison.

Table A.3: Entry Parameters Using Different $|S|$

	$\|S\| = 60,000$	$\|S\| = 55,000$	$\|S\| = 65,000$	$\|S\| = 70,000$
λ	2.913	2.686	2.411	2.289
constant	1.790	1.934	2.141	2.278
I(east)	0.426	0.489	0.519	0.529
I(north)	-0.319	-0.323	-0.377	-0.393
I(northeast)	0.326	0.373	0.393	0.425
I(south)	1.106	1.217	1.342	1.410
I(west)	0.180	0.205	0.248	0.259
ruggedness	0.772	0.835	0.930	0.985
% in season	-0.002	-0.002	-0.004	-0.003
population density	0.005	0.005	0.006	0.006

Notes: his table reports the point estimates of the scale parameter, λ, and entry cost parameters using the nested fixed-point algorithm. Entry cost is assumed to be a function of the location's region, the ruggedness of the location, the percentage of rice that is grown in season at the location, and the population density. Parameters are estimated using data from 2012-2018. The first column shows the estimates from the baseline specification; the estimates in the first column are the same as those in Table 1.8 and are provided here for ease of comparison.

A.4 Counterfactuals

A.4.1 Calculating Change in Rice Production

In this section, I illustrate how I compute the new output level. Solving the farmer's maximization problem (1.17) for the first order condition gives the optimal quantity of intermediate input:

$$X = \beta \frac{p^f}{\tau_{fm}} \frac{y}{w^X} \tag{A.1}$$

Plugging this back into the production function gives:

$$y = \left(A\overline{H}^{\gamma}\overline{L}^{\alpha}\right)^{\frac{1}{1-\beta}} \left(\frac{\beta}{w^X}\right)^{\frac{\beta}{1-\beta}} \left(\frac{p^f}{\tau_{fm}}\right)^{\frac{\beta}{1-\beta}} \tag{A.2}$$

Let y' be the new output corresponding to the new price $p^{f\prime}$ and new iceberg trade cost τ'_{fm}, then we have:

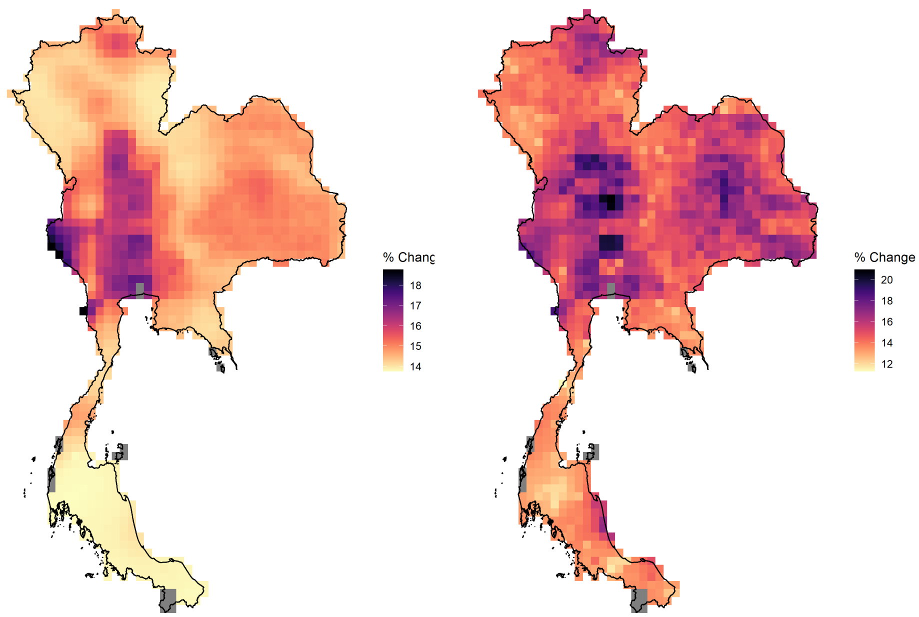
$$\frac{y'}{y} = \left(\frac{p^{f\prime}/\tau'_{fm}}{p^f/\tau_{fm}}\right)^{\frac{\beta}{1-\beta}} \tag{A.3}$$

A.4.2 Additional Figures for Improvement in Road Infrastructure

Figure A.1: Plot of Percentage Change in Farmer Income

(a) Baseline N

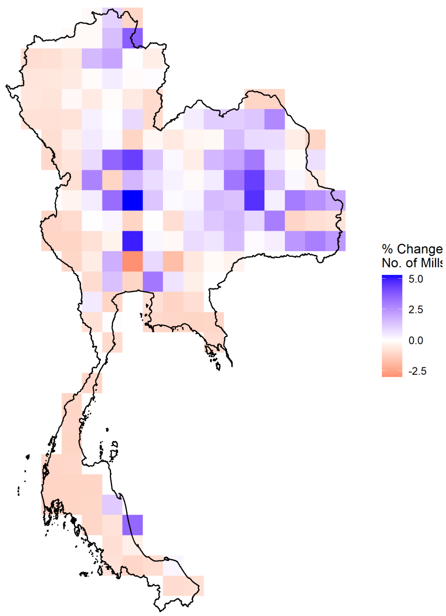
(b) Flexible N



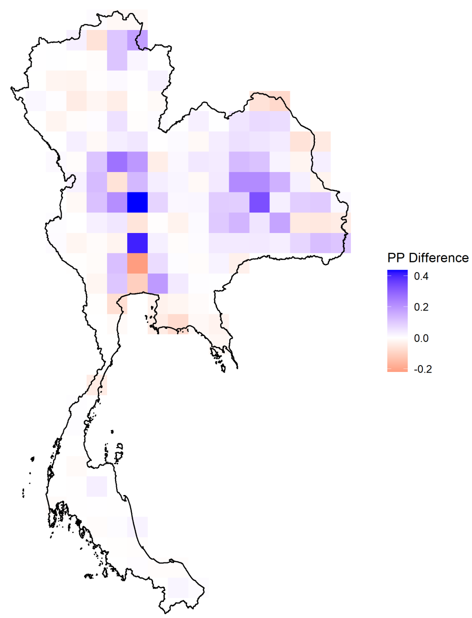
Notes: Percentage change in farmer income after a 9.09% reduction in the iceberg trade costs. Panel (a) shows the percentage change when the number of mills is held fixed at the baseline level. Panel (b) shows the percentage change when mills are allowed to change their entry-location decisions.

Figure A.2: Difference before and after Mills Can Change Their Entry Decisions

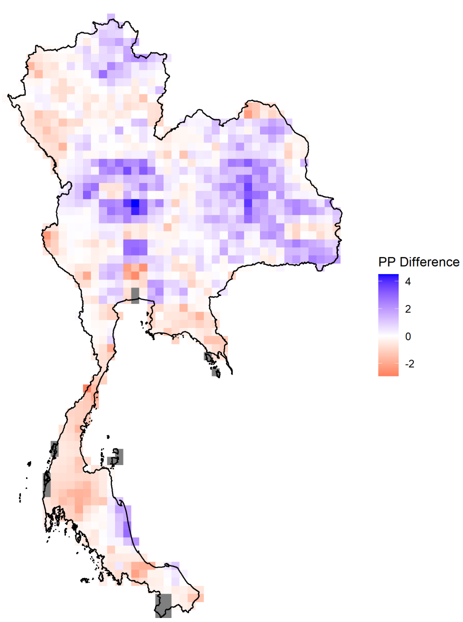
(a) $\%\Delta N$



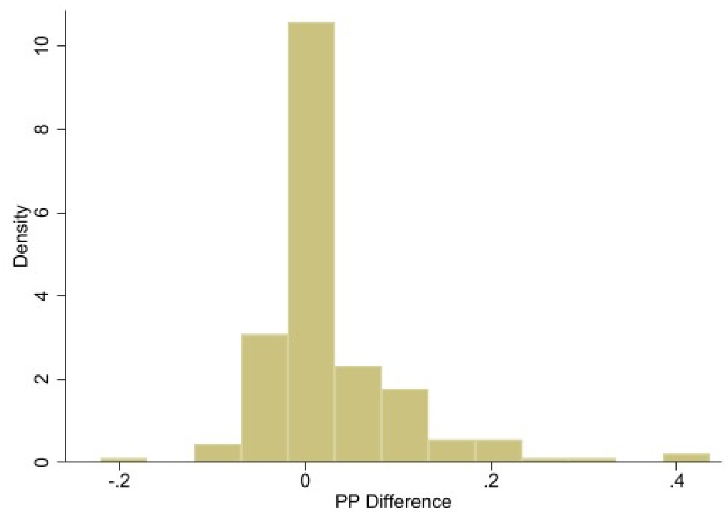
(b) PP Difference in $\%\Delta p_l^f$



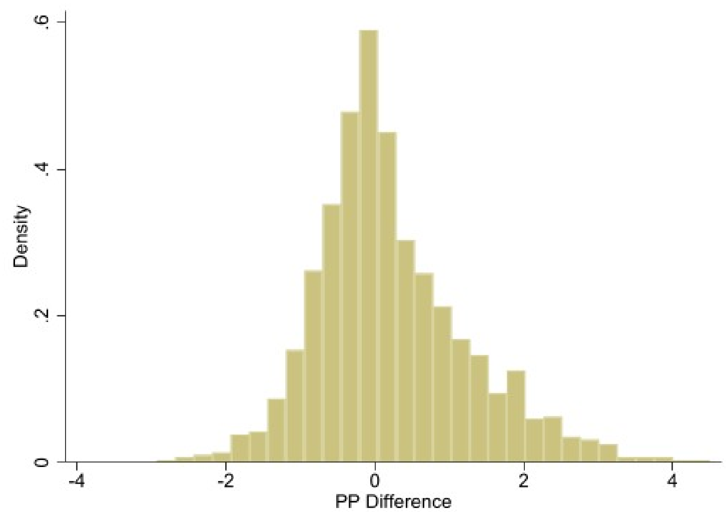
(c) PP Difference in $\%\Delta$ Farmer Income



(d) Percentage Point Change in $\%\Delta p_l^f$ after Allowing N to Change



(e) Percentage Point Change in %Δ Income after Allowing N to Change



Notes: Changes in counterfactual results from a 9.09% reduction in the iceberg trade costs before and after mills are allowed to change their entry-location decisions. Panel (a) shows heatmap of the percentage change in the number of mills. Panels (b) and (d) show of the percentage point difference in the percentage change in farmer prices. Panels (c) and (e) show the percentage point difference in the percentage change in farmer income. A positive percentage point difference means that the percentage increase in farmer income (farmer price) is larger after accounting for mills' entry response.

A.4.3 Thai Rice NAMA

A.4.3.1 Mapping Projects to the Model

The Thai Rice NAMA aims to promote farmers to adopt low emission technology. The project targets farmers in six provinces in the Central Plains: Chainat, Ang Thong, Pathum Thani, Singburi, Ayutthaya, and Suphanburi (SNRD Asia and the Pacific, 2017). Publicly available information on the project suggests that the technology will reduce farmers' costs by 53% and increase crop yields by 8%. The project expects that the required investment will break even within a year (NAMA Facility, n.d.).

I map the technology improvement into the model, I modify the farmer's production function to take the following form:

$$y_f = A_f \overline{H}_f^{\gamma} \overline{L}_f^{\alpha} (B_f X_f)^{\beta} \tag{A.4}$$

where B is the intermediate input augmenting technology. Using the profit maximizing quantity of intermediate input (A.1), farmer's optimal output is:

$$y_f = \left(A_f \overline{H_f}^{\gamma} \overline{L}_f^{\alpha}\right)^{\frac{1}{1-\beta}} B_f^{\frac{\beta}{1-\beta}} \left(\frac{\beta}{w_f^X}\right)^{\frac{\beta}{1-\beta}} \left(\frac{p_f^f}{\tau_{fm}}\right)^{\frac{\beta}{1-\beta}} \tag{A.5}$$

Let y' be the new output corresponding to the new price $p^{f\prime}$ and new technology A' and B', then we have:

$$\frac{y_f'}{y_f} = \left[\frac{A_f'}{A_f}\left(\frac{B_f'}{B_f}\right)^{\beta}\right]^{\frac{1}{1-\beta}} \left(\frac{p_f^{f\prime}}{p_f^f}\right)^{\frac{\beta}{1-\beta}} \tag{A.6}$$

I map the 8% increase in crop yield as $\frac{A_f'}{A_f} = 1.08$ and the 53% reduction in cost as $\frac{B_f'}{B_f} = \frac{1}{0.47}$. Since $\beta = 0.25$, we have $\frac{A_f'}{A_f}\left(\frac{B_f'}{B_f}\right)^{\beta} = 1.30$, which is equivalent to approximately 30% increase in productivity.

To map the investment cost into the simulation, I assume that the investment will break even in one year and that estimates were made using current prices. I assume that farmers are completely present biased and only care about the return in the current period. Therefore, in the simulation, I assume that the investment cost is such that farmers will break even at the baseline prices. Specifically

$$\text{investment cost}_f = p^f_{f,baseline}\left[\frac{A'_f}{A_f}\left(\frac{B'_f}{B_f}\right)^{\beta}\right]^{\frac{1}{1-\beta}} y_{f,baseline} - p^f_{f,baseline} y_{f,baseline} \quad \text{(A.7)}$$

where investment cost_f is the investment cost for farmer f, $p^f_{f,baseline}$ is the price that farmer f receives in the baseline scenario, and $y_{f,baseline}$ is farmer f's output in the baseline scenario.

A.4.3.2 Algorithm to Compute Socially Optimal Equilibrium

I adopt the following algorithm to compute the socially optimal equilibrium in the second counterfactual scenario.

1. Start by guessing that all targeted farmers invest in the new technology.

2. Compute the Bayesian Nash Equilibrium and simulate the mills' entry decisions.

3. Solve for equilibrium farmer prices.

4. Find which targeted farmers are willing to adopt the new technology at the new equilibrium prices. Farmers will adopt the new technology if

$$\left[\frac{A'_f}{A_f}\left(\frac{B'_f}{B_f}\right)^{\beta}\right]^{\frac{1}{1-\beta}} \left(\frac{p^{f\prime}_f}{p^f_f}\right)^{\frac{\beta}{1-\beta}} y_f p^{f\prime}_f - \left(\frac{p^{f\prime}_f}{p^f_f}\right)^{\frac{\beta}{1-\beta}} y_f p^{f\prime}_f > \text{investment cost}_f \quad \text{(A.8)}$$

   where variables without dash denote the baseline level. If farmers who are willing to invest are the same as the guess, then stop. Otherwise repeat step

2-4.

A.4.4 Perfect Competition

In this section, I consider the counterfactual results if the rice mills have no market power. To compute equilibrium under perfect competition, I assume that there is no markup and that farmer prices are equal to the retail prices.

A.4.4.1 Improvement in Road Infrastructure

Table A.1 reports the percentage change in farmer income and Table A.2 reports the percentage change in farm gate prices. Note that the percentage change when rice mills have no market power is calculated relative to the baseline where rice mills have no market power. There are two main takeaways from this exercise. First, the gains to farmers are homogeneous when rice mills have no market power. Second, the percentage increase in farmer income is larger when rice mills have market power. The intuition behind the results is as follows.

When rice mills have no market power, the farmer prices, which are the prices that mills give to farmers, are not affected by the trade costs; farmers always receive the retail prices regardless of the trade costs. Therefore, when there is no market power, farmer income only increases because of two channels: 1) direct lower cost of transporting rice from the farm to the mill, and 2) increase in farmers' rice production. Since lower trade costs affects all farmers in the same way, there is no heterogeneity in the gains to farmers.

However, when rice mills have market power, farmer prices are affected by trade costs and rice mills' entry response. Trade costs impact farmers' threat points in the Nash bargaining problem, which impacts the equilibrium farmer prices. In places with higher mill density, farmers' threat points form a larger percentage of the equilibrium farmer prices. Therefore, lower trade costs have greater impact on farmer prices in places with higher mill density. Additionally, mills' entry response affects mill density, which in turn affects farmer prices. Changes in farmer prices generate heterogeneity in the gains to farmers.

Table A.1: % Change in Farmer Income following 9.09% Reduction in Trade Costs

	% Change in Farmer Income		
	No market power	Baseline N	Flexible N
Aggregate	13.55	15.79	16.75
Top 10% (avg.)	13.55	16.14	17.27
Bottom 10% (avg.)	13.55	14.54	13.84
SD	0.01	0.82	1.50

Notes: This table reports the percentage change in farmer income following a country-wide 9.09% decrease in iceberg trade costs. The first column reports the results when rice mills have no market power. The second column reports the results when the number of mills in each location is held the same as in the baseline scenario. The third column reports the results when mills are allowed to change their entry and location decisions. The second and the third columns are the same as the results in Table 1.9 and are provided here for ease of comparison.

Table A.2: % Change in Farm Gate Price following 9.09% Reduction in Trade Costs

	% Change in Farm Gate Price		
	No market power	Baseline N	Flexible N
Average	10.00	10.88	11.02
Top 10% (avg.)	10.00	11.92	12.65
Bottom 10% (avg.)	10.00	10.65	10.20
SD	0.00	0.59	1.09

Notes: This table reports the percentage change in farm gate prices following a country-wide 9.09% decrease in iceberg trade costs. Farm gate price is the farmer prices accounting for trade cost i.e. $\frac{p^f_m}{\tau_{fm}}$. The first column reports the results when rice mills have no market power. The second column reports the results when the number of mills in each location is held the same as in the baseline scenario. The third column reports the results when mills are allowed to change their entry and location decisions.

A.4.4.2 Opportunity for Farmers to Invest in New Technology

Under perfect competition, the farmer prices are equal to the retail price and are unaffected by the number of mills. The retail prices are higher that the baseline prices when mills have market power. The return to investment is greater than the investment cost. Therefore, if mills have no market power, there is only one equilibrium in which all targeted farmers invest in the new technology.

A.5 Data Appendix

A.5.1 Mill

My dataset for rice mills comprise of firms that are registered under rice milling category, specifically under TSIC code 10611. However, firms registered in the dataset may not be actively operating the rice mill in a given year. To address this concern, I only consider mills that report at least 100 THB revenue in their balance sheet in a given year to be operating in that given year. Additionally, to ensure that I do not count firms that are registered under the wrong category in my analysis, I only consider firms that have the words "rice", "mill", or "agriculture" (or the Thai counterpart) in either their name or their listed business purpose as rice mills.

To ensure that firms generally only have one rice mill, I examine the list of rice mills that are active in 2021 from the Department of Internal Trade. In 2021, there are active mills. 95% of these mills are individually owned. In addition, firms that have more than one mill generally have mills in areas with a large number of mills. Therefore, undercounting the mills that belong to those firms do not significantly impact my estimated level of local competition.

Table A.1: Number of Active Mills in 2021 from the Department of Internal Trade

No. of mills per firm	No. of firms
1	1,015
2	18
3	4
4	1

APPENDIX B

Appendix for Chapter II

B.1 Data

B.1.1 Constructing Flow Accumulation

The flow accumulation measure is the key simulated quantity that forms the basis of our instrumental variable strategy. It was introduced by Frachetti et al. (2017) and, in simple terms, is a sum of seasonal nomadic migrations over 20 human generations. We briefly describe its construction.

Frachetti et al. (2017) first construct their three base raster datasets. First, using Global Multi-Resolution Terrain Elevation Data (GMTED2010) with a pixel resolution of 30 arcseconds (about 1 km) within the inner Asian corridor, the researchers define the lowland and highland boundary at 750 m elevation. Next, they use a multispectral eMODIS image transformed into Normalized Difference Vegetation Index (NDVI) values from August 2008 at the peak of the grassland productivity to generate an NDVI raster averaged over seven days. Using this averaged NDVI raster and further information on fodder value and range productivity of biologically documented highland pasture types, the authors assign vegetation classes to each cell. Last, using the two most fertile classes of vegetation, they also create an animal weight raster which corresponds to 16 animals per hectare, the average range capacity for inner Asian highland grasslands.

Botanical and archaeological evidence suggests that despite climate and geographical change over Central Asia in the past 4000 years, the grassland vegetation is mostly unchanged (Khotinskiy, 1984). Thus, modern imagery like eMODIS to calculate NDVI and modern measures of highland pasture productivities may be used to simulate historical flow accumulation measures.

Having constructed their base rasters, Frachetti et al. (2017) begin their recursive algorithm. The following steps are iterated 500 times to simulate 500 years of flow patterns. First, they randomly generate 5,000 lowland campsites. Using these campsites as sources and the vegetation classes generated previously as weights, the researchers apply the "Cost Distance" tool in ArcGIS to generate a cost distance raster. The cost distance raster gives the distance, for each grid cell, to the nearest campsite for each cell in the raster based on the least-accumulative cost. The cost distance raster, which was calculated using measures of pasture quality, and the animal weight raster are then used as inputs to the ArcGIS tool "Flow Accumulation", which produces a hypothetical count of animals flowing from the best pastures into each cell across the highlands region. Reverse flows are prohibited. This final raster is the flow accumulation measure (Figure 2.5) that we use in this paper.

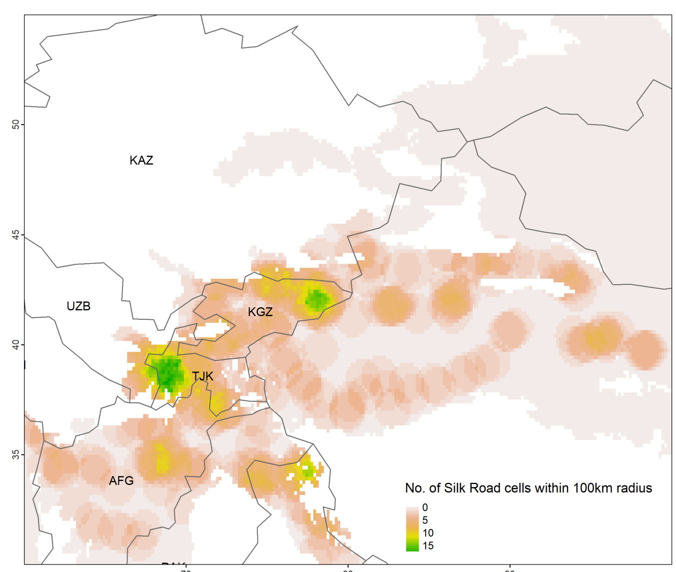
B.2 Robustness Checks

In this section, we present the additional robustness checks that we perform. All our robustness checks reported below use our baseline IV specification with the VIIRS night lights data as a measure of modern development.

Excluding outliers: We first exclude outliers from our analysis. To ensure that the negative relationship between proximity to Silk Road site and modern development is not driven by the extreme values in the data, we exclude observations with VIIRS values in the top and bottom 2 percentiles from our analysis. The first two columns of Table B.1 present results. We still observe a negative and significant relationship between proximity to Silk Road site and night lights intensity after excluding the outliers.

Alternative measure of proximity to the Silk Road: In our analyses throughout the paper, we use the shortest distance to the nearest Silk Road site as a measure of proximity to the Silk Road. As a robustness check, we construct an alternative measure by constructing the variable c_{di}, which measures the number of Silk Road cells that can be reached within distance d from cell i. We call this the connectedness of cell i to the Silk Road.[1] We show this measure in Figure B.1, in which we use 100km as a distance cutoff.

Figure B.1: No. of Silk Road cells within 100km



Notes: This figure presents the number of Silk Road cells within 100km radius.

[1]This measure is similar to the one used in Bakker et al. (2019).

Table B.1: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Excluding outlier		Using connectivity measure		Using 0.083 × 0.083 degree cells		Using 4.167 × 4.167 degree cells	
	Distance to Silk Road site	Night lights (VIIRS)	Distance to Silk Road site	Night lights (VIIRS)	Distance to Silk Road site	Night lights (VIIRS)	Distance to Silk Road site	Night lights (VIIRS)
Distance to Silk Road site		-0.028***				-0.088***		-0.117***
		(0.007)				(0.025)		(0.028)
No. of Silk Road cells within 100 km				0.106***				
				(0.026)				
Distance to herding path	0.182***		-0.189***		0.181***		0.230***	
	(0.036)		(0.041)		(0.034)		(0.030)	
Caloric suitability index	-0.046***	-0.002***	0.051**	-0.005*	-0.033**	-0.004**	-0.061***	-0.006**
	(0.016)	(0.001)	(0.023)	(0.003)	(0.013)	(0.002)	(0.018)	(0.003)
Ruggedness	-0.053*	-0.005***	0.043	-0.018***	-0.038	-0.015***	-0.081***	-0.018***
	(0.028)	(0.001)	(0.027)	(0.004)	(0.024)	(0.003)	(0.030)	(0.006)
Precipitation	0.259***	0.007***	-0.042	0.006	0.249***	0.024***	0.292***	0.032**
	(0.050)	(0.003)	(0.071)	(0.009)	(0.048)	(0.009)	(0.051)	(0.015)
Distance to river	-0.025***	-0.002***	0.015	-0.004**	-0.027***	-0.005***	-0.028***	-0.008**
	(0.007)	(0.001)	(0.011)	(0.002)	(0.007)	(0.001)	(0.008)	(0.003)
Elevation	0.016	-0.012***	-0.181*	-0.025*	0.006	-0.035***	0.059	-0.035*
	(0.116)	(0.004)	(0.107)	(0.013)	(0.107)	(0.013)	(0.109)	(0.019)
Crop-Suitability-Indices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NDVI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	25.785		21.488		27.870		60.212	
N	15,732	15,733	17,125	17,126	65,305	65,306	2,984	2,984

Notes: This table presents results from additional robustness check exercises. Distance to Silk Road site, distance to herding path, and number of Silk Road cells within 100km are standardized. All other variables are log-transformed. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 2 degrees using Bartlett kernel. Crop-suitability-indices include indices for wheat, rice, barley, flax, and millet. All regressions include a constant. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We then use this connectivity measure in place of our standard distance to Silk Road site measure. The results are reported in the third and fourth columns of Table B.1. As expected, there is a positive relationship between the connectedness to the Silk Road and the intensity of the night lights. As the number of Silk Road cells within 100km increases by one standard deviation, the night lights intensity increases by 11.2%.

Alternative grid sizes: Our baseline unit of observation is a 0.167 degrees $\times$0.167 degrees grid cell. We now check if our results are robust to the sizes of the cells. We first construct an alternative dataset using 0.083 degrees $\times$ 0.083 degrees grid cells, which is half the width and height of our baseline grid cells. Columns 5 and 6 of Table B.1 report the results. We then consider an alternative dataset with grid cells that are 25 times the width and height of our baseline grid cells. The results are shown in columns 7 and 8 of Table B.1. Overall, our results are robust to different cell sizes.

Constructing instrument with different cutoffs: Due to computational feasibility, we set a flow value of 1.5 million as a cutoff to construct the instrument in this paper. We now check the robustness of our results to different cutoff values. Table B.2 shows the results when we construct the instrument using 1 million and 2 million as our cutoff values. Our result is robust to different cutoff values.

Table B.2: IV Results Using Different Cutoffs to Construct an Instrument

	1 million cutoff		2million cutoff	
	First stage	Second stage	First stage	Second stage
	Distance to Silk Road site	Night lights (VIIRS)	Distance to Silk Road site	Night lights (VIIRS)
Distance to Silk Road site		-0.093***		-0.111***
		(0.025)		(0.033)
Distance to herding path	0.204***		0.171***	
	(0.029)		(0.036)	
Caloric suitability index	-0.042***	-0.004*	-0.042***	-0.005**
	(0.014)	(0.002)	(0.014)	(0.002)
Ruggedness	-0.047*	-0.017***	-0.049*	-0.018***
	(0.026)	(0.004)	(0.026)	(0.004)
Precipitation	0.258***	0.026**	0.256***	0.030**
	(0.047)	(0.011)	(0.048)	(0.012)
Distance to river	-0.025***	-0.005***	-0.025***	-0.005***
	(0.007)	(0.002)	(0.007)	(0.002)
Elevation	0.045	-0.039***	0.002	-0.043***
	(0.103)	(0.015)	(0.106)	(0.016)
Crop-Suitability-Indices	Yes	Yes	Yes	Yes
NDVI	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
F-stat	49.635		23.072	
N	17,125	17,125	17,125	17,125

Notes: This table presents results from additional robustness check exercises. Distance to Silk Road site and distance to herding path are standardized. All other variables are log-transformed. Standard errors are adjusted to allow for spatial clustering as in Conley (1999), with a bandwidth of 2 degrees using Bartlett kernel. Crop-suitability-indices include indices for wheat, rice, barley, flax, and millet. All regressions include a constant. *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX C

Appendix for Chapter III

C.1 Sample Construction

- My data spans from 1995-2007. In order to identify entry into and exit from the export market, I restrict my sample to 1996-2007.
- I exclude plants that at any point report a negative total sales revenue, a total sales revenue that is less than sales revenue from export, or a value of gross output that is less than the value added. I also exclude plants with output growth higher than 400 percent or plants with output growth that is higher than 100 percent and is not accompanied by raw material growth.

C.2 Alternative Productivity Estimation Methods

In the main analysis of the paper, I use the productivity estimated using the method proposed by Levinsohn and Petrin (2003). As robustness checks, I estimate the productivity using the methods proposed by Ackerberg et al. (2015) and Wooldridge (2009) and re-evaluate regression (3.1) using the alternative estimated productivity. We can see that the results in Table C.1 are very similar to the baseline results that use productivity estimated following Levinsohn and Petrin (2003).

C.3 Static Problem Derivation

Plant produces output with a Cobb Douglas production function $\bar{y}_i = A_i L_i^{\alpha_L} K_i^{\alpha_K}$ and the variable cost function is given by $VC(\bar{y}_i) = wL_i + RK_i$. Cost minimization means the capital-labor ratio of a plant is given by

$$\frac{K_i}{L_i} = \frac{\alpha_K}{\alpha_L} \frac{w}{R}$$

which gives me the cost functions

$$\begin{aligned} VC(\bar{y}) &= \phi \bar{y}^{\frac{1}{\alpha_L + \alpha_K}} \\ MC(\bar{y}) &= \frac{\phi}{\alpha_L + \alpha_K} \bar{y}^{\frac{1}{\alpha_L + \alpha_K} - 1} \end{aligned}$$

where $\phi = \frac{1}{A}^{\frac{1}{\alpha_L + \alpha_K}} \left[w \left(\frac{\alpha_L}{\alpha_K} \frac{R}{w} \right)^{\frac{\alpha_K}{\alpha_L + \alpha_K}} + R \left(\frac{\alpha_K}{\alpha_L} \frac{w}{R} \right)^{\frac{\alpha_L}{\alpha_L + \alpha_K}} \right]$.

Profit maximizing plant sets price equals to a markup over marginal cost

$$\begin{aligned} p(\bar{y}) &= \frac{\sigma}{\sigma - 1} MC(\bar{y}) \\ p^*(\bar{y}) &= \frac{\tau}{e} \frac{\sigma}{\sigma - 1} MC(\bar{y}) \end{aligned}$$

Assuming market clears, $y_i = c_i = \left(\frac{p_i}{P} \right)^{-\sigma} \frac{E}{P}$ and $y_i^* = c_i^* = \left(\frac{p_i^*}{P^*} \right)^{-\sigma} \frac{E^*}{P^*}$. Therefore, I have

$$\bar{y}_i = \left(\frac{p_i}{P} \right)^{-\sigma} \frac{E}{P} + \tau \left(\frac{p_i^*}{P^*} \right)^{-\sigma} \frac{E^*}{P^*}$$

Substituting this into the marginal cost equation and then into the price equation

Table C.1: Productivity Comparisons Using Different Methods of Productivity Estimation

	Ackerberg et al. (2015)			Wooldridge (2009)		
	$t = -1$	$t = 0$	$t = 1$	$t = -1$	$t = 0$	$t = 1$
I(incumbent exporter)	0.236***	0.259***	0.252***	0.248***	0.270***	0.262***
	(0.041)	(0.046)	(0.042)	(0.042)	(0.046)	(0.042)
I(surviving entrant)	0.102*	0.119*	0.107*	0.107*	0.123*	0.109*
	(0.050)	(0.054)	(0.050)	(0.051)	(0.054)	(0.051)
I(old exiter)	0.059	0.072	0.054	0.060	0.075	0.051
	(0.052)	(0.054)	(0.054)	(0.053)	(0.055)	(0.054)
I(nonexporter)	-0.321***	-0.315***	-0.331***	-0.320***	-0.316***	-0.334***
	(0.040)	(0.045)	(0.041)	(0.041)	(0.045)	(0.041)
Constant	4.442***	4.425***	4.409***	4.719***	4.705***	4.690***
	(0.045)	(0.049)	(0.046)	(0.046)	(0.049)	(0.047)
ISIC 3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,984	30,978	30,980	30,984	30,978	30,980

Notes: This table reports regression results from equation (3.1) using productivity estimated following Ackerberg et al. (2015) and Wooldridge (2009). Productivity is the dependent variable. I(group) is an indicator for each group based on export statistics. The baseline is the characteristic of plants that are one-year exporters. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

gives us

$$p = (\frac{\sigma}{\sigma - 1}\frac{\phi}{\alpha_L + \alpha_K})^{\frac{\alpha_L+\alpha_K}{(1-\sigma)(\alpha_L+\alpha_K)+\sigma}}(P^{\sigma-1}E + \mathbb{I}_{xi}\tau^{1-\sigma}e^{\sigma}P^{*\sigma-1}E^{*})^{\frac{1-\alpha_L-\alpha_K}{(1-\sigma)(\alpha_L+\alpha_K)+\sigma}}$$

C.4 Additional Tables

Table C.2: Percentage of Export Exiters by Export Spell and Industry between 1999-2006

a Industries with more than 15 exporters

2-Digit ISIC Cide	Export Spell 1	2	3	4	>=5	No. of Exporters	No. of Exiters
15	32.8%	17.9%	6.9%	4.8%	37.6%	203.1	28.9
17	30.1%	18.9%	13.6%	3.5%	34.0%	49.8	10.2
18	30.9%	28.2%	6.3%	7.0%	27.5%	30.2	8.8
19	45.7%	10.8%	7.2%	3.1%	33.2%	28.4	6.4
20	37.7%	11.5%	11.9%	9.2%	29.7%	59.5	10.5
21	37.5%	11.1%	6.4%	3.3%	41.7%	35.7	6.2
22	37.5%	25.0%	6.3%	0.0%	31.3%	17.3	4.0
24	32.9%	20.3%	4.7%	4.0%	38.1%	88.4	13.2
25	39.1%	14.5%	8.0%	1.6%	36.8%	67.2	12.8
26	23.6%	33.3%	4.8%	5.2%	33.1%	23.5	3.2
27	27.1%	27.1%	14.3%	11.2%	20.2%	25.6	3.2
28	33.6%	23.6%	13.7%	7.5%	21.6%	45.8	9.2
29	44.8%	23.1%	10.7%	5.2%	16.1%	35.2	8.2
36	32.2%	19.0%	4.2%	8.0%	36.7%	30.6	6.5
Average	34.7%	20.3%	8.5%	5.3%	31.3%	52.9	9.4

b Industries with less than 15 exporters

2-Digit ISIC Cide	Export Spell 1	2	3	4	>=5	No. of Exporters	No. of Exiters
30	0%	0%	0%	0%	0%	0.2	0.0
31	54%	20%	14%	0%	13%	12.5	2.7
32	30%	10%	40%	0%	20%	3.8	1.1
33	14%	21%	21%	14%	29%	10.3	1.3
34	27%	46%	12%	7%	7%	7.6	1.8
35	17%	33%	17%	0%	33%	3.8	1.2
Average	24%	22%	17%	4%	17%	635%	133%

The table shows the average percentage of Exiters by export spell between 1996-2006.

Table C.3: List of ISIC industries

15 - Manufacture of food products and beverages
16 - Manufacture of tobacco products
17 - Manufacture of textiles
18 - Manufacture of wearing apparel; dressing and dyeing of fur
19 - Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
20 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
21 - Manufacture of paper and paper products
22 - Publishing, printing and reproduction of recorded media
23 - Manufacture of coke, refined petroleum products and nuclear fuel
24 - Manufacture of chemicals and chemical products
25 - Manufacture of rubber and plastics products
26 - Manufacture of other non-metallic mineral products
27 - Manufacture of basic metals
28 - Manufacture of fabricated metal products, except machinery and equipment
29 - Manufacture of machinery and equipment n.e.c.
30 - Manufacture of office, accounting and computing machinery
31 - Manufacture of electrical machinery and apparatus n.e.c.
32 - Manufacture of radio, television and communication equipment and apparatus
33 - Manufacture of medical, precision and optical instruments, watches and clocks
34 - Manufacture of motor vehicles, trailers and semi-trailers
35 - Manufacture of other transport equipment
36 - Manufacture of furniture; manufacturing n.e.c.
37 - Recycling

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