Transport Infrastructure and Firm Location Choice in Equilibrium: Evidence from Indonesia’s Highways

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Abstract

Transport improvements make it easier for firms to reach customers from a given site, encouraging them to agglomerate. On the other hand, by expanding access to cheaper labor and land, lower transport costs make producing in more sites feasible, promoting dispersion. To better understand how transport improvements affect the spatial distribution of economic activity, I study how the location choices of new manufacturers responded to changes in road quality in Indonesia. Using new data, I document massive upgrades to Indonesia’s highway networks during the 1990s, a period in which national transportation funding increased by 83 percent. I first show that these road improvements were accompanied by a significant dispersion of manufacturing activity, and that different industries responded in ways predicted by theory. To make better counterfactual predictions, I develop a structural model of location choice in which firms face a tradeoff: locating closer to demand sources requires firms to pay higher factor prices. The model predicts that some location characteristics relevant to firms are determined in equilibrium, necessitating the use of instrumental variables. I estimate a random coefficients logit model with endogenous choice characteristics and find significant differences in firms’ willingness to pay for greater market access across different industrial sectors. Counterfactual policy simulations suggest that new toll roads connecting urban areas would cause a modest amount of industrial suburbanization. In contrast, upgrading rural roads would have little or no effect on equilibrium firm locations.

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1 Introduction

In many developing countries, investments in transport infrastructure are growing at an astonishing pace. China’s total spending on transport projects increased from $9.2 billion in 2000-2004 to $26.4 billion in 2005-2009, while India’s spending increased from $2.9 billion to $29.4 billion between the same periods.\(^1\) The goal of these projects is to lower transport costs between different regions. But as regions become better connected, the spatial distribution of economic activity that emerges remains difficult to predict.

Better transportation networks might induce firms to locate outside of congested urban agglomerations, so that they can access cheaper land and labor. The possibility for dispersion is stressed by policymakers who believe that transport improvements can bring more jobs and firms to less developed regions. For instance, in national planning documents, Indonesia’s government has stated that transportation investments promote “the equitable distribution and dissemination of development efforts, penetrating the isolation and backwardness of remote areas”.\(^2\) As another example, when the Suramadu Bridge opened in 2009, connecting Surabaya, Indonesia’s second largest city, to the less densely populated island of Madura, Indonesia’s President Yudhoyono said that “Madura will be much more developed as a result of the bridge”.\(^3\) Indeed, classic models in urban economics (Alonso 1964, Mills 1967, Muth 1969) and economic geography (Helpman 1998) suggest mechanisms through which lower transport costs induce a dispersion of firms and workers to more peripheral areas.

On the other hand, better roads make firms in existing cities more profitable by bringing them closer to other markets. Because of this, lower transport costs could intensify the self-reinforcing home market effects that cause agglomerations to form and grow. In the influential core-periphery model of Krugman (1991), reducing trade costs between two regions causes firms to agglomerate, pulling the entire manufacturing sector into one region. Thus, road improvements may actually exacerbate spatial inequalities instead of reducing them. Despite the prominent role that transport costs play in models of urban economics and economic geography, we currently have limited knowledge about their actual effects on firm location choices and, consequently, how they affect the growth paths of different regions. Moreover, we have few tools at our disposal to predict what equilibria would look like if new road programs were implemented, whether they be highways that connect major cities or upgrades to rural roads.

\(^1\)These figures, stated in constant 2000 U.S. dollars, are taken from the World Bank’s Private Participation in Infrastructure (PPI) Project Database.

\(^2\)This quotation is taken from a planning document describing transportation development objectives in Repelita VI (author’s translation). Similar sentiments are echoed in other planning documents.

\(^3\)This quotation is taken from Faisal, Ahmad and Harsaputra, Indra “Suramadu bridge touted to boost economy, create jobs” The Jakarta Post 11 June 2009.
This paper makes several contributions to our understanding of how transport costs affect the spatial distribution of economic activity by exploiting unique data on a large road improvement program in Indonesia. During the 1970s and 1980s, quality paved highways in Indonesia consisted of only a few major arteries connecting provincial capitals and other large cities. However, in the early 1990s, there was an 83 percent increase in funding allocated for road improvements, and road networks throughout the archipelago were rapidly improved. Upgrading projects were not uniform over space or time, producing substantial variation in transport improvements that can be used to estimate their effects.

Using new panel data on the quality of major highways, I first present reduced form evidence suggesting that Indonesia’s road improvements induced a moderate, statistically significant dispersion of manufacturing activity. During the same period in which road improvement projects were occurring, the spatial concentration of manufacturing employment fell by more than 20 percent. Interestingly, the amount of dispersion varied across industries in ways that are predicted from theory. For instance, the spatial concentration of producers of perishable goods, which deteriorate rapidly in transit and need to be consumed close to where they are produced, did not change significantly over the period, while it fell substantially for producers of durable goods. Although I see evidence of dispersion, new firms did not move to the most remote parts of Indonesia; instead, they suburbanized, locating increasingly in neighboring areas of existing agglomerations. Using a series of linear panel regressions, I estimate positive and significant average effects of road improvements on new manufacturing establishments and employment.

On its own this reduced form analysis only partially sheds light on the mechanisms behind these results, which hinders our ability to make counterfactual predictions. For instance, if firms move to new locations in response to better market access, their presence will drive up local wages and rents in these areas, and this will, in turn, affect the location choices of other firms. Predictions about what would happen if new roads were built may be inaccurate if these general equilibrium responses are not taken into account. To explain the relative importance of different mechanisms, and to make better counterfactual predictions, I develop and estimate a structural model of firm location choice.

I present a multiple-region model of monopolistic competition and regional trade (e.g. Head and Mayer [2004]), designed to capture two sources of the costs and benefits of agglomerations. One key prediction of the model is that firm profits depend on a location’s market potential [Harris 1954], a weighted average of real regional incomes, where the weights decline with transport costs. This demand force pulls firms to locate in existing agglomerations. However, because local supply schedules for land and labor are upward sloping, locating in agglomerations is costly. Hence, firms face a tradeoff: those who locate closer to demand
sources must pay higher factor prices for production. The model also allows for sectoral differences in the willingness to substitute between different location characteristics, motivated by the industry differences highlighted in the reduced form analysis. With some additional distributional assumptions on the unobserved components, I show how parameters of the model can be estimated with discrete choice techniques.

Identifying these parameters is challenging, since many characteristics that firms observe when determining where to operate (including local wages, rents, and access to other markets) are themselves affected by the decisions that other firms make, creating possible simultaneity problems. New road improvements may also be targeted to particular areas, and estimates of the effects of better market access may be confounded with the fact that areas with better roads were selected by policymakers, creating targeting bias. Moreover, without data on how location characteristics vary over time, it is impossible to distinguish features of firm profit functions that depend on these characteristics from those that depend on fixed natural productive amenities, many of which may be unobserved.

To overcome these identification problems, I combine the new panel data on road quality with techniques from industrial organization that allow researchers to estimate discrete choice models with endogenous choice characteristics (Berry et al., 1995). Panel data on road quality and market access enable me to control for time-invariant unobservables that may be correlated with the provision of infrastructure. For example, in Indonesia, long-term spatial plans dictated that certain areas would be targeted for road improvements. These plans were revised infrequently, and to the extent that they were adopted, controlling for location fixed effects enables me to remove the targeting bias from parameter estimates. Fixed effects also allow me to separate from parameter estimates the effects of other unobserved factors, such as time-invariant productive amenities.

To deal with simultaneity problems associated with identifying choice parameters, I combine location fixed effects with sequential moment restrictions. Under these restrictions, regional productivity shocks are innovations, unpredictable given past information, and lagged location characteristics can serve as instruments for current location characteristics. Although this identification strategy maintains certain assumptions, it strictly weakens the identification assumptions required for estimation with fixed effects alone.

After estimating the model, I discuss its predicted substitution patterns, showing that location pairs which are closer to one another along a range of distance measures have stronger cross-elasticities. The parameter estimates also suggest that there is substantial heterogeneity in firms’ willingness to pay for greater market access across industrial sectors. For instance, food producers, textile firms, and sporting-goods manufacturers all have stronger preferences for locating closer to large markets than makers of wood products, which tend to locate closer...
Finally, I use the model to predict what would have happened to industrial locations under two realistic counterfactual scenarios: the on-time construction of the Trans-Java Expressway and an improvement to certain rural roads. The Trans-Java Expressway is a series of proposed toll roads connecting cities along the northern coast of Java. Originally planned for operation in 1994, it has been mired in construction delays and remains incomplete. Using the model to simulate what would have happened to industrial locations, I find that the toll roads would have induced a moderate degree of increased suburbanization. With better roads, manufacturing activity would have moved further outside of existing urban centers, but firms would not have relocated to the remotest parts of Indonesia. In contrast, I find that upgraded rural roads have little if any significant effects on industrial locations, despite claims often made by policymakers to the contrary.

This paper contributes to a growing literature that studies the effects of transport infrastructure through the lens of trade theory (e.g. Michaels, 2008; Donaldson, 2010) or urban economics (e.g. Baum-Snow, 2007). While prior work has used models in which trade is driven by Ricardian comparative advantage or factor endowments, this paper uses a model that focuses on trade driven by increasing returns to scale and imperfect competition. This class of models is used frequently in economic geography, and this paper also contributes to a long-standing research program that focuses on testing such models (e.g. Davis and Weinstein, 2003; Redding and Sturm, 2008). Within this literature, there is a line of research that uses discrete choice models to estimate firm location choices, dating back to Carlton (1983). Most papers in this literature estimate choices for a single cross-section of firms (Coughlin et al., 1991; Head et al., 1995; Henderson and Kuncoro, 1996; Head and Mayer, 2004), and this paper builds upon prior work by using panel data, which allow me to distinguish between the effects of observed location characteristics and the effects of unobservable fixed factors.

Most importantly, to the best of my knowledge, prior work has not addressed the fundamental endogeneity problems associated with estimating firm location choices. The fact that a location’s wages, rents, and market potential are determined in equilibrium necessitates the use of a model and conditional moment restrictions for identification. By deriving the estimating equations from an explicit theoretical framework, constructing a time-varying measure of transport costs from a new dataset on road quality, estimating the model on a panel of new firms, and using structural econometric techniques to address the endogeneity of location characteristics, this paper aims to extend the empirical literature on firm location choices and transportation. While the results discussed here are undoubtedly specific to Indonesia, the model and empirical techniques advanced could be readily applied to examine the impact of regional policies on firms in other settings.
The rest of this paper is structured as follows: Section 2 describes Indonesia’s road construction program and manufacturing activity in the late 1980s and 1990s. Section 3 describes a new dataset on road quality in Indonesia and discusses how these data are used to construct proxies for transport costs. It also discusses the data on newly entering manufacturing firms and location characteristics. Section 4 presents reduced form evidence on how road improvements induced greater dispersion of manufacturing activity. To obtain more accurate counterfactual predictions, Section 5 presents a structural model of monopolistic competition and regional trade, discussing how to identify and estimate its parameters. Section 6 presents parameter estimates from the choice model and discusses the predicted locational substitution patterns. In Section 7, I use the model to predict what would have happened to industrial locations under various counterfactual scenarios, and Section 8 concludes.

2 Roads and Manufacturing in Indonesia

Although known for political repression, violence, and corruption, Suharto’s regime in Indonesia (1967-1998) had an extraordinary development record. During the three decades in which he was in power, GDP grew by an average of 5% per year, and the poverty rate fell from 60% in the mid 1960s to around 10% in the early 1990s (Hill 2000). One potential contributor to Indonesia’s economic success was the government’s investments in major public works programs, including improvements to transport infrastructure.

Indonesia’s roads, many of which were built by Dutch colonists in the 18th and 19th centuries, were left to crumble and deteriorate under the leadership of Indonesia’s first president, Sukarno (1945-1967). After coming to power in 1967 as the second president of Indonesia, Suharto quickly recognized the need to improve the country’s infrastructure, and he made road improvements a priority of his first two five-year development plans, Repelita I (1969-1974) and Repelita II (1974-1979).4 However, funding was insufficient for broad transport improvements, and the projects undertaken involved upgrading connections between major urban centers.5

After the collapse of oil revenues in the late 1970s, spending on road infrastructure slowed considerably and was not a priority of either Repelita III (1979-1984) or Repelita IV (1984-1989). However, manufacturing began growing rapidly by the end of the decade, and roads that were improved in the 1970s required heavy maintenance. This encouraged a shift in

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4In Bahasa Indonesia, the phrase rencana pembangunan lima tahun is literally translated as “five year development plan”. In characteristic Indonesian fashion, this phrase is seldom spelled out but instead expressed by the acronym Repelita.

5Surveys of transportation improvements in Indonesia during this period are difficult to find in the literature, but Leinbach (1989) and Azis (1990) provide some useful discussion.
development priorities during the 1990s. Table 1 shows the massive increase in funding allocated to improving roads between Indonesia’s fourth, fifth, and sixth five-year development plans. During Repelita IV, the total budget for road improvements was $2.1 billion. This was increased by 84 percent in Repelita V (1989-1994), to a sum of $3.9 billion. Transportation investments were the single largest item of the budget during Repelita V, forming nearly 18 percent of total planned development expenditures. Funds for road improvements in Repelita VI (1994-1999) were planned to be kept at similar levels as the first half of the decade, but the Asian financial crisis of 1997-1998 and its concurrent political upheaval resulted in less spending than originally intended.

During the 1990s, road improvements were substantial and aimed at a wider variety of projects than before. Explicit attention was given to connecting sparsely populated areas, and to infrastructure improvements outside of the major islands. The large increases in budgeted spending translated into huge improvements in the network. According to new data described in the next section, in 1990, 84 percent of Sulawesi’s roads were unpaved. However, after a decade, only 46 percent of the network remained unpaved. In Sumatra, 68 percent of the network was unpaved in 1990, but by 2000, only 30 percent of the network was unpaved.

Importantly, these road improvements were also designed to adhere to long-term national spatial plans. Such plans dictated that particular regions should receive infrastructure improvements, and they were revised very infrequently (approximately once a decade). This suggests that the road authorities did not regularly respond to changes in outcomes, and it also suggests that location fixed effects can remove much of the targeting bias.\footnote{This idea comes from conversations with the highway authorities at DPU. Unfortunately, I do not have access to the exact national spatial plans that were used, but it is worth noting that in every planning and budgeting document I do have access to, no information is provided at levels below the province.}

As the road network rapidly improved, Indonesia’s manufacturing sector grew considerably. From 1985 to 1992, manufactured exports grew at an average annual rate of over 20 percent in real terms, while the share of labor intensive manufactures grew from 40 percent of exports in 1982 to over 60 percent in 1992.\footnote{For more details on the rise of labor-intensive manufacturing in Indonesia, see Hill (2000).} However, after the Asian Financial Crisis, in which Indonesia experienced a massive exchange-rate depreciation that caused a financial crisis and political upheaval, spending on transport infrastructure slowed considerably. Moreover, local governments began to assert more authority during Indonesia’s program of decentralization, and this involved transferring the maintenance of many national roads to local governments. Anecdotal evidence suggests that many local governments did not have the capacity to maintain the roads under their jurisdiction, and roads began to deteriorate.

\footnote{These figures are all quoted in constant 2000 U.S. dollars.}
3 Data and Measurement

In this section, I first define kabupatens, the spatial unit of analysis used in my empirical work. Then, I present new data on Indonesia’s highway improvements and their subsequent deterioration, and I explain how they are used to construct a panel of transport cost estimates between locations. Finally, I discuss Indonesia’s Survei Industry (SI), an annual census of manufacturing firms with more than 25 employees.

3.1 Spatial Unit of Analysis

Throughout the paper, I focus only on the islands of Java, Sumatra, and Sulawesi, since these are the three islands with the largest amounts of population and manufacturing activity, and I use Indonesia’s kabupatens (districts) as the spatial unit of analysis. The kabupaten is the second administrative division in Indonesia, nested below the province. Because many kabupatens were divided and partitioned into new kabupatens after the fall of Suharto, I aggregate back to the 1990 definitions in order to achieve a consistent geographic unit of analysis. The sample contains 185 kabupatens, with a median land area of 1,498 square kilometers. This is slightly smaller than the size of U.S. counties, which have a median area of 1,595 square kilometers. Indonesia’s major cities are also given separate identifiers, and these designations are also used in the analysis.9

3.2 Data on Road Quality

Many of the major roads used in Indonesia today have been around in some form for centuries, meaning that their effects can only be studied by using variation in quality over time. This type of variation is different from the spatial variation in infrastructure access used in prior work (e.g. [Michaels 2008, Donaldson 2010]). An understanding of the effects of road quality improvements should be very relevant for policymakers acting in developing countries, since it is generally cheaper to repair existing roads than to build new ones.

Data on the evolution of road quality come from a unique source: Indonesia’s Integrated Road Management System (IRMS), maintained by the Department of Public Works (De-

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9Note that roughly 13 percent of the firm-year observations in my sample were reclassified by aggregating kabupaten codes. Most of the reclassified observations (35,901 observations) were due to collapsing the five separate Jakarta codes into a single code. An additional 6,660 observations (0.2 percent of the sample) were reclassified by aggregating adjacent rural regions with small amounts of manufacturing activity. See Appendix Section C.2 for more details.
partemen Pekerjaan Umum, or DPU). In the late 1980s, DPU began to conduct extensive annual surveys of its road networks, collecting data along the kilometer-post intervals of all major highways. Road quality surveys were conducted by a team of surveyors, who measured the surface type and width of road segments and also collected longitudinal data for computing the international roughness index (IRI). The original dataset is extremely detailed, with more than 1.2 million kilometer-post-interval-year observations. Although some of the road-link identifiers changed as roads were upgraded and reclassified, it is possible to merge the kilometer-post interval data to shapefiles of the road networks. This yields a panel of quality measures along major inter-urban roads from 1990 to 2007. Figures 1, 2, and 3 depict the evolution of pavement along the highway networks of Java, Sumatra, and Sulawesi respectively. These show considerable spatial variation in the timing and extent of the improvements, and they also highlight the magnitude of the road improvement program.

3.3 Measuring Transport Costs

In the Indonesian context, measuring the cost of transporting goods between regions is extremely challenging. A common approach in the trade literature is to first estimate a gravity equation, using detailed data on regional trade flows, and to back out transport costs from parameter estimates. Unfortunately, regional trade flow data have never been systematically collected in Indonesia, so this approach is infeasible. Another method involves backing out transport costs from price differences (e.g., Donaldson 2010). This requires invoking an iceberg trade costs assumption (Samuelson 1954), prior knowledge of where certain goods are produced, and observations of prices of that good in various locations. Although Indonesia’s central statistical agency, Badan Pusat Statistik (BPS), collects detailed data on goods prices used in constructing the CPI, they do so only for a limited number of provincial capital cities, making it difficult to exploit much spatial variation. Moreover, many of these provincial capitals are also ports, so trade between them would not necessarily rely on using the road network. It is also difficult to pin down goods that are only produced in a single location.

Faced with these challenges, I construct a proxy for transport costs using the available data on road quality. The measure is based on road roughness: when faced with potholes,

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10 The international roughness index (IRI) is a measure of road quality that was developed by the World Bank in the 1980s. It is constructed as the ratio of a vehicle’s accumulated suspension motion (in meters), divided by the distance travelled by the vehicle during measurement (in kilometers). See Appendix Section C.1.2 for more details on IRI and how it was measured.

11 Appendix Section C.1 provides more detail about the road quality data, particularly the process of merging the interval data to network shapefiles and the creation of variables.

12 See Anderson and Van Wincoop (2004).
ragged pavement, or unpaved surfaces, drivers slow down, and this reduction in speed increases travel time and hence the cost of transport. Of course, there is not a one-to-one relationship between road roughness and speed, because drivers choose the speed at which they travel, and different preferences for ride smoothness or the desired arrival time might induce different choices of speed.

Yu et al. (2006) provide a mapping between subjective measures of ride quality and roughness at different speeds. This mapping can be used to determine the maximum speed that one can travel over a road with a given roughness level while maintaining a constant level of ride quality. Given this roughness-induced speed limit, it is straightforward to calculate travel times along network arcs and to compute the shortest path between different regions, using travel time as the single cost factor (Dijkstra, 1959). Note that the travel times on road sections were computed using speeds derived from the extremely detailed kilometer-post-interval roughness data, which were then aggregated to form cost measures along the network arcs. In order to allow for travel between islands, I use data on the locations of major ports and estimate travel times between them, effectively linking all of the regions together in one transport cost matrix.

Travel time is a useful way of measuring transport costs, because it is correlated with distance (and hence fuel consumption) and should also be related to drivers’ wage bills. From surveys of trucking firms throughout Indonesia, the Asia Foundation (2008) found that fuel and labor costs were the largest contributors to vehicle operating costs, reinforcing confidence in the travel time measure. While most of the variation in travel times comes from changes in road quality for existing roads, some new toll roads were also constructed during the period (mostly on Java), creating variation in physical distances (and speeds) that is also captured in the measure.

Table 2 presents summary statistics of average transport costs between a given kabupaten and all other kabupatens on that island for Java, Sumatra, and Sulawesi, for the period 1990-2005. Physical distances did not change substantially, because only a few toll roads opened up over the period, and these new roads were confined exclusively to Java. The average distance

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13See Appendix Section C.1.4 for more details. Note that the travel time measure incorporates a continuous measure of road quality, the international roughness index (IRI), rather than a simpler binary measure for whether or not a road is paved. This was done to better match the transportation literature, but both measures are highly correlated.

14For more details, see Appendix Section C.1.6

15Fuel and labor costs amounted to 53 percent of vehicle operating costs on average, according to the survey. Other significant cost factors included lubricants and tires (13%), and other maintenance costs (4%), all of which should increase as cars are driven on rougher roads.

16Toll roads were coded with minimum levels of roughness when they are introduced. Because the fee for using toll roads is generally very small compared to the value of goods or services shipped, I ignore it when measuring transport costs.
falls very slightly, but travel times decrease significantly from 1990 to 2000 (17 percent). Although physical distances remained unchanged in Sumatra, travel times fell by 24 percent, on average, from 1990 to 2000. Similarly, average travel times in Sulawesi fell by 38 percent over the time period, despite any change in physical distances. The rapid deterioration of road quality from 2000 to 2005 is also quite apparent.

The average summary statistics presented here mask substantial geographic and temporal variation in the areas that received the largest reductions in transport costs. For instance, in Java, the largest reductions in travel times over the 1990-2000 period occurred for Central Java, while in Sumatra, the largest reductions occurred for the provinces of Riau, Jambi, Bengkulu, and South Sumatra. For Sulawesi, the provinces that received the largest improvements in average transport costs were Gorontalo and South Sulawesi.\textsuperscript{17}

### 3.4 Survey of Manufacturing Firms

The estimates of travel times between regions are combined with a plant-level survey: Indonesia’s Annual Survey of Manufacturing Establishments (Survei Tahunan Perusahaan Industri Pengolahan, or SI). The SI is intended to be a complete annual enumeration of manufacturing plants with 20 or more employees. Administered by the Indonesia’s central statistical agency (Badan Pusat Statistik, or BPS), the survey is extremely detailed, recording information on plant employment sizes, their industry of operation, cost variables, and measures of value added. Importantly for this work, enumerators recorded each plant’s operating location at the kabupaten level, enabling me to link firms to data on transport costs and other location characteristics.\textsuperscript{18}

While I use the entire panel of firms to construct measures of spatial concentration and location characteristics, I often treat the data as a repeated cross-section of new firms. In practice, firms in the dataset do not change their kabupaten of residence.\textsuperscript{19} New firms are counted when they appear in the dataset having never appeared before. Occasionally firms were not surveyed during their first year of operation, but since enumerators record each firm’s starting year, I can accurately time the entry of all firms in the sample.\textsuperscript{20} Throughout the analysis, I dropped all firms that were coded as state-owned enterprises (less than 3 percent of all firm-year observations), since these firms are less likely to be governed by

\textsuperscript{17}These trends are documented visually in Appendix Figures D.1, D.2, and D.3.

\textsuperscript{18}Throughout the discussion, I use plants and firms interchangeably, because it is likely that less than 5% of plants in the dataset are operated by multi-plant firms (Blalock and Gertler, 2008).

\textsuperscript{19}When firms do change locations, it is generally due to a coding error, since they typically switch back to their original location in the next year.

\textsuperscript{20}Note that the starting year variable was not collected between 2001 and 2005. For some firms appearing in these years, the starting year was taken from the 2006 dataset, but in cases where it could not be obtained, entry is determined by the first year that the plant’s unique identifier appears in the panel.
market forces.

The SI is also used to construct time-varying location characteristics, including wage rates, commercial land values, and indirect tax rates. A location’s wage rate was constructed by taking the median wage rate for all manufacturing workers in that location and time. Commercial land values were taken by averaging the firm’s book (or estimated, if book was not reported) value of land capital, then taking the median across all firm-level observations in a given location and year. Land values are difficult to measure in some cases, since only 54% of firm-year observations reported land values, and the lack of precisely estimated rental rates is a major caveat to the results. A location’s indirect tax rate is defined as the median share of the value of a firm’s output that is spent on indirect taxes, which include establishment license fees, building and land taxes, and sales taxes. Portions of these taxes are set independently by kabupaten governments and vary across space and time.

4 Trends in Industrial Location

Using these data, I now present reduced form evidence on how the locations of Indonesian manufacturing plants changed in response to changes in transport costs. Lower transport costs raise the profitability of existing cities and may be expected to further intensify agglomerations (Krugman 1991). On the other hand, by giving firms access to cheaper factors of production, they might encourage firms to disperse (Helpman 1998). To determine which prediction is more relevant empirically, I first examine how industrial concentration measures evolved over time for different industries. Next, I discuss trends in how new firms located in different types of regions. Finally, I link the changes in observed industrial concentrations to changes in market access.

4.1 Measures of Industrial Concentration

From 1985 to 1996, the manufacturing sector in Indonesia was marked by substantial growth in the number of new firms. As firms entered the market, they increasingly moved away from existing agglomerations, reducing industrial concentration across space. The literature provides several measures of industrial concentration, but my main results focus on the Ellison and Glaeser (1997) index.21 This employment concentration index was constructed using plant-level data for every 5-digit industrial classification and year, and Panel A of

21Because the Ellison and Glaeser (1997) explicitly accounts for industrial concentration, it is useful for analyzing my dataset since many industries are dominated by a small number of large firms, and the plant size distributions change significantly over time, potentially skewing results. However, results using a simpler spatial Herfindahl can be found in Appendix Figure D.4.
Figure 4 depicts how the mean and median of this index evolved over time. The graph shows a striking reduction in the index, from an average of 0.058 in 1985 to 0.039 in 1996, a fall of over 30 percent. To put this change in perspective, in 1985, the median concentration of manufacturing industries in Indonesia (0.044) was 70 percent larger than the U.S.’s median index in 1987 (0.026), according to Ellison and Glaeser (1997). By 1996, Indonesia’s median concentration index fell to roughly equal that of the U.S. in 1987.

A variety of industries experienced reductions in concentration over the period. Other Manufacturing (ISIC 39), which includes the production of sporting goods (ISIC 39030) and toys (ISIC 39040), showed the largest reductions in concentration. The furniture and wood products industry (ISIC 33) also experienced dispersion, with major reductions for producers of wood veneer and excelsior (ISIC 33114), home furnishings (ISIC 33230), and handicraft and wood carving (ISIC 33140). Interestingly, textiles (ISIC 32) was the only industry group not to experience any overall reduction in concentration, with the median 5-digit industry experiencing a 10 percent increase in concentration over the period.

However, within industries, there were substantial differences in concentration trends. For instance, while storable processed foods, such as coconut and palm oil (ISIC 31151) and canned, processed seafood (ISIC 31140) dispersed, more perishable food products, such as tofu and tempe (ISIC 31242) and ice (ISIC 31230) remained flat or experienced increases in concentration. One hypothesis suggested by this comparison is that, during a period of large transport improvements, producers of durable goods may experience reductions in concentration, while producers of highly perishable products will remain unaffected. Highly perishable products need to be produced very close to where they are consumed, while more durable goods can be produced farther away, provided that transport costs are sufficiently low.

Moreover, while finished metal, machines, and electronics (ISIC 38) experienced a modest reduction in concentration over the period, manufacturers of radios and television (ISIC

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22 Note that in selecting the sample of industries for the analysis, I dropped industries if they were missing too many firm-year observations to construct a consistent measure over time or if they had fewer than 10 firms throughout the period. In a few instances, similar ISIC codes were merged together in order to avoid dropping both from the sample.

23 The change in average concentration is statistically significant at an $\alpha = 0.05$ level using a two-sample comparison of means ($t = 2.542$, 2-sided $p$-value = 0.0126, 1-sided $p$-value = 0.0063). Note that these results on dispersion are very different from Sjoberg and Stoholm (2004), who argue that over the 1980-1996 period, spatial concentration remained more or less unchanged. There are several reasons for discrepancies between my analysis and theirs, but the most important, I suspect, is that I use kabupatens as my spatial unit of analysis, while they use provinces. Since much of the changes I observe take place within provinces, it is not surprising that they find mixed results, while I find evidence pointing towards dispersion. Moreover, I also use a finer level of industrial classification (5-digit ISIC) to compute these indices, and I have access to surveys for every year. Without proper cleaning, these indices are very sensitive to outliers (misreported employment), especially for industries with a smaller number of firms.

24 More detail on the changes in concentration can be found in Appendix Tables D.1 and D.2
38320) and producers of optical and photographic equipment (ISIC 38500) experienced increases in concentration. These industries are more skill intensive than others and are probably more subject to Marshallian agglomeration economies than other manufacturers. This suggests that while road improvements might induce the dispersion of producers of low skill goods, they may not affect industries in which strong external economies are important.

To explore differential trends in concentration measures across different types of industries, I first classified 5-digit industries into either durables or non-durables, based on their reported inventory shares of output.\textsuperscript{25} Using these classifications, Panel B of Figure 4 depicts how, over the 1990s, both spatial concentration measures fell more rapidly for durable goods (high inventory shares) than for non-durables.\textsuperscript{26} This largely confirms our predictions. If transport improvements enable firms to take advantage of cheaper access to land and labor in remote areas, durable goods should be more likely to relocate than non-durable goods, since non-durables are perishable and must be consumed in close proximity to where they are produced.

### 4.2 Regional Trends

Another way of exploring the reductions in concentration is to investigate changes in how different types of regions received new plants. Figure 5 depicts the shares of new firms locating in cities (defined as of 1990), in kabupatens that are neighbors of cities, in neighbors of neighbors of cities, and in other kabupatens, classified as rural. In 1985, 40 percent of new firms located in cities, but by 1996, only 24 percent of new firms located in cities. Neighbors of cities experienced a 10 percentage point increase in the share of new firms (from 33 percent in 1985 to 43 percent in 1996), while neighbors-of-neighbors experienced a 9 percentage point increase (from 13 percent in 1985 to 22 percent in 1996). Rural shares are mostly flat, however, suggesting that transportation improvements might bring firms to areas near cities, but not to the remotest parts of Indonesia.\textsuperscript{27}

As further evidence of the different trends in location across industries, Table 3 decomposes the changes of new firms into those resulting from durable goods and from non-durable goods. It is apparent that most of the changes in new firm shares are coming from durable goods firms, which should be the most responsive to changes in transport costs. For instance, of the 16 percentage point reduction in the share of new firms locating in cities between 1985 and 1996, 10 percentage points is attributable to firms with high inventory shares, while only

\textsuperscript{25}Durable goods industries are classified as those goods whose inventories were, on an average of plant-years, greater than or equal to 10 percent of output, while non-durables have inventory shares less than 10 percent of output.

\textsuperscript{26}The difference-in-difference and differential trends estimates are reported in Appendix Table D.4

\textsuperscript{27}Reclassifying kabupatens by physical centroid distance to the nearest 1990 city reveals similar trends.
6 percent is attributable to firms with low inventory shares.

4.3 Regression Analysis

We can summarize the effects of road improvements on the activity of new manufacturing plants by fitting a series of regression functions with region-specific intercepts, exploiting variation in the timing and placement of road improvements across regions in Indonesia. Let $r = 1, \ldots, R$ index regions (kabupatens), let $j = 1, \ldots, J$ index industrial sectors, and let $t = 1, \ldots, T$ index years. Also, define $MP_{rt}$ to be a region’s *market potential* in year $t$ (Harris, 1954):

$$MP_{rt} = \sum_{d=1}^{R} \frac{Y_{dt}}{T_{rdt}}$$

This is weighted average of each region’s GDP, $Y_{dt}$, where the weights decline in travel times, $T_{rdt}$. To construct $MP_{rt}$, I use annual data on real non-oil gross domestic product for each kabupaten and the annual roughness-induced travel time measure of transport costs between kabupaten pairs. As road improvements bring region $r$ closer to other larger markets, $MP_{rt}$ increases. In Section \[ of this paper, a similar market potential variable emerges from a model of monopolistic competition and regional trade, and it captures all of the spatial interactions between firms in different regions.

In Table \[, we begin by estimating models of the following form:

$$y_{rjt} = \beta MP_{rt} + \varepsilon_{rjt}$$

where $\varepsilon_{rjt}$ is an error term. The dependent variable, $y_{rjt}$, is the log of one plus the number of new firms (or new employees) appearing in a region-sector-year cell.\[ Dropping observations with zeros does not substantially change estimated effect sizes or confidence intervals; see Appendix Table \[.

One concern with this regression function is that the outcome variable, $y_{rjt}$, might be simultaneously determined with local GDP, $Y_{rt}$, which is included in the construction of market potential instruments:

$$\mathbb{E} \left[ \nu_{rjt} \mid \delta_r, \delta_j, \delta_t, z_{r1}^{MP}, \ldots, z_{rT}^{MP} \right] = 0 \quad (3)$$

\[Dropping observations with zeros does not substantially change estimated effect sizes or confidence intervals; see Appendix Table \[.\]
potential, $MP_{rt}$. To address possible simultaneity bias, I use a base-weighted version of market potential, $z^M_{rt}$, as instruments for actual market potential. The formula for $z^M_{rt}$ looks just like (1), except that the GDP weights are fixed to equal regional GDP in 1985 (i.e. $Y_{dt} = Y_{d,1985}$ for all $t$). Because I partial out all region-specific effects in these regressions, all of the variation in the predicted market potential comes from changes in transport costs. This specification controls for all time-invariant unobservables that influence outcomes for particular sectors and for particular regions, and it also controls for all national unobservables that affect outcomes in each year.

In the second and third columns, we weaken the restrictions on the error term by adding more fixed effects. The second column adds a full set of sector-year effects, controlling not only for time-invariant unobservables that affect regions, but also for any omitted variables that influence outcomes differently in different sectors over time. The third column allows for differential trends in the outcome variable across different provinces. In all specifications, robust standard errors are clustered at the region level, allowing for both serial correlation in the disturbances over time and also for arbitrary correlation between the disturbances affecting different industries in the same region.

Overall, the estimates show significant positive associations between market potential and new manufacturing activity. The dependent variable and explanatory variables are both expressed in logs, so that the coefficients can be interpreted as elasticities. A ten percentage increase in a region’s market potential results in an approximately 1.3 percent increase in new firms and a 4.6 percent increase in new employees. The effect sizes are smaller when we allow for province trends, but they remain positive and statistically significant.

Since market potential varies only at the region-year level, the above specifications cannot rule out the possibility that other time-varying, region-specific confounders might actually be driving the results. However, since we have industry-level data, and we know that certain industries (e.g. durable goods producers) are more likely to be influenced by better market access, we can exploit variation within region-years in the effects of market potential across sectors. In the fourth column, we estimate models of the following form:

$$y_{rj} = \gamma (D_j \times MP_{rt}) + \varepsilon_{rj}$$

where $D_j$ is an indicator for whether or not the industry is a producer of durable goods (or low-skill goods), and $\varepsilon_{rj}$ is defined as follows:

$$\varepsilon_{rj} = \delta_{rt} + \delta_{jt} + \nu_{rj}$$

These specifications do not allow us to estimate the entire effect of improving market poten-
tial. Instead, they deliver estimates of the differential effect of market potential improvements on durable goods producers, relative to non-durables producers. The coefficients estimates are small, but still significant at conventional levels. Relative to non-durables producers, a ten percent increase in a region’s market potential results in a 0.2 percent increase in new durable goods plants and a 0.7 percent increase in jobs for the durable sector.

As a further check on the potential endogeneity of road improvements, I conduct a placebo exercise, estimating the effects of unbuilt sections of the Trans-Java Expressway. If policymakers targeted areas for receiving road improvements based on region-specific, time-varying unobservables that affect firm location choices, then we would expect the unbuilt tollways to have spurious effects on new firms and employment. Table 5, Columns 1-3, reports estimates of the effects of these unbuilt toll roads and finds no significant coefficient estimates. Moreover, the estimates of the effects of market potential, controlling for the unbuilt expressway lines, are nearly identical to those reported in Table 4.

Another potential problem is that the strict exogeneity assumption, (3), does not allow for any feedback between lagged unobservables and future regressors. But if policymakers targeted faster growing areas with better infrastructure, we would expect past unobservables, \( \nu_{rjt-1} \), to be correlated with the future history of transport cost variables, \( z_{r,t}^{MP}, z_{r,t+1}^{MP}, \ldots, z_{r,T}^{MP} \). To allow for feedback, I weaken (3) to a series of sequential moment restrictions:

\[
\mathbb{E} \left[ \nu_{rjt} \mid \delta_r, \delta_j, \delta_t, z_{r,1}^{MP}, \ldots, z_{r,t-1}^{MP} \right] = 0 \quad t = 1, \ldots, T
\]

This is a weak exogeneity assumption (Chamberlain, 1992), stating that the current values of \( \nu_{rjt} \) are shocks, uncorrelated with the past regressors; however, the current values of \( \nu_{rjt} \) are allowed to be correlated with future values of the regressors. It is also a strictly weaker identification assumption; if (3) holds, than so does (4), but the converse is not true. Sequential moment restrictions open up a variety of possible estimation strategies, but I simply choose to estimate the model in first differences, using lagged changes in market potential IVs \( (z_{r,t-1}^{MP} - z_{r,t-2}^{MP}) \) as instruments for the current change in market potential \( (MP_{r,t} - MP_{r,t-1}) \). Results are reported in Table 5, Columns 4-6. Although the point estimates are somewhat smaller than before, the estimates are still positive and significant at conventional levels.

\( ^{29} \)Negative project selection is clearly a concern, as it would invalidate the legitimacy of the placebo exercise. I argue in Section 7 that the Trans-Java Expressway was not built for idiosyncratic reasons, having more to do with the corrupt way the construction rights were auctioned off than any possible negative selection of the project.
4.4 Summary

Overall, this analysis indicates that during the sample period, Indonesia has experienced significant reductions in industrial concentration. Areas that received expanded market potential as a result of the road improvement program experienced a growth in manufacturing activity and employment, on average. Moreover, different industries responded to these road improvements in predictable ways. Taken together, this is strongly suggestive evidence in refutation of the predictions of [Krugman (1991)].

While this reduced form analysis has shed some light on the relevance of different theoretical predictions, it does not allow us to distinguish between different mechanisms driving the results, and it may not be useful for predicting the impacts of different road programs. The estimated regression coefficients were obtained using one specific source of policy variation, and they may not be invariant to different policy regimes. As some regions attract firms because of better market access, this will affect equilibrium factor prices (wages and rents) in those locations, altering the choices of other firms. Predictions of what would happen to firm locations that ignore factor price responses may be inaccurate. To quantify the relative importance of different mechanisms and provide a richer set of counterfactual predictions, in the next section I develop and estimate a structural model of firm location choice.

5 Structural Model

In this section, I extend the firm location choice model of [Head and Mayer (2004)] in several ways. First, I explicitly allow for multiple industrial sectors, highlighting the importance of sectoral differences in location choice parameters. Next, I also allow for unobserved productive amenities, common to all firms and all industries, that shift marginal cost functions at particular locations. Because the model implies that unobservable amenities will be directly correlated with wages, rents, and other factors influencing marginal costs, identification of the choice model’s parameters requires conditional moment restrictions and estimation becomes substantially more involved. Finally, in the original model, firms ignore the effect that their location choices have on wages and rents at chosen locations, but here I allow for upward sloping labor and land supply curves. After presenting the model, I discuss how to estimate its parameters.

5.1 Setup

There are $R$ regions, indexed by $r = 1, ..., R$. As in [Krugman (1991)], there are also two sectors: a constant returns to scale agricultural sector, and an imperfectly competitive man-
ufacturing sector. Each region \( r \) is endowed with a mass of workers, \( L_r \), and workers decide whether to work in agriculture or manufacturing, based on a heterogeneous taste parameter. Workers are perfectly mobile between sectors within a region, but they cannot move between regions. In this sense, the model is short-run, unlike many long-run spatial equilibrium models in urban economics that allow for labor mobility (e.g. Roback 1982, Busso et al. 2010). \(^{30}\)

5.2 Consumer Preferences

There are two types of goods consumed by individuals: manufactured and agricultural products. Manufactured goods are differentiated products produced in one of \( K_s \) industrial sectors, indexed by \( k = 1, ..., K_s \). Let \( N^k_r \) denote the set of industry \( k \) varieties produced in region \( r \). Consumers in region \( r \) choose varieties from each industry and region, and a quantity of the agricultural good, \( A \), to maximize the following utility function:

\[
U = \frac{C}{\eta} \left( \prod_{k=1}^{K_s} M^k_k \right)^{A^{1-\mu}} \quad \text{where} \quad \sum_{k=1}^{K_s} \mu_k + \mu = 1 \tag{5}
\]

This utility function represents Cobb-Douglas preferences over both agriculture and CES aggregates of manufacturing varieties for each industry, \( M_k \), which are given by:

\[
M_k = \left[ \sum_{d=1}^{R} \left\{ \int_{j \in N^k_r} q^k(j) \frac{\sigma_k-1}{\sigma_k} dq \right\} \right] \quad \sigma_k \geq 1, \ k = 1, ..., K_s
\]

where \( q^k(j) \) is the quantity of industry \( k \)'s variety \( j \) consumed, and \( \sigma_k \) is an industry-specific parameter governing the elasticity of substitution between an industry's varieties. As \( \sigma_k \) tends to 1, varieties in that industry become less substitutable for one another, weakening competition in the industry. As \( \sigma_k \) grows larger, the varieties in industry \( k \) become more substitutable, and competition grows more intense.

Note that the utility function contains a scale factor, \( C/\eta \). While \( C \) is just a constant used to normalize the scale of indirect utility, \( \eta \) is a heterogeneous taste parameter, reflecting an individual’s disutility from working in manufacturing. \(^{31}\) The scale factor does not enter into worker utility if the individual works in agriculture (i.e. \( \eta = 1 \)); otherwise, \( \eta \) is continuously distributed over \([1, \infty)\), with c.d.f. \( F_\eta(\cdot) \). A larger draw of \( \eta \) corresponds to a worker who

\(^{30}\)In principle, the assumption of labor immobility can be weakened, for instance if we allow workers to have idiosyncratic tastes for living in particular locations (Moretti 2010). Crucially, we need some degree of fixity to ensure that factor prices are locally upward sloping.

\(^{31}\)The formula for \( C \) is given by \( C^{-1} = (1-\mu)^{-1} \prod_{k=1}^{K_s} \mu_k^k \).
does not like working in manufacturing and must require a larger wage to induce him to switch sectors.

We solve the consumer’s optimization problem by first choosing optimal bundles within a given industry and then by determining how to distribute income across industries. Using this approach, it is straightforward to show that in region \( r \), demand for variety \( j \) in industry \( k \) is given by:

\[
d^k_r(j) = \frac{p^k_r(j)^{-\sigma_k} \mu_k Y_r}{(P^k_r)^{1-\sigma_k}}
\]

(6)

where \( Y_r \) denotes region \( r \)'s nominal income, and \( P^k_r \) is given by:

\[
P^k_r = \left[ \sum_{d=1}^{R} \left\{ \int_{i \in K_r^k} p^k_r(i)^{1-\sigma_k} d_i \right\} \right]^{\frac{1}{1-\sigma_k}}
\]

(7)

This represents region \( r \)'s CES price index for industry \( k \) varieties.\(^{32}\)

5.3 Agriculture

Depending on their draws of \( \eta \), workers decide whether to work in agriculture or manufacturing. The agricultural good is freely traded across locations, and produced under constant returns to scale, with labor as its only factor of production. Hence, a worker’s agricultural wage is equal to his or her marginal product, and we can normalize \( w_A = p_A \equiv 1 \), so that the agricultural wage is the numeraire. A worker in region \( r \) with taste parameter \( \eta \) will work in manufacturing if and only if:

\[
V_{r,M} = \frac{w_r}{\eta \prod_{k=1}^{K_r} (P^k_r)^{\mu_k}} > \frac{1}{\prod_{k=1}^{K_r} (P^k_r)^{\mu_k}} = V_{r,A}
\]

This implies that the share of workers who opt to work in manufacturing in region \( r \) is given by:

\[
s_r = Pr \{ \eta \leq w_r \} \equiv F_r (w_r)
\]

(8)

Hence, the supply of manufacturing workers in region \( r \) is given by \( L_r = \bar{L}_r s_r = \bar{L}_r F_r (w_r) \). We assume that \( F_r'(\cdot) \geq 0 \) for all \( r = 1, \ldots, R \), so that local labor supply curves are upward sloping.

\(^{32}\)For a derivation of (6) and (7), see Appendix Section A.1
5.4 Manufacturing and Trade

Manufacturing varieties are produced with increasing returns to scale under Dixit-Stiglitz imperfect competition. Conditional on operating in region $r$, the cost to produce a quantity $q_r^k(i)$ of variety $i$ in industry $k$ is given by:

$$ c \left[ q_r^k(i) \right] = F_r^k + m_r(i)q_r^k(i) $$

(9)

where $F_r^k$ represents fixed costs of production in region $r$. The marginal cost of producing a unit of variety $i$ is given by:

$$ m_r(i) = A_{ir}w_r^i r_r^\gamma_i $$

(10)

where $w_r$ denotes local wages, $r_r$ denotes local rents, and $A_{ir}$ is a cost measure specific to each variety and location. Note that the entire marginal cost function is specific to the industry, operation region, and the variety, not least because the parameters $\delta_i$ and $\gamma_i$ are allowed to vary across varieties.

Because of fixed costs, firms choose a single location in which to produce, shipping their products to all other locations. All firms face industry-specific iceberg transport costs, representing the amount that must be produced in region $r$ in order to deliver one unit of the product to region $d$ (Samuelson [1954]). This is denoted by $\tau_{rd}^k \geq 1$. Due to the transport technology, $(\tau_{rd}^k - 1)$ units of the good “melt away” while being transported, so that only 1 unit is delivered to the destination region. We make three assumptions about transport costs: first, that $\tau_{rr}^k = 1$ for all regions $r$, so that transport within a region is costless. Second, transport costs are assumed to satisfy a triangle inequality, so that $\tau_{rd}^k \leq \tau_{rs}^k + \tau_{sd}^k$ for all $s = 1, \ldots, R$. This assumption rules out any cross-region arbitrage opportunities in transport. Finally, for simplicity, we assume that the transport cost for industry $k$ is just an industry-specific constant times the travel time measure, $T_{rd}$:

$$ \tau_{rd}^k = \eta^k T_{rd} \quad \text{for all } k = 1, \ldots, K_s $$

(11)

Since $T_{rd}$ denotes the travel time based on the quality of road infrastructure, this assumption allows for the products of industries to melt away at different rates while their goods are being shipped between locations.\footnote{In principle, the relationship between travel times, $T_{rd}$, and transport costs, $\tau_{rd}^k$, could be calibrated, for example by using international trade flow data (Head and Mayer [2004]).}

The form of the consumer’s utility function implies that all consumers in all locations consume every variety of every industry. Conditional on locating in region $r$, a firm in industry $k$ has gross profits (ignoring fixed costs) that are equal to the sum of profits obtained from
shipping its output to all destination locations:

\[ \Pi_r^k(i) = \sum_{d=1}^{R} \pi_{rd}^k(i) = \sum_{d=1}^{R} \left( p_{rd}^k(i) - m_r(i) \right) q_r^k(i) \]

Firms are operating under Dixit-Stiglitz monopolistic competition, and they choose prices ignoring their effects on regional industry price indices, \( P_r^k \). From the structure of competition and consumer demands, we can show that the firm’s optimal pricing formula is given by:

\[ p_{rd}^k(i) = \left( \frac{\sigma_k}{\sigma_k - 1} \right) m_r(i) \tau_{rd}^k \]  

(12)

This expression implies a mill pricing strategy, as \( p_{rd}^k(i) = \tau_{rd}^k p_r^k(i) \).\(^{34}\) Moreover, prices are just industry-specific markups over the firm’s marginal cost, with the size of the markup is governed by the size of \( \sigma_k \), the elasticity of substitution.

Note that a firm’s gross profits from locating in region \( r \) and shipping to region \( d \) are given by:

\[ \pi_{rd}^k(i) = \left( p_{rd}^k(i) - m_r(i) \tau_{rd}^k \right) q_r^k(i) \]

Plugging in expressions for consumer demand \( (6) \), transport costs \( (11) \), and optimal pricing \( (12) \), we can rewrite this expression as:

\[ \pi_{rd}^k(i) = \gamma_k \left( m_r(i) \right)^{1-\sigma_k} Y_d \left( \frac{P_d^k}{T_{rd}} \right)^{-(1-\sigma_k)} \]

where \( \gamma_k \) is a constant specific to industry \( k \), and \( P_d^k \) denotes the price index for industry \( k \)'s products consumed in region \( d \).\(^{35}\)

Summing across destination locations, we obtain the firm’s total gross profits from locating in region \( r \):

\[ \Pi_r^k(i) = \gamma_k \left( m_r(i) \right)^{1-\sigma_k} \left[ \sum_{d=1}^{R} Y_d \left( \frac{P_d^k}{T_{rd}} \right)^{-(1-\sigma_k)} \right] \]

(13)

This expression tells us that a firm’s profits from operating in region \( r \) depend an industry-

\(^{34}\)Here, \( p_r^k(i) = \sigma_k m_r(i)/(\sigma_k - 1) \) is the firm’s local price, just a simple markup over marginal cost. A derivation of (12) can be found in Appendix Section A.2.

\(^{35}\)The exact form of the constant \( \gamma_k \) is given by:

\[ \gamma_k = \frac{1}{\sigma_k} \left( \frac{\sigma_k \eta^k}{\sigma_k - 1} \right)^{1-\sigma_k} \mu_k \]

This constant is depends on the industry’s elasticity of substitution, transport cost parameters, and Cobb-Douglas budget share parameters for industry \( k \).
specific constant, $\gamma_k$, marginal costs, as well as the expression in brackets which is defined as the industry-specific real market potential:

$$RMP^k_r \equiv \sum_{d=1}^{R} Y_d \left( \frac{P^k_d}{T_{rd}} \right)^{-(1-\sigma_k)}$$

This is a weighted sum of regional incomes, where the weights decline in transport costs and increase in the price index for that specific industry. In this model, market potential is the single variable that captures all of the spatial interactions between firms in different locations. It links firm profits from locating in region $r$ to transport costs between that region and all others. As a location becomes closer to larger demand markets, $RMP^k_r$ increases.

The industry-specific real market potential is closely related to another variable, nominal market potential, discussed in an older literature on economic geography and regional science [Harris, 1954]:

$$NMP_r = \sum_{d=1}^{R} \left( \frac{Y_d}{T_{rd}} \right)$$

The difference between $NMP_r$ and $RMP^k_r$ is that real market potential explicitly accounts for competition, through the inclusion of price indices.\(^{36}\)

I use real non-oil gross domestic product data to proxy for $Y_d \left( P^k_d \right)^{-(1-\sigma_k)}$. To the extent that locally, gross domestic production is not equal to domestic incomes or that the statistical agencies are not using price indices that match those from the theory, the market access variable used in the estimation will be mis-measured. In some specifications, I also allow the data to predict the relationship between travel times and $(\tau^k_{rd})^{(1-\sigma_k)}$.

### 5.5 Firm Location Choices

Firms locate in region $r$ if and only if their expected operating profits minus fixed costs from operating in region $o$ are greater than those of all other locations. Following Head and Mayer [2004], we assume that the fixed cost of locating in region $r$ for a firm operating in industry $k$, $F^k_r$, is the same across all locations, i.e. $F^k_r = F^k$ for all $r = 1, \ldots, R$. Given this assumption, fixed costs do not play any role in location choices and can be ignored.

Define $V^k_r(i)$ to be firm $i$’s value function for region $r$, a simple transformation of operating

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\(^{36}\)In the formula for real market potential, the price index can be thought of as a measure of the intensity of competition. Lower price indices correspond to locations with lower markups and fiercer competition, while higher price indices correspond to larger markups and weaker competition. Firms in industry $k$ want to locate in regions that are closer to larger markets, but this preference is tempered by the competitiveness of those locations, reflected in the price indexes.
profits minus fixed costs:

\[ V^k_r(i) \equiv \frac{\ln \Pi^k_r(i) - \ln \gamma_k - F^k}{\sigma_k - 1} = \frac{1}{\sigma_k - 1} \ln RMP^k_r - \ln (m_r(i)) \]

Taking logs of (10), we have:

\[ \ln (m_r(i)) = \delta_i \ln (w_r) + \gamma_i \ln (r_r) + \ln (A_{ir}) \]

Assuming that we can decompose the idiosyncratic portion of the cost function into a vector of observable cost shifters, \( c_r \), a single unobserved component, \( \xi_r \), and a firm-location specific error term, \( \varepsilon_{ir} \), we can write:

\[ \ln (A_{ir}) = c'_r \theta_i - \xi_r - \varepsilon_{ir} \]

It is useful to think of \( \xi_r \) as an unobserved productive amenity (e.g., average ability of the workforce, or quality of life in region \( r \)), which shifts marginal costs for all firms and all industries. The term \( \varepsilon_{ir} \) is an idiosyncratic, firm and region specific component of marginal costs, which we further assume is distributed i.i.d. type 1 extreme value across locations for each firm. Collecting all of the observable cost shifters into a single \((K \times 1)\) vector, \( x_r = (\ln (w_r), \ln (r_r), c'_r)' \) and the idiosyncratic technology parameters into another \((K \times 1)\) vector, \( \beta_i = (\delta_i, \gamma_i, \theta_i)' \), we can rewrite the log of marginal costs as:

\[ \ln (m_r(i)) = x'_r \beta_i - \xi_r - \varepsilon_{ir} \]

Define \( D_i \) to be a \((L \times 1)\) vector of firm-specific observables, for example, a full set of indicators for whether or not firm \( i \) operates in particular industries. Also, let \( v^k_i \) denote a random valuation component for \( x_{r,k} \), the \( k \)-th element of the vector \( x_r \). More precisely, \( v^k_i \) is firm \( i \)'s idiosyncratic sensitivity to marginal cost variable \( k \), which we assume are normally distributed and scaled to have zero mean and unit variance. Also, define \( \alpha^k = 1/(\sigma_k - 1) \).

Using this notation, we can write the firm’s value function as:

\[ V^k_r(i) = \alpha_i \ln RMP^k_r - x'_r \beta_i + \xi_r + \varepsilon_{ir} \]  

where

\[ \alpha_i = \bar{\alpha} + \sum_{l=1}^{L} \pi_{\alpha,l} D_{i,l} + \bar{\sigma}_{\alpha} v_i \]

\[ \beta_{i,k} = \bar{\beta}_k + \sum_{l=1}^{D} \pi_{k,l} D_{i,l} + \bar{\sigma}_k v_i \quad k = 1, \ldots, K \]
In this setup, $\pi_{k,l}$ is a coefficient measuring how $\beta_{i,k}$ varies with firm characteristics, while $\sigma_k$ represents the standard deviation of firm valuations for $x_{r,k}$.

Given this setup, we can write the value (or transformed operating profits) a firm gains from choosing location $r$ as follows:

$$V_{ri} = \alpha_i \ln RMP_r^k + \sum_{k=1}^{J} x_{r,k} \beta_{ki} + \xi_r + \varepsilon^k_{ir}$$

$$= \left\{ \sigma \ln RMP_r^k + \sum_{k=1}^{J} x_{r,k} \beta_k + \xi_r \right\}$$

$$+ \left\{ \sum_{l=1}^{D} (D_{i,l} \alpha_a + \sigma_a v_i) \ln RMP_r^k + \sum_{k=1}^{K} \left( \sum_{l=1}^{D} (D_{i,l} \pi_k + \sigma_k v_i) x_{r,k} \right) \right\} + \varepsilon_{ir}$$

$$= \delta_r + \mu_{ri} + \varepsilon_{ir}$$

The first term in this expression, $\delta_r$, is the mean valuation of choosing location $r$ and is common to all firms in all industries. It depends on $(\alpha, \beta)'$, the mean technology parameters, as well as $\xi_r$, the unobserved productive amenity. The second term, $\mu_{ri}$, represents mean-zero heteroskedastic deviations from the mean valuation, capturing the effects of the sectoral differences. Firm $i$ in industry $k$ chooses to operate in location $r$ if $V_r^k(i) > V_d^k(i)$ for all other locations, $d$. This implicitly defines the set of observed and unobserved variables that lead to the choice of location $r$. Formally, we can denote this set by $A_r$:

$$A_r = A_r(x, \xi_r, \delta_; \theta_2) = \{(D_i, v_i, \varepsilon_{ir}) | V_r^k(i) \geq V_d^k(i) \forall d = 1, ..., R\}$$

### 5.6 Identification of the Choice Model

In an ideal experiment for studying firm location choices, we would randomly assign locations with factor prices, infrastructure access, and exogenous geographic features, and we would record firms’ location choice responses. However, in observational studies, market access and other cost shifters are not randomly assigned, and instead reflect a host of factors, such as the availability of commercial land for real estate, local supplies of labor and consumers, and other characteristics unobserved to researchers. If unobserved productive amenities are present, they will raise the profitability of locating in certain regions, which, ceteris paribus, increases the number of workers and firms who locate in certain regions, raising incomes. Hence, the model implies that market access, wages, and rents will be directly correlated with unobserved productive amenities. This necessitates the use of instrumental variables: variables that are correlated with the endogenous choice characteristics but uncorrelated with
omitted factors explaining the choices of firms.

Distinguishing between between omitted factors, such as natural advantages, and other theories in understanding why agglomerations form is a classic identification problem in empirical urban economics \cite{Ellison1999}. While cross-sectional instruments are clearly useful, finding them is challenging and their exclusion restrictions are often difficult motivate. However, if unobserved natural advantages are constant over time, the use of panel data and fixed effects can help us distinguish between natural advantages and transport cost theories.

Panel data is useful for another reason: if firm cost-functions are time-invariant, it makes sense that as location characteristics change, with increases or decreases in wages, rents, and market access, the identifying power of our model improves. Although the parameters of the model could, in principle, be estimated from data on a single cross-section, with firms making only one choice, such an approach seems far removed from the ideal experiment of repeatedly assigning locations with different bundles of characteristics and observing responses \cite{Nevo2000}. Nevertheless, in most applications of discrete choice to location decisions, authors only study a cross-section of firm choices.

To improve the identifying power of the discrete choice model, I estimate the parameters using variation in location characteristics over time.\footnote{One serious objection to this approach is that over time, firm technologies are changing, and to the extent that this is the case, panel data are not helpful. Note that this is also a problem in the literature on estimating production functions \cite{Olley1996}. While I cannot rule out this possibility, \cite{Wiel2000} (and work cited therein) suggests that Indonesian manufacturing in the 1990s and early 2000s is characterized by a strong absence of technical progress. This is one reason why post-crisis manufacturing growth has been so slow.} Abusing notation, collect all of the choice characteristics for location $r$ at time $t$ as $x_{rt} = [\ln MP, x'_rt]^T$, and let $\beta_r = (\alpha_r, \beta'_r)$ collect all of the choice parameters. With multiple time periods, firm $i$’s value function for location $r$ at time $t$ is the following:

$$V_{irt} = \delta_{rt} + \sum_i (D_i\beta_i + v_i\sigma)'x_{rt} + \varepsilon_{irt}$$

where the mean valuation terms, $\delta_{rt}$, are given by:

$$\delta_{rt} = x_r'\overline{\beta} + \xi_t + \xi_r + \nu_{rt}$$

Here, $\xi_r$ represents any time-invariant unobserved productive amenity for region $r$ (e.g. favorable geography). The term $\xi_t$ represents an aggregate time effect, separate for all urban or non-urban areas at year $t$. The term $\nu_{rt}$ can be thought of as an unobserved, time-varying productivity shock specific to location $r$ at time $t$. 


I make use of two different conditional moment restrictions on $\nu_{rt}$ to identify the choice parameters. The first is similar to a strict exogeneity condition in linear panel models (Chamberlain, 1984):

$$E \left[ \nu_{rt} \mid \xi_r, \xi_t, x_{r1}, ..., x_{rT}, z_{MP1}, ..., z_{MPT} \right] = 0$$

(15)

In words, this restriction says that once we condition on the unobserved fixed factor, $\xi_r$, the productivity shocks are uncorrelated with the entire history of the location characteristics, $x_{r1}, ..., x_{rT}$, and the history of market potential instruments, $z_{MP1}, ..., z_{MPT}$. As in Section 4, I use market potential with fixed 1985 output weights, so that all of the variation in the predicted $MP_{rt}$ comes from changes in transport costs. Making use of this restriction is a large improvement over existing work, but in practice it may not always hold. For instance, if policymakers were targeting more productive areas with better infrastructure, we would expect past productivity shocks, $\nu_{r,t-1}$, to be correlated with future market access, $x_{rt}, x_{r,t+1}, ..., x_{rT}$.

Motivated by these dynamic targeting concerns, a second conditional moment restriction relaxes the first:

$$E \left[ \nu_{rt} \mid \xi_r, \xi_t, x_{r1}, ..., x_{r,t-1}, z_{MP1}, ..., z_{MPT} \right] = 0$$

(16)

This is a weak exogeneity moment restriction (Chamberlain, 1992), stating that current productivity shocks are innovations, uncorrelated with all previous realizations of the $x_{rt}$’s and $z_{MPT}$’s. Note that this is a strictly weaker identifying assumption than (15), and if (15) holds, than so does (16).

### 5.7 Estimation of the Choice Model

The assumption on the joint distributions of $v^s$ and $\varepsilon_{irt}$ gives rise to an expression for the conditional probability that firms with $i$ characteristics choose location $r$ at time $t$:

$$P_{irt} = \int \frac{\exp\{\delta_{rt} + \sum_{k=1}^{K} x^k_{rt} (\bar{\sigma}_k v_{ti} + \pi_{ki} D_{i1} + \ldots + \pi_{kD} D_{iD})\}}{1 + \sum_{d=1}^{R} \exp\{\delta_{dt} + \sum_{k=1}^{K} x^k_{dt} (\bar{\sigma}_k v_{ti} + \pi_{ki} D_{i1} + \ldots + \pi_{kD} D_{iD})\}} dF(v^s)$$

(17)

where the value from choosing the outside option is normalized to zero in each period.\(^{38}\)

I estimate the choice model using a two step procedure. In the first step, I estimate the $\delta_{jt}$’s and $\theta_2$ using maximum simulated likelihood. Although a full search over the $\delta_{jt}$’s and $\theta_2$ is possible, in practice, because of the large number of locations in the dataset and

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\(^{38}\)Note that because I do not observe new firms in every location at every time period, the outside option (roughly, locating outside of kabupatens on Java, Sumatra, and Sulawesi) changes across years. However, the outside option is chosen on average by 6.1 percent of entrants in a given year, and it is never chosen by more than 10 percent of firms.
the multiple years over which those locations are observed, it is computationally difficult. Consequently, I maximize the simulated likelihood function only over $\theta_2$. For each value of $\theta_2$, I choose $\delta_{jt} = \delta_{jt}(\theta_2)$ to ensure that the mean valuation components satisfy a market share constraint \cite{Berry1994}.

In the second step, to recover the linear parameters, I fit the following regression function, making use of conditional moment restrictions (15) and (16):

$$\tilde{\delta}_{rt} = x'_{rt}\beta + \xi_r + \xi_{c(r),t} + u_{rt} + \nu_{rt}$$

where $u_{rt} \equiv \widetilde{\delta}_{rt} - \delta_{rt}$ denotes measurement error. Specific details, such as how to compute the gradient in the maximum likelihood step and how to work out standard errors, correcting for the fact that the $\tilde{\delta}_{rt}$’s are estimated, can be found in Appendix Section 3.

6 Results

6.1 Constant Coefficient Logit Results

Table 3 presents results from estimating a constant coefficient version of the random coefficients logit model. This effectively sets $\sigma$ and $\pi$ equal to zero in (17), and the mean technological parameters are estimated from linear regression \cite{Berry1994}. The exact form of the linear regression the following:

$$y_{rt} \equiv \ln(s_{rt}) - \ln(s_{0t}) = x'_{rt}\beta + \xi_r + \xi_{c(r),t} + \varepsilon_{rt}$$

where $s_{rt}$ is the share of new firms in year $t$ who locate in region $r$, and $s_{0t}$ is the share who choose the outside option of locating in other regions in Indonesia.

This specification is used to highlight some aspects of the methodology and contrast it with that used in prior work. Columns 1 and 2 present estimates of the mean technology parameters for a single cross-section of firms, here using all firms appearing in the 1990 survey to construct market shares. Column 1 includes no other control variables, while Column 2 adds several fixed controls (e.g. elevation, ruggedness, type of land). Though not always statistically significant, the signs on rent variables in columns 1 and 2 are positive, suggesting that firms are more profitable when they locate in places with larger land costs. These

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39 This two-step estimation procedure is similar to that used in \cite{Langer2010} in studying demographic preferences for new vehicles, although that study uses second-choice data.

40 Locations in the model consist of all districts on Java, Sumatra, and Sulawesi, and the outside share consists of locations in the outer provinces (Bali, Kalimantan, Maluku, and Irian Jaya). On average, the outside share was chosen by approximately 6 percent of new firms.
positive coefficients are not exclusively a feature of my dataset; for instance, [Head and Mayer 2004] find significant positive wage coefficients in many of their specifications predicting the locations of Japanese car manufacturers in Europe. The problem is that the wage and rent variables are correlated with unobservable productive amenities, and without access to richer panel data, estimation on a single cross-section of firms cannot recover accurate parameter estimates. This is the same problem observed by [Berry et al. 1995] in their study of consumer demand for cars; a conditional logit gives a positive relationship between prices and demand, but this is because prices are correlated with unmeasured product quality.

Columns 3-8 use the entire panel of locations (from 1990-2005), market shares are constructed using new firms only, and market potential is instrumented using \( z_{r t}^{MP} \), which is a market potential variable with fixed 1985 GDP weights. Estimation proceeds using 2-step GMM, and all specifications include location fixed effects and rural-urban year dummies, which should control for any time-invariant unobservable productive amenities, as well as any unobserved productive amenities that are common across rural and urban locations in each year. Robust standard errors are clustered at the location level, which allows for arbitrary serial correlation in the errors for each region over time [Arellano 1987]. Column 3 shows that the wage coefficient, which was previously imprecisely estimated, is now negative and statistically significant. Coefficients on rents are also negative and significant. The coefficient on market potential is large and statistically significant, and the ratio of the factor price and market potential coefficients suggests that firms would be willing to accept a 7.6 percent wage increase or an 14.4 percent rent increase for a 1 percent increase in a location’s market potential.

In Column 4, I allow the effect of distance in the market potential variable to vary non-linearly. Recall that the market potential variable used in the analysis, \( MP_{rt} \), was defined as

\[
MP_{rt} = \sum_{d=1}^{R} \frac{Y_{dt}}{T_{r dt}}
\]

where \( Y_{dt} \) is real GDP for region \( d \) at time \( t \), and \( T_{r dt} \) is the roughness-based transport cost measure, measured as the travel time (in hours) between locations \( r \) and \( d \) at time \( t \). In Column 4, I use a market potential variable that is defined differently:

\[
\tilde{MP}_{rt} = \sum_{d=1}^{R} \left( \frac{Y_{dt}}{f(T_{r dt})} \right)
\]

where

\[
f(T_{r dt}) = \delta_0 + \delta_1 T_{r dt} + \delta_2 T_{r dt}^2 + \delta_3 T_{r dt}^3
\]
Estimation of this specification proceeds by using non-linear least squares. Column 4 shows large, statistically significant coefficients for a third-order polynomial. The implied distance-function and pointwise confidence bands are depicted graphically in Figure [7]. From this figure, it appears that markets within 5-6 hours of reach are not discounted very heavily, but as travel times increase beyond 5-6 hours, the discounts grow rapidly. Thus, when choosing locations, firms seem to care much more about their access to nearby markets than they do about accessing farther away markets.

In Column 5, I replace the market potential variable with the (log) density of paved roads. Road density is used frequently as a proxy for the quality of local infrastructure, and its coefficient is sometimes interpreted to reflect market access. Although both measures are positively correlated, when included in Column 5, the point estimate on road density is small and is not statistically significant. Examining the impact of road density on the locations of a single cross-section of Indonesian manufacturers, [Deichmann et al., 2005] find a similar non-result for eight out of the fifteen industries they studied. They claim that finding “suggest[s] that improvements in transport infrastructure may only have limited effects in attracting industry”. Another possibility is that road density is a poorly measured version of market access, or that whether or not roads are paved is not as important as how rough they are, and whether they can be travelled over quickly.

To the extent that other infrastructure improvements were occurring at the same time as the road improvements, my estimates might be biased, picking up more than they should. In Column 6, in addition to the market potential variable, I include as a dependent variable the log of the median percentage of electricity consumed by firms in the region that is produced by the state electricity company, *Perusahaan Listrik Negara* (PLN). Electricity provision was improved dramatically over the sample period, but the coefficients on this variable, while large, are only significant at the 10 percent level. Moreover, the coefficient on market potential is only attenuated slightly when including electricity provision, suggesting that the electricity effects do not overwhelm the market potential effects. In Column 7, when we add the variable for indirect taxes, which has large effects and is statistically significant, the coefficient on electricity is no longer significant. Column 8 reports the preferred specification.

Column 9 adds a full set of province-year effects to the model, so that all of the variation in the explanatory variables comes from regional variation in wages, rents, taxes, and market access for a given province year. It is reassuring that coefficient estimates on wages, rents and taxes are largely similar, but the coefficient estimate on market potential nearly doubles in size. In Column 10, I estimate with the weak exogeneity moment restrictions. The rent coefficient is no longer significant, and the effects of market potential double (as well as their

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41 The density of paved roads is measured as total km of paved roads per 100 km² of land.
standard errors).

6.2 Random Coefficient Logit Results

Table 7 displays results from the two-step BLP estimation on the full dataset of 17,684 new firms choosing one of over 100 locations over a 15 year period. The reported model is parsimonious: I’ve only included mean effects for wages, rents, and taxes, and interaction terms for the market potential. Overall, for six of the seven industrial categories, we find that market potential had a positive and statistically significant effect on location choice. The only industrial category that does not have a positive market potential effect is wood products (ISIC 33), which is most likely due to the fact that producers of wood products typically locate very close to forests, their sources of raw materials.\textsuperscript{42} The largest coefficient was for other products, which were also the most likely to have experienced dispersion over the period (see Section 4).

Heterogeneity across firms in their willingness to substitute between better market access and lower wages (or rents) is readily apparent from the positive standard deviation coefficient. The estimates of the mean parameters (and the single standard deviation estimate) imply that 99 percent of other products producers have positive valuations for market potential, while only 54 percent of wood products producers have positive valuations for market potential. Over 80 percent of each of the other industries had firms with positive market potential valuations.

Another way of evaluating the fit of the model is to determine whether or not its implied substitution patterns are reasonable. Locations that are more substitutable for one another should have stronger cross-elasticities, while those that are less substitutable should have smaller cross-elasticities. Define the cross-market potential elasticity between location $k$ and $j$ at time $t$, denoted $\eta_{jk,t}^{MP}$, as follows:

$$\eta_{jk,t}^{MP} = \frac{-\partial \log s_{jt}}{\partial \log MP_{kt}}$$

This elasticity tells us the percentage decrease in the share of new firms choosing location $j$ that would result from a one-percent increase in market access for location $k$. We would expect $\eta_{jk,t}^{MP}$ to be positive; increasing market potential in location $j$ should decrease demand for location $k$. We would also expect that this elasticity would be larger for locations that are closer together physically, or in terms of various characteristics (e.g. GDP levels, population).

\textsuperscript{42}This somewhat reconciles the fact that while wood producers were one of the largest firms to experience dispersion in the dataset, but we only found modest reduced form impacts of market potential on the locations of new firms. Better roads clearly do not explain all of the dispersion.
For instance, if market access is improved in Jakarta, we would expect location shares of nearby regions in Western Java to be reduced more than locations that are farther away (i.e. remote kabupatens on Sulawesi).

Overall, estimates of the median cross-market potential elasticity across firms are positive almost everywhere. In only 251 of the 33,241 location $i$-$j$ pairs were the median cross elasticities positive, and in those cases they were extremely small.\(^{43}\) To summarize the relationship between cross-market potential elasticities and various location characteristics, we estimate linear regressions in Table 8. These regressions take the following form:

$$\eta_{jk}^{MP} = \gamma_j + \gamma_k + \beta D_{jk} + \varepsilon_{jk}$$

where $D_{jk}$ is a variable measuring the distance between $j$ and $k$ on some particular characteristic, and $\gamma_j$ and $\gamma_k$ are location-specific intercepts. The reported regression results show strong negative relationships between $\eta_{jk}^{MP}$ and physical distance, differences in 1985 population levels, and differences in 1985 GDP levels. Hence, as locations grow closer together to one another along several dimensions, the cross market potential elasticity between those locations becomes larger. This suggests that our model is delivering the sort of rich substitution patterns that we would expect.

### 7 Counterfactual Simulations

One advantage of estimating the structural parameters of the model is that it can now be used to predict what would have happened to industrial locations had different road improvement programs been undertaken. The first counterfactual simulation involves the on-time construction of the Trans-Java Expressway, a planned road program that has yet to be fully completed. I contrast results from this simulation with those from implementing a rural roads program, designed to upgrade and improve highways in more remote parts of Java, Sumatra, and Sulawesi.

#### 7.1 Overview: Trans-Java Expressway and Rural Road Upgrades

The Trans-Java Expressway was planned in the early 1990’s under Suharto’s New Order, as part of Repelita V. A map of all sections of the proposed expressway is depicted in Figure 8. Finished sections are depicted in thick black lines, while unfinished sections are in red. The

\(^{43}\)Note that the unit of analysis is the median cross-elasticity, where the median is taken over each of the years in the dataset. That there were a total of 183 locations, giving us 33,489 pair observations, since it is not necessarily the case that $\eta_{jk}^{MP} = \eta_{kj}^{MP}$. However, in some cases a location was not observed in the same year as others, so that our total location pairs in the analysis are 33,241.
expressway was intended to be a contiguous tollway spanning approximately 1,100 km, linking Jakarta to Surabaya along Java’s densely populated North coast. This would strengthen the connection between major cities along the coast, providing high-speed access and allowing for much faster transport.

Instead of tendering the expressway as a single contract, Suharto divided the project into 18 separate concessions, and in an episode emblematic of the corrupt practices of his regime, auctioned off those concessions to companies owned by his friends and family. During the Asian Financial Crisis, construction was suspended and many of the companies that held concessions to build different sections of the Trans-Java Expressway collapsed into default. Concessions often passed to different owners, creating construction delays. Difficulty in acquiring the land to build these roads and reduced state power to enforce eminent domain have also slowed progress, especially in the post-Decentralization period.

To predict what would have happened to industrial locations had this highway actually been built, I first construct the tollway in 1994 (when it was supposed to have been finished) and then recalculate transportation costs between regions.

This type of road program, involving the connection of major cities, is very different from programs that aim to improve rural roads. Since it is likely that firm locations will be affected differently by different types of road programs, I contrast the predictions of the Trans-Java Expressway simulation with those of a project that upgrades roads in rural areas. This involves bringing over 11,000 km of roads in rural kabupatens up to the average roughness levels for roads of the same function class. After the roads are improved in the dataset, transportation costs are recalculated between regions as before.

With these two different counterfactual transport cost matrices, I make predictions for firm location choices using three different techniques. As a baseline, I first make predictions of what would have happened using a simple reduced form regression of firm location choice on market access. Next, I use the model to provide an upper bound on industrial relocation, essentially ignoring the general equilibrium factor price responses. Finally, I make predictions using the full structural model.

Note that when I conduct these simulations, I make two crucial simplifying assumptions. The first is that the process of entry is exogenous; the same set firms that actually entered over

44 For instance, the rights to build a 35 km section connecting Kanji to Pejagan were sold to PT Bakrie & Brothers. Aburizal Bakrie had old ties to Suharto, starting in the late 1970s with several joint ventures, including major real estate projects, rubber plantations, and a scheme involving illicit sales of Pertamina’s crude oil to foreign investors.

45 Moreover, some concessionaires may never have intended to build and only hung on to their rights so that they could be resold. For instance, Davidson (2010b) explains how the concession for a 116 km section between Cikampek and Palimanan was successfully flipped to a Malaysian company in 2008 by a group of investors, including then vice-president Jusuf Kalla.

46 For more on road classifications in Indonesia, see Appendix Section C.1
the 1994-2005 period also enter in the counterfactual simulations. One could imagine that large road improvement programs could affect entry directly, but my model and estimating framework are not equipped to allow for this possibility. Hence, the results can only speak to a reshuffling of existing firms between locations over time.

Additionally, I also assume that the share of new firms who choose to locate outside of Java, Sumatra, and Sulawesi, \( s_{0t} \), remains unchanged during the counterfactuals. This may seem innocuous, but it has implications. For instance, if the Trans-Java Expressway is constructed, this will lower transport costs to the affected regions, raise every location’s market potential, and improve profitability everywhere. If we allowed \( s_{0t} \) to change, it would fall rapidly and all “inside” location shares, \( s_{rt} \), would increase. The problem with this is that it ignores the fact that market potential in the outside locations will also be improved, raising the profitability of choosing the outside option. Because the characteristics affecting the choice of the outside option are not explicitly specified or used in the choice model, there is no way to allow for this sort of response. Although I cannot rule out the possibility that some firms who chose the outside option would now choose to locate in Java, Sumatra, and Sulawesi, again the model is not suited for examining this.

### 7.2 Reduced Form Prediction

For a baseline prediction for the location choices that would have resulted from new road improvements, I estimate a simple linear relationship between log market potential and the inverted market shares ([Berry](1994)):

\[
y_{dt} = \alpha_d + \alpha_t + \beta MP_{dt} + \varepsilon_{dt}
\]

After estimating this relationship, I predict what would have happened if market potential were constructed using current GDP weights but new transport costs, \( T^c_{odt} \):

\[
MP_{ot}^c = \sum_{d=1}^{r} \frac{Y_{dt}}{T^c_{odt}}
\]

This reduced form prediction ignores several features predicted by the full model. First, changes in transport costs will change firms’ location choices. When firms move to new locations, they will produce different levels of output, and hence the equilibrium GDP weights in \( MP_{ot}^c \) will change; here, we fix weights to their actual levels. Second, new firm locations will shift factor prices in different regions, and these responses are ignored. Nevertheless, this reduced form prediction provides a benchmark that I can use to compare with predictions based on the model.
7.3 Model-Based Upper Bound

If we ignore factor price changes, firms will move to areas with better market access, but they won’t suffer the consequences of higher production costs. Hence, a model-based prediction that ignores factor price responses should provide an upper bound on the home-market effect induced agglomeration caused by road improvements. Under this scenario, we should see maximal increased industrial concentration as a result of the road improvements. To implement this prediction, I do the following:

Step 1: Take draws for the current simulated history, $\varepsilon_{ijt} \sim E(1)$ and $v^s \sim N(0, 1)$. Note that firms get individual, independent draws for $\varepsilon_{ijt}$, but the industrial draws of $v^s$ are the same for each industry throughout all years of the current simulation.

Step 2: For a given year $t = 1994, ..., 2005$, I construct a starting value ($s = 0$) counterfactual market potential, using the current output and simulated transport cost measures.

$$MP_{rt}^0 = \sum_{d=1}^{r} \frac{Y_{dt}}{T_{rdt}}$$

Step 3: Given the simulated draws, counterfactual market potential, and current factor prices, I predict new location choices.

Step 4: Next, conditional on $MP_{rt}^0$, I use the model to predict each firm’s output at their newly chosen location, $q_{it}^c$. Firms’ new outputs will be larger in higher market potential locations, but lower in places with higher factor costs.

Step 5: After predicting firms’ counterfactual outputs, we construct new output weights for each location by adding the total output for the set of firms who choose that location, $C_d$, to that location’s actual output and subtracting the lost outputs from the set of firms who move away, $D_d$:

$$Y_{dt}^c = Y_{dt} + \sum_{i \in C_d} q_{dt}(i)^c - \sum_{i \in D_d} q_{dt}(i)^c$$

This gives us a new counterfactual market potential for each location.

Step 6: Using the new market potential variable, we feed this into Step 2 and repeat steps 2-5 until “convergence”. For this exercise, I stop when less than 5 percent of firms have chosen different locations than were chosen in the previous iteration.

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47 For precise details on how this is done, see Appendix Section A.3.

48 Note that in this step, I am using output and income interchangeably, assuming that larger firm outputs correspond to larger worker incomes.
An attractive feature of this simulation is that all of the required parameters have been estimated from the choice model; there is no need for additional calibration. Since the model I develop may have multiple equilibria for certain parameter values, this algorithm for equilibrium selection will typically choose an equilibrium that is close to the actual one.

### 7.4 Full Structural Prediction

This is the same as above, except that we use the model to obtain expressions for factor demands. After specifying labor and land supply functions, we can recompute factor market equilibria after firms relocate. Hence, we insert a step in the algorithm from Section 7.3 as follows:

**Step 4A:** Conditional on the current iteration’s market potential, $MP^0_{rt}$, and factor prices $(w^0_{rt}, r^0_{ot})$, we predict each location’s new wages and rents. From the model’s cost function, it is easy to show that firm $i$’s demand for labor is given by:

$$L^*_i(q_r(i), w, r) = \alpha_i A_{ir} w^{\alpha_i - 1} r^{\beta_i}$$

After adding up individual labor demands at each location, we equate the location’s demand for labor with local labor supply and solve for new equilibria. In practice, we use a Taylor approximation to linearize firms’ individual labor demands, so that they can be computed and added together rapidly. A location’s labor supply is specified as:

$$L^*_r = \gamma_r + \eta w_r$$

We try different values of $\eta = 1, 0.5$, and for each of these values, we choose $\gamma_r$ so that initially, the labor market is in equilibrium. In theory, we could also solve for equilibrium land prices in each iteration, but because there are so many missing land values, we simply use a reduced form hedonic prediction to allow land values to respond to changes in market potential (the regression equation is shown in Table 9 Column 4). The hedonic prediction and the approximate solution to labor market equilibria give us a new set of factor prices at each location.

The full structural simulation emphasizes the fact that when firms move to locations, their demands for factors will drive up the prices of land and labor. This will, in turn, affect the location decisions of other entrants. Hence, it incorporates the full set of agglomeration and

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49For more details on this step, see Appendix Section A.4
dispersion forces in the structural model, and should therefore give more realistic predictions than before.

7.5 Simulation Results

Table 10 reports the actual and counterfactual new firm counts across the two different scenarios, by province and simulation method. Column 1 reports the actual new firm counts, and columns 2-4 report counterfactual new firm counts for the Trans-Java Expressway simulations. Each simulation was run 1000 times, and 95 percent confidence intervals for changes in new firms were constructed using the empirical distribution of location outcomes across simulations.

Overall, the reduced form simulation (column 2), the model-based upper bound (column 3), and full simulation results (column 4) all tell a similar story: building the Trans-Java Expressway would have induced a small number of firms to locate away from Sumatra and Sulawesi, into the areas in Java that were most affected by the highway. However, the precision of these estimates and their magnitudes varies depending on whether we focus on the reduced form or the structural predictions. In particular, the reduced form predictions suggest that firms would have moved from all over Sumatra and Sulawesi to relocate in Java, but the structural predictions are much noisier and suggest that only two provinces in Sumatra (North Sumatra and Riau) and one province in Sulawesi (South Sulawesi) would have been adversely affected. The small size of the predicted effects is likely due to the fact that the location fixed effects drive a substantial amount of variation in observed location choices.\textsuperscript{50}

Columns 5-7 report counterfactual new firm counts for the rural road upgrading simulation. Again, the overall direction of the reduced form and model-based upper bound predictions is similar, but significance and magnitudes vary. For instance, the reduced form simulation predicts that all provinces in Java would have suffered significant losses in firms to areas in Sulawesi and northern provinces in Sumatra. However, the model-based upper bound predicts that industrial relocation would have only occurred between Jakarta, West Java, and Riau; changes for the other provinces are insignificant. However, the full structural prediction does not yield any significant differences between the actual and counterfactual new firm counts. Overall, the absence of large, statistically significant effects from this simulation suggest that rural road programs may not affect the location choices of firms.

Note that the model based upper bound simulations (columns 3 and 6) show more re-

\textsuperscript{50}Note that while Java appears unaffected under the full simulation, this is partly due to aggregation; no provinces experienced significant increases in new firms, but two kabupatens on the northern coast of Java (Cirebon (3211) and Jepara (3320)) experienced positive increases in firms.
location than the full simulations (columns 4 and 7). This is expected because the model based upper bound ignores factor price responses, and once these are incorporated in the full simulation, this tends to mitigate the effects of increased market potential.

8 Conclusion

This paper has made several contributions to our understanding of how road improvements affect the location decisions of firms and, hence, the spatial distribution of economic activity. Using new data that documents a large road improvement program in Indonesia, I provide reduced form evidence showing that better market access for regions near cities is associated with a dispersion of manufacturing firms. Lower transport costs affected different industries in ways predictable from theory; for instance, durable goods producers were much more prone to dispersion than perishable goods producers, who need to locate very close to their sources of demand. These dispersion effects may have resulted from specific features of the road program, or the fact that land is so scare in Indonesia.

Next, I develop a structural model of monopolistic competition and regional trade, in which firms face a tradeoff between greater market access and higher production costs. To estimate the model’s parameters, I use techniques from industrial organization that allow researchers to estimate discrete choice models with endogenous choice characteristics. I find significant differences between firms willingness to pay for improved market access across different industrial sectors, and I find that the model demonstrates rich patterns of substitution between different locations.

Finally, I use the model to predict what would have happened to industrial location decisions had two different transportation projects actually been undertaken: the on-time construction of the Trans-Java Expressway, and an upgrade to rural roads. My predictions suggest that the Trans-Java Expressway would have caused a modest number of firms to relocate from Sumatra and Sulawesi to the places in Java that were most affected by the toll roads. However, the rural roads program did not induce a statistically significant relocation of firms between provinces. Thus, despite claims made by politicians about the job creating effects of road improvements, I find that industrial locations would be largely stable in response to rural road programs.

This paper has focused on using the model to make counterfactual predictions, leaving aside important questions about social welfare for future research. While rural roads might not have substantially altered firm location choices, they should clearly bring important consumption benefits to rural areas, affecting welfare in ways that the current model cannot capture. A full welfare analysis would also incorporate heterogeneous labor mobility and
determine whether road improvements bring spatial surpluses to affected areas, driving jobs away from unaffected regions and lowering welfare in these places, or if they have national productive effects that compensate potential losers.

A major limitation of the paper is that the model developed is static in nature, but it is estimated and simulated dynamically. Using panel data for estimation considerably weakens the identifying restrictions required for estimation, but this comes at a cost: namely, a looser correspondence between the model and how it is estimated. Future research should endeavor to extend the structural model to a full dynamic setting.
References


### Table 1: Transportation Budgets for Indonesia’s 5-Year Development Plans

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Roads</td>
<td>2.1</td>
<td>3.9</td>
<td>3.9</td>
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<tr>
<td>Railways and Freight</td>
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<td>0.8</td>
<td>0.7</td>
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<tr>
<td>Ports and Shipping</td>
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<td>0.7</td>
<td>0.5</td>
</tr>
<tr>
<td>Airports and Aircraft</td>
<td>0.7</td>
<td>0.8</td>
<td>0.7</td>
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<tr>
<td><strong>Total</strong></td>
<td><strong>4.6</strong></td>
<td><strong>6.2</strong></td>
<td><strong>5.8</strong></td>
</tr>
<tr>
<td><strong>Transport as a Percentage of Total Allocations</strong></td>
<td><strong>11.6</strong></td>
<td><strong>17.6</strong></td>
<td><strong>18.8</strong></td>
</tr>
</tbody>
</table>

Source: Various planning documents for Indonesia’s five year development plans (*Rencana Pembangunan Lima Tahun*, abbreviated as *Repelita*). The table reports billions of U.S. dollars allocated to spending on transportation. Budget figures were converted to 2000 USD using OECD data on annual CPI indices and exchange rates.
Table 2: Transport Cost Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Java</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Segment Length</td>
<td>375.44</td>
<td>375.44</td>
<td>374.87</td>
<td>374.87</td>
</tr>
<tr>
<td>(233.79)</td>
<td>(233.79)</td>
<td>(233.32)</td>
<td>(233.32)</td>
<td></td>
</tr>
<tr>
<td>N = 5671</td>
<td>N = 5671</td>
<td>N = 5671</td>
<td>N = 5671</td>
<td></td>
</tr>
<tr>
<td>Roughness-based Travel Time</td>
<td>4.59</td>
<td>4.16</td>
<td>3.81</td>
<td>4.51</td>
</tr>
<tr>
<td>(2.68)</td>
<td>(2.54)</td>
<td>(2.27)</td>
<td>(2.69)</td>
<td></td>
</tr>
<tr>
<td>N = 5671</td>
<td>N = 5671</td>
<td>N = 5671</td>
<td>N = 5671</td>
<td></td>
</tr>
<tr>
<td>Paved Road Share</td>
<td>0.46</td>
<td>0.77</td>
<td>0.79</td>
<td>0.80</td>
</tr>
<tr>
<td>(0.50)</td>
<td>(0.42)</td>
<td>(0.41)</td>
<td>(0.40)</td>
<td></td>
</tr>
</tbody>
</table>

| **Sumatra**     |       |       |       |       |
| Segment Length  | 725.83| 725.83| 725.83| 725.83|
| (436.00)        | (436.00) | (436.00) | (436.00) |
| N = 2145        | N = 2145 | N = 2145 | N = 2145 |
| Roughness-based Travel Time | 10.74 | 9.49  | 8.12  | 9.62  |
| (6.24)          | (5.58) | (4.82) | (5.79) |
| N = 2145        | N = 2145 | N = 2145 | N = 2145 |
| Paved Road Share| 0.32  | 0.56  | 0.70  | 0.71  |
| (0.46)          | (0.50) | (0.46) | (0.46) |

| **Sulawesi**    |       |       |       |       |
| Segment Length  | 683.69| 683.69| 683.69| 683.69|
| (494.97)        | (494.97) | (494.97) | (494.97) |
| N = 561         | N = 561 | N = 561 | N = 561 |
| Roughness-based Travel Time | 13.77 | 10.59 | 8.50  | 8.89  |
| (10.33)         | (7.03) | (5.78) | (6.08) |
| N = 561         | N = 561 | N = 561 | N = 561 |
| Paved Road Share| 0.16  | 0.33  | 0.54  | 0.55  |
| (0.36)          | (0.47) | (0.50) | (0.49) |

Source: IRMS and author’s calculations. For segment length and roughness-based travel times, the unit of observation is a pair of kabupatens on the same island. For percentage paved roads, estimates are taken from the detailed kilometer-post-interval data. Standard deviations in parentheses.
Table 3: Changes in New Firm Shares: 1985-1996

<table>
<thead>
<tr>
<th>Δ Share of New Firms</th>
<th>Change Corresponding To ...</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1985 – 1996</td>
</tr>
<tr>
<td>Cities</td>
<td>-0.159</td>
</tr>
<tr>
<td>Neighbors of Cities</td>
<td>0.095</td>
</tr>
<tr>
<td>Neighbors of Neighbors</td>
<td>0.099</td>
</tr>
<tr>
<td>Rural</td>
<td>-0.022</td>
</tr>
<tr>
<td>Other</td>
<td>-0.012</td>
</tr>
</tbody>
</table>

Source: SI and author’s calculations. A total of 51 out of 218 kabupatens were classified as Cities in 1990. “Neighbors of Cities” are kabupatens that share a border with 1990 cities; there were 60 kabupatens in this category. “Neighbors of Neighbors of Cities” are kabupatens that share a border with kabupatens who share a border with 1990 cities; there were 78 kabupatens in this category. The remaining 29 kabupatens are categorized as “Rural”. In classifying, some kabupatens fit into multiple categories, and when this occurred, the kabupaten was assigned to the group closest to cities as possible.
### Table 4: Reduced Form Regressions

#### Panel A: New Firms

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MP(_{rt})</strong></td>
<td>0.122</td>
<td>0.122</td>
<td>0.076</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.031)**</td>
<td>(0.031)**</td>
<td>(0.015)**</td>
<td></td>
</tr>
<tr>
<td><strong>MP(_{rt}) \times Durable(_j)</strong></td>
<td></td>
<td></td>
<td></td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.008)**</td>
</tr>
<tr>
<td><strong>Adj. R(^2)</strong></td>
<td>-0.004</td>
<td>-0.003</td>
<td>-0.004</td>
<td>-0.062</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>50320</td>
<td>50320</td>
<td>50320</td>
<td>50320</td>
</tr>
<tr>
<td><strong>F-Statistic</strong></td>
<td>15.822</td>
<td>15.832</td>
<td>25.858</td>
<td>6.000</td>
</tr>
<tr>
<td><strong>Kabupaten FE</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td><strong>Year FE</strong></td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sector FE</strong></td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sector-Year FE</strong></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Province Trends</strong></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td><strong>Kabupaten-Year FE</strong></td>
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<td></td>
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<td>Yes</td>
</tr>
</tbody>
</table>

#### Panel B: Employment

<table>
<thead>
<tr>
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<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MP(_{rt})</strong></td>
<td>0.432</td>
<td>0.432</td>
<td>0.271</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.089)**</td>
<td>(0.089)**</td>
<td>(0.070)**</td>
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</tr>
<tr>
<td><strong>MP(_{rt}) \times Durable(_j)</strong></td>
<td></td>
<td></td>
<td></td>
<td>0.067</td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td>(0.027)**</td>
</tr>
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<td><strong>Adj. R(^2)</strong></td>
<td>-0.004</td>
<td>-0.003</td>
<td>-0.004</td>
<td>-0.062</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>50320</td>
<td>50320</td>
<td>50320</td>
<td>50320</td>
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<tr>
<td><strong>F-Statistic</strong></td>
<td>23.256</td>
<td>23.270</td>
<td>15.153</td>
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<td><strong>Kabupaten FE</strong></td>
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<td>Yes</td>
<td></td>
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<tr>
<td><strong>Year FE</strong></td>
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<tr>
<td><strong>Sector FE</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sector-Year FE</strong></td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Province Trends</strong></td>
<td></td>
<td></td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td><strong>Kabupaten-Year FE</strong></td>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
</tbody>
</table>

Unit of observation is a region-industry-year. Robust standard errors in parentheses, clustered at the kabupaten level. * denotes significant at the 10% level, ** denotes significant at the 5% level, and *** denotes significant at the 1% level.
Table 5: Reduced Form Regressions: Robustness

<table>
<thead>
<tr>
<th>Panel A: New Firms</th>
<th>IV w/ Placebo</th>
<th>IV Sequential Moments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>MP&lt;sub&gt;rt&lt;/sub&gt;</strong></td>
<td>0.120</td>
<td>0.120</td>
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<tr>
<td></td>
<td>(0.031)**</td>
<td>(0.031)**</td>
</tr>
<tr>
<td><strong>UNBUILT TOLL ROAD</strong></td>
<td>-0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td>in Kabu. r (t ≥ 1994)</td>
<td>(0.011)</td>
<td>(0.011)</td>
</tr>
<tr>
<td><strong>ADJ. R²</strong></td>
<td>-0.004</td>
<td>-0.003</td>
</tr>
<tr>
<td><strong>N</strong></td>
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<td>50320</td>
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<td><strong>F-STATISTIC</strong></td>
<td>8.395</td>
<td>8.400</td>
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<td><strong>YEAR FE</strong></td>
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<tr>
<td><strong>SECTOR FE</strong></td>
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<tr>
<td><strong>SECTOR-YEAR FE</strong></td>
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<td>Yes</td>
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<tr>
<td><strong>PROVINCE TRENDS</strong></td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td><strong>Lagged Diff MP-85 IV</strong></td>
<td>.</td>
<td>.</td>
</tr>
</tbody>
</table>

| Panel B: Employment               | IV w/ Placebo                  | IV Sequential Moments                  |
|                                   | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   |
| **MP<sub>rt</sub>**               | 0.430 | 0.430 | 0.300 | 0.234 | 0.234 | 0.238 |
|                                   | (0.092)** | (0.092)** | (0.066)** | (0.081)** | (0.081)** | (0.082)** |
| **UNBUILT TOLL ROAD**             | -0.004 | -0.004 | 0.062 |       |       |       |
| in Kabu. r (t ≥ 1994)             | (0.046) | (0.046) | (0.050) |       |       |       |
| **ADJ. R²**                       | -0.004 | -0.003 | -0.004 | -0.000 | -0.000 | -0.000 |
| **N**                             | 50320 | 50320 | 50320 | 44030 | 44030 | 44030 |
| **F-STATISTIC**                   | 11.749 | 11.756 | 10.210 | 8.293 | 8.296 | 8.374 |
| **KABUPATEN FE**                  | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| **YEAR FE**                       | Yes   | .     | .     | Yes   | .     | .     |
| **SECTOR FE**                     | Yes   | .     | .     | Yes   | .     | .     |
| **SECTOR-YEAR FE**                | .     | Yes   | Yes   | .     | Yes   | Yes   |
| **PROVINCE TRENDS**               | .     | .     | Yes   | .     | .     | Yes   |
| **Lagged Diff MP-85 IV**          | .     | .     | .     | Yes   | Yes   | Yes   |

Unit of observation is a region-industry-year. Robust standard errors in parentheses, clustered at the kabupaten level. * denotes significant at the 10% level, ** denotes significant at the 5% level, and *** denotes significant at the 1% level.
<table>
<thead>
<tr>
<th>Table 6: Constant Coefficient Logit Results</th>
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<tr>
<td><strong>OLS (1990)</strong></td>
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<td>WAGE_RATE</td>
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<td></td>
</tr>
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<td>LAND_VALUE</td>
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<td>MP</td>
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<td>ADJ. R²</td>
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<td>Rural-Urban YEAR FE</td>
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<td>Market Potential IV</td>
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<tr>
<td>Province-Year FE</td>
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<tr>
<td>Dynamic Panel IVs</td>
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<tr>
<td>WTP for MP with wages</td>
</tr>
<tr>
<td>WTP for MP with taxes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses, clustered at the kabupaten level. * denotes significant at the 10% level, ** denotes significant at the 5% level, and *** denotes significant at the 1% level. In all columns except column 5, the adjusted R-squared reported is the “within R-squared” obtained by estimating the equation in mean-deviation form.
### Table 7: Random Coefficients Logit Results: Fixed Effects

<table>
<thead>
<tr>
<th>Overall Mean</th>
<th>Foods &amp; Beverages</th>
<th>Textiles &amp; Clothing</th>
<th>Wood Products</th>
<th>Chemicals &amp; Oil Prods.</th>
<th>Ceramics, Glass, &amp; Non-Metals</th>
<th>Finished Metal Products</th>
<th>Other Products</th>
<th>Standard Deviations σ</th>
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<tbody>
<tr>
<td>WAGE_RATE</td>
<td>-0.156</td>
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<td></td>
<td>(0.053)**</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>LAND_VALUE</td>
<td>-0.066</td>
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<tr>
<td></td>
<td>(0.030)**</td>
<td></td>
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<td></td>
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<tr>
<td>MP</td>
<td>0.954</td>
<td>1.075</td>
<td>0.093</td>
<td>1.539</td>
<td>1.778</td>
<td>1.385</td>
<td>2.078</td>
<td>0.953</td>
</tr>
<tr>
<td></td>
<td>(0.405)**</td>
<td>(0.416)**</td>
<td>(0.407)***</td>
<td>(0.407)***</td>
<td>(0.551)***</td>
<td>(0.415)***</td>
<td>(0.405)***</td>
<td>(0.055)***</td>
</tr>
<tr>
<td>INDTAX_RATE</td>
<td>-6.491</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(2.688)**</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

The model is estimated on the full sample of the new firms dataset. There are 17,684 firms across all years choosing locations, and given the variation in the choice set across years, there are a total of 2,442,084 observations. The first step mixed logit model was estimated with 100 scrambled Halton draws for each industry. The estimated simulated log-likelihood was equal to $-19410.56$, and the simulated likelihood ratio index is equal to $\rho = 1 - \frac{SLL(\beta)}{SLL(0)} = 0.7769$. Standard errors in parentheses, computed using asymptotic GMM results and the delta method [see Appendix B.3 for more details]. * denotes significant at the 10% level, ** denotes significant at the 5% level, and *** denotes significant at the 1% level.
### Table 8: Cross Market Potential Elasticity Regressions

<table>
<thead>
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<th></th>
<th>Median $\eta_{jk}$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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</thead>
<tbody>
<tr>
<td><strong>Physical Distance</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Abs. Population Difference</strong></td>
<td>-2.586</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.406)***</td>
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<td></td>
</tr>
<tr>
<td><strong>Abs. GDP Difference</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Adj. $R^2$</strong></td>
<td>0.831</td>
<td>0.835</td>
<td>0.833</td>
<td></td>
</tr>
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<td><strong>N</strong></td>
<td>33241</td>
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<td>33241</td>
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</tr>
<tr>
<td><strong>Region $j$ FE</strong></td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Region $k$ FE</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

The unit of analysis is a location $j$-$k$ pair, and the dependent variable is 1000 times the median $\eta_{jk}^{MP}$, where the median is taken over all years in which both locations were chosen by firms. The rescaling was used to make the parameter estimates reasonably sized. Robust standard errors in parentheses, clustered at the region $j$ level. * denotes significant at the 10% level, ** denotes significant at the 5% level, and *** denotes significant at the 1% level.

### Table 9: Hedonic Regressions

<table>
<thead>
<tr>
<th></th>
<th><strong>Wages</strong></th>
<th><strong>Land Values</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>MP</strong></td>
<td>0.583</td>
<td>0.577</td>
</tr>
<tr>
<td></td>
<td>(0.274)**</td>
<td>(0.277)**</td>
</tr>
<tr>
<td><strong>Adj. $R^2$</strong></td>
<td>0.889</td>
<td>0.888</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>2960</td>
<td>2960</td>
</tr>
<tr>
<td><strong>F Statistic</strong></td>
<td>340.316</td>
<td>402.648</td>
</tr>
<tr>
<td><strong>Kabupaten FE</strong></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Year FE</strong></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Rural-Urban Year FE</strong></td>
<td>.</td>
<td>Yes</td>
</tr>
</tbody>
</table>

The unit of analysis is a region-year. Robust standard errors in parentheses, clustered at the region level. * denotes significant at the 10% level, ** denotes significant at the 5% level, and *** denotes significant at the 1% level.
Table 10: Actual and Counterfactual New Firms, 1994-2005

<table>
<thead>
<tr>
<th>Province</th>
<th>Actual (1)</th>
<th>Trans-Java Highway</th>
<th>Rural Road Upgrades</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>RF (2)</td>
<td>MBUB (3)</td>
</tr>
<tr>
<td>Aceh</td>
<td>45</td>
<td>44</td>
<td>45</td>
</tr>
<tr>
<td>North Sumatra</td>
<td>375</td>
<td>365−</td>
<td>365−</td>
</tr>
<tr>
<td>West Sumatra</td>
<td>72</td>
<td>70−</td>
<td>71</td>
</tr>
<tr>
<td>Riau</td>
<td>436</td>
<td>435−</td>
<td>439−</td>
</tr>
<tr>
<td>Jambi</td>
<td>44</td>
<td>43−</td>
<td>44</td>
</tr>
<tr>
<td>South Sumatra</td>
<td>124</td>
<td>121−</td>
<td>121</td>
</tr>
<tr>
<td>Bengkulu</td>
<td>20</td>
<td>19−</td>
<td>20</td>
</tr>
<tr>
<td>Lampung</td>
<td>60</td>
<td>59−</td>
<td>59</td>
</tr>
<tr>
<td>Dki Jakarta</td>
<td>996</td>
<td>994−</td>
<td>980</td>
</tr>
<tr>
<td>West Java</td>
<td>3591</td>
<td>3584−</td>
<td>3555</td>
</tr>
<tr>
<td>Central Java</td>
<td>1793</td>
<td>1825+</td>
<td>1841+</td>
</tr>
<tr>
<td>DI Yogyakarta</td>
<td>301</td>
<td>303+</td>
<td>305</td>
</tr>
<tr>
<td>East Java</td>
<td>2617</td>
<td>2621+</td>
<td>2632</td>
</tr>
<tr>
<td>North Sulawesi</td>
<td>140</td>
<td>137−</td>
<td>140</td>
</tr>
<tr>
<td>Central Sulawesi</td>
<td>45</td>
<td>44−</td>
<td>45</td>
</tr>
<tr>
<td>South Sulawesi</td>
<td>229</td>
<td>224−</td>
<td>227−</td>
</tr>
<tr>
<td>Southeast Sulawesi</td>
<td>98</td>
<td>96−</td>
<td>97</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations. Column 1 reports the actual number of new firms who located in each province. Columns 2-4 report the counterfactual number of new firms if the Trans-Java Expressway had been constructed, and Column 4-6 reports results for the upgraded rural roads scenario. For each scenario, each of the three simulation methods (reduced form (RF), model-based upper bound (MBUB), and full structural prediction (Full)) was conducted 1000 times. For each counterfactual and simulation method, 95 percent confidence intervals were constructed using the empirical distribution of location outcomes for all simulations. The + symbol denotes a statistically significant increase in the number of new firms, relative to the actual number, while the − denotes a statistically significant decrease.
Source: IRMS and author's calculations. Thick black lines correspond to road sections that are 80 percent paved or greater, while thin black lines correspond to road sections that are less than 80 percent paved.
Figure 2: Evolution of Pavement on Sumatra’s Road Network

Source: IRMS and author’s calculations. Thick black lines correspond to road sections that are 80 percent paved or greater, while thin black lines correspond to road sections that are less than 80 percent paved.
Figure 3: Evolution of Pavement on Sulawesi’s Road Network

Source: IRMS and author’s calculations. Thick black lines correspond to road sections that are 80 percent paved or greater, while thin black lines correspond to road sections that are less than 80 percent paved.
Figure 4: Trends in the Ellison and Glaeser (1997) Index

(A) All industries

(B) Durable Goods vs. Non-Durable Goods

Source: SI data and author’s calculations. Lines depict annual means or medians of different indices of industrial concentration across 5-digit industries, as well as means by industry type. Grey bar denotes crisis period (1997-1999). Regressions of industrial concentration measures across industry years on a set of year dummies (or a trend) indicate that the observed reductions are statistically significant, beginning in the Ellison and Glaeser (1997) index (see Table D.3). From difference-in-difference regressions (see Appendix Table D.4), the change in the Spatial Herfindahl for durable goods industries, relative to non-durable goods, was -0.05 (s.e. 0.019). Similar magnitudes for difference-in-difference estimates can be found for the Ellison and Glaeser Index, though the estimates are noisier.
Figure 5: Share of New Firms Locating in Different Types of Kabupatens

Source: SI data and author's calculations. Lines depict shares of new firms locating in different types of kabupatens within Java, Sumatra, and Sulawesi. Grey bar denotes crisis period (1997-1999). A total of 51 out of 218 kabupatens were classified as Cities in 1990. “Neighbors of Cities” are kabupatens that share a border with 1990 cities; there were 60 kabupatens in this category. “Neighbors of Neighbors of Cities” are kabupatens that share a border with kabupatens who share a border with 1990 cities; there were 78 kabupatens in this category. The remaining 29 kabupatens are categorized as “Rural”. In classifying, some kabupatens fit into multiple categories, and when this occurred, the kabupaten was assigned to the group closest to cities as possible.
Partially linear regression was implemented using the sorting and differenced-based procedure discussed in Yatchew (1997), using first-order differencing. All regressions have kabupaten-specific intercepts and rural-urban-year-specific intercepts; these intercepts form the linear portion of the regression. Following Yatchew (1997), we tested the null hypothesis that $H_0 : f(MP) = \gamma$. This involves computing $V = \sqrt{T(s_{res}^2 - s_{diff}^2)/s_{diff}^2}$, where $s_{res}^2$ is the residual variance of the full partially linear model, and $s_{diff}^2$ is the residual variance under the null hypothesis. Under $H_0$, $V \sim N(0,1)$ and it was calculated to be $\hat{V} = 2.050$, hence the null hypothesis was rejected ($p$-value $= 0.020$).
The $x$ axis is $\tau$ (roughness-based travel time, in hours), and the $y$ axis is $\hat{f}(\tau) = \hat{\delta}_0 + \hat{\delta}_1 \tau + \hat{\delta}_2 \tau^2 + \hat{\delta}_3 \tau^3$, where the $\delta$'s are estimated in Table [4] Column 5. Pointwise 95 percent confidence bands are depicted in grey.
Figure 8: Map of the Trans-Java Expressway

Source: Departemen Pekerjaan Umum.
A Derivations for the Model and Counterfactuals

A.1 Consumer Demands

To derive the consumer demands for individual varieties, first let $E_k$ represent consumer expenditures on industry $k$. To choose optimal bundles of varieties from industry $k$, we setup the following Lagrangian:

$$L_k = M_k + \lambda_k \left( E_k - \int_0^1 p_k(j)q_k(j) \, dj \right)$$

Taking the derivative of this with respect to $q_k(j)$, we have:

$$\frac{\partial L_k}{\partial q_k(j)} = \left( \frac{\sigma_k}{\sigma_k - 1} \right) \left( \int_0^1 q_k(j)^{\frac{\sigma_k - 1}{\sigma_k}} \right) \frac{1}{\sigma_k - 1} \frac{1}{\sigma_k - 1} \left( \frac{\sigma_k - 1}{\sigma_k} \right) q_k(j)^{\frac{1}{\sigma_k} - 1} - \lambda_k p_k(j)^{\sigma_k} = 0$$

$$\Rightarrow \left( \int_0^1 q_k(j)^{\frac{\sigma_k - 1}{\sigma_k}} \right) \frac{1}{\sigma_k - 1} q_k(j)^{\frac{1}{\sigma_k} - 1} = \lambda_k p_k(j)^{\sigma_k}$$

Rearranging terms, we have:

$$\left( \int_0^1 q_k(j)^{\frac{\sigma_k - 1}{\sigma_k}} \right) = \lambda_k p_k(j)^{\sigma_k} q_k(j)^{\frac{1}{\sigma_k}}$$

$$\Rightarrow M_k \lambda_k^{-\sigma_k} p_k(j)^{1-\sigma_k} = q_k(j)^{\sigma_k}$$

(18)

Now, multiplying both sides by $p_k(j)$ and integrating over the set of varieties, we have:

$$M_k \lambda_k^{-\sigma_k} p_k(j)^{1-\sigma_k} = p_k(j)q_k(j)$$

$$M_k \lambda_k^{-\sigma_k} \left( \int_0^1 p_k(j)^{1-\sigma_k} \, dj \right) = \int_0^1 p_k(j)q_k(j) \, dj = E_k$$

So, rearranging, we have:

$$M_k \lambda_k^{-\sigma_k} = \frac{E_k}{\int_0^1 p_k(j)^{1-\sigma_k} \, dj}$$

(19)

Plugging (19) into (18), we arrive at the following expression:

$$q_k(j) = \frac{p_k(j)^{-\sigma_k} E_k}{\int_0^1 p_k(j)^{1-\sigma_k} \, dj} = \frac{p_k(j)^{-\sigma_k} E_k}{(P^k)^{1-\sigma_k}}$$

where $P^k$ is the price index defined in (7).

All that remains is to determine $E_k$, the share of the budget spent on manufacturing varieties from industry $k$. But, note that (5) is just a Cobb-Douglas utility function over the CES manufacturing indices. Hence, the budget shares are determined by the $\lambda_k$'s, and $E_k = \lambda_k Y$. 

60
A.2 Firm Pricing

To derive the profit-maximizing prices that firms charge for varieties, note that a firm’s profits from operating in region $o$ and shipping goods to region $d$ are given by:

$$\pi^k_{od}(i) = \left( p^k_{od}(i) - m^k_o(i) w^k_{od} \right) q^k(i)$$

Note that expression takes into account the iceberg transport costs assumption, that in order to deliver one unit of the variety to region $d$, $\tau^k_{od}$ units must be produced.

Taking the derivative of this profit function with respect to $p^k_{od}(i)$, we have:

$$\frac{\partial \pi^k_{od}(i)}{\partial p^k_{od}(i)} = q^k(i) + \left( p^k_{od}(i) - m^k_o(i) w^k_{od} \right) \frac{\partial q^k(i)}{\partial p^k_{od}(i)}$$

Setting this expression equal to zero and rearranging, we have:

$$q^k(i) + p^k_{od}(i) \left( \frac{\partial q^k(i)}{\partial p^k_{od}(i)} \right) = \left( m^k_o(i) w^k_{od} \right) \frac{\partial q^k(i)}{\partial p^k_{od}(i)}$$

We compute $\left( \frac{\partial q^k(i)}{\partial p^k_{od}(i)} \right)$ using the consumer’s demand function, $Q$, and noting that because of the Dixit-Stiglitz structure of competition, firms ignore the effect that their prices have on the price index for their industry in region $d$, $P^k_d$. This gives us:

$$\left( \frac{\partial q^k(i)}{\partial p^k_{od}(i)} \right) = -\sigma_k \left( \frac{\mu^k_o \hat{Y}_d}{P^k_d} \right)^{1-\sigma_k}$$

from which (12) follows immediately.

A.3 Firm Outputs at Counterfactual Locations

We first need an expression for each firm’s total output. Remembering that firms have to overproduce to satisfy export demands, their total output is given by the following:

$$q^*_{od}(i) = \sum_{d=1}^{R} \tau^*_{od} q^*_{od}(i)$$
Using the firm’s optimal pricing formula, (12), and the demand function, (6), the equilibrium production quantities for exports to region \( d \) from region \( o \) are given by:

\[
q_{od}^*(i) = \left[ \frac{\sigma_k}{\sigma_k - 1} \rho_{od} m_0^k(i) \right]^{-\sigma_k} \mu_k Y_d \left( P_d^k \right)^{1-\sigma_k}
\]

Plugging this expression into the one above and simplifying, we obtain the following:

\[
q_o(i) = \sum_{d=1}^R \tau_{od}^k \left[ \frac{\sigma_k}{\sigma_k - 1} \rho_{od} m_0^k(i) \right]^{-\sigma_k} \mu_k Y_d \left( P_d^k \right)^{1-\sigma_k}
\]

\[
= \theta_k \left[ m_0^k(i) \right]^{-\sigma_k} \sum_{d=1}^R \tau_{od}^k \left( \frac{\sigma_k}{\sigma_k - 1} \right)^{-\sigma_k} \left( \frac{m_0^k(i)}{m_o^k} \right)^{-\sigma_k} Y_d \left( P_d^k \right)^{1-\sigma_k}
\]

\[
= \theta_k \left[ m_0^k(i) \right]^{-\sigma_k} RMP_o^k
\]

where \( \theta_k \) is an industry-specific constant, given by:

\[
\theta_k = \mu_k \left( \frac{\sigma_k}{\sigma_k - 1} \right)^{-\sigma_k} \left( \eta^k \right)^{1-\sigma_k}
\]

and \( \eta^k \) is the industry-specific multiplier for transport costs. Hence, the model implies that a firm’s total output in equilibrium is given by:

\[
q_{ot}(i) = \theta_k m_{ot}(i)^{-\sigma_k} RMP_{ot}
\]

(21)

The parameter \( \sigma_k \) is the industry-specific elasticity of substitution parameter, which we can get by inverting the coefficient on market potential \( L \) from the choice model estimation:

\[
\hat{\sigma}_k = 1 + \frac{1}{\beta_{MP,k}}
\]

In order to avoid estimating \( \theta_k \), it will be useful to first take the a ratio of counterfactual outputs in new location \( n \) to actual outputs, then to take logs:

\[
\ln (q_{it}(i)^c) = \ln (q_{ot}(i)) - \sigma_k \ln \left( m_{nt}(i)^c / m_{ot}(i) \right) + \ln (RMP_{nt}^c / RMP_{ot}^c)
\]

(22)

We have everything we need to compute this expression, except for a measure of the firm’s total marginal costs, \( m_{ot}(i) \). To get this, recall that the firm’s value function (whose parameters we estimate in the choice model) is defined by:

\[
V_{ot} = \frac{1}{\sigma_k - 1} \ln (RMP_{ot}) - \ln \left( m_{ot}(i) \right)
\]

In Section 5.3 I show how we can write this value function as the sum of a mean profit term, \( \delta_{ot} \), common to all firms and industries, a mean-zero heteroskedastic deviation from this mean profit
term, $\mu_{oit}$, and an idiosyncratic error term:

$$V_{oit} = \delta_{ot} + \mu_{oit} + \varepsilon_{oit}$$

This implies that we can write the log of firm marginal costs as:

$$\ln \left( m^k_{ot}(i) \right) = \frac{1}{\sigma_k - 1} \ln (RMP_{ot}) - \delta_{ot} - \mu_{oit} - \varepsilon_{oit}$$

Note that in the special case where $\mu_{oit}$ contains only an industry-dummy interaction and random coefficient on the market potential variable, we can write:

$$\ln \left( m^k_{ot}(i) \right) = [\beta_{MP} - \beta(i)] \ln (RMP_{ot}) - \delta_{ot} - \varepsilon_{oit}$$

This implies that we can write a firm’s new output in new counterfactual location, $n$, as the following:

$$\ln q_{int}(i)^c = \ln q_{ot}(i) + (1 - \sigma_k [\beta_{MP} - \beta(i)]) \{\ln (RMP_{nt}^c) - \ln (RMP_{ot})\}$$

$$+ \sigma_k (\delta_{int}^n - \delta_{ot}) + \sigma_k (\varepsilon_{int} - \varepsilon_{iot})$$

Using this formula, we can predict counterfactual outputs in the new locations.

### A.4 Counterfactual Factor Demands

In the model, we are essentially estimating the parameters of a cost function that looks like the following:

$$C(q_o(i), w, r, t) = F + A_o w_o^{\alpha_i} r_o^{\beta_i} q_o(i)$$

where $w_o$ is the local wage (in levels), $r_o$ is the local land price (in levels), and $A_o$ is the local productive amenity. The parameters $\alpha_i$, $\beta_i$, and $\gamma_i$ are firm-specific and estimated in the BLP routine.

From Sheppard’s Lemma, we know that the partial derivative of the cost function with respect to the factor price will give us the cost-minimizing input demand functions:

$$L^* (q_o(i), w, r, t) = \frac{\partial C}{\partial w} = \alpha_i A_o w_o^{\alpha_i - 1} r_o^{\beta_i} q_o(i)$$

$$= \alpha_i \left[ \frac{m_o(i)}{w_o} \right] q_o(i)$$

$$T^* (q_o(i), w, r, t) = \frac{\partial C}{\partial r} = \beta_i A_o w_o^{\alpha_i} r_o^{\beta_i - 1} q_o(i)$$

$$= \beta_i \left[ \frac{m_o(i)}{r_o} \right] q_o(i)$$

Plugging in the expression for output, (21), we can rewrite these demand functions as follows:

$$L^* (q_o(i), w, r, t) = \alpha_i \theta_k \left[ \frac{m_o(i)^{1-\sigma_k}}{w_o} \right] RMP_o$$

$$T^* (q_o(i), w, r, t) = \beta_i \theta_k \left[ \frac{m_o(i)^{1-\sigma_k}}{r_o} \right] RMP_o$$

A similar ratio trick to (22) will allow us to eliminate the constant, $\theta_k$, from these expressions.
B Logit Model Estimation

In the paper, I develop and estimate a choice model that allows for endogenous choice characteristics, as in the usual random coefficients logit framework (Berry et al., 1995). Each firm \( i \) is indexed by an industrial sector \( s \) and chooses one of \( j = 1, \ldots, J_t \) locations at time \( t = 1, \ldots, T \). Locations are either urban or non-urban locations, and this feature is indexed by \( u(j) \in \{0,1\} \). There are \( i = 1, \ldots, N_s \) firms in each sector \( s \). For each sector \( s \), I take \( R = 100 \) scrambled Halton draws from a \( N(0,1) \) distribution to compute the random coefficients component of the choice probabilities. In practice, I use the 5-digit ISIC codes as sector identifiers. Draws are taken once for each industry and used for all firms in that industry, so that they are the same across industry-years.

Conditional on a realization of \( \mathbf{v}_s = (v_{1s}, \ldots, v_{Ks})' \), the probability that firm \( i \) in sector \( s \) chooses location \( j \) at time \( t \) is given by:

\[
\hat{P}_{isjt} = \frac{\exp\{x_{jt}'\beta + \xi_{jt} + \sum_{k=1}^{K} x_{kt}^j (\sigma_k v_{ks} + \pi_k D_{d1} + \ldots + \pi_k D_{D})\}}{1 + \sum_{m=1}^{J_t} \exp\{x_{mt}'\beta + \xi_{mt} + \sum_{k=1}^{K} x_{kt}^m (\sigma_k v_{ks} + \pi_k D_{d1} + \ldots + \pi_k D_{D})\}}
\]

(25)

where we normalize the value of choosing the outside option to zero, and the unobserved choice component, \( \xi_{jt} \), is given by:

\[
\xi_{jt} = \xi_j + \xi_{u(j)t} + v_{jt}
\]

I have access to a census of manufacturing firms, and so assuming there is no sampling error, I have both the macro data (the total probability that firms choose a particular location at time \( t \)) as well as the micro data.

Noting that the terms \( x_{jt}'\beta + \xi_j + \xi_{u(j)t} + v_{jt} \) are common to all individuals, we can write:

\[
\delta_{jt} = x_{jt}'\beta + \xi_j + \xi_{u(j)t} + v_{jt}
\]

Crucially, the unobserved component of the mean valuation, \( v_{jt} \), which creates all of the estimation problems in usual random coefficient discrete choice models, is entirely subsumed within the \( \delta_{jt} \)'s.

Let \( \theta_1 = (\beta', \xi')' \) denote the linear parameters of the model, which are subsumed within the \( \delta_{jt} \)'s, and let \( \theta_2 = (\pi', \sigma')' \) denote the non-linear parameters of the model, including the coefficients on the demographic interactions as well as the standard deviation terms. To estimate \( \theta = (\theta_1, \theta_2)' \), I make use of the following 2-step estimation routine:

1. **Step 1:** Estimate the \( \delta_{jt} \)'s and \( \theta_2 \) using maximum simulated likelihood.

   • Although full maximum simulated likelihood is theoretically possible, in practice it is computationally infeasible. My dataset has over 100 locations, each of which are observed for possibly 15 years, so the \( \delta_{jt} \) parameter space is way too large to search over. Consequently, I maximize the simulated likelihood function only over \( \theta_2 \). For each value of \( \theta_2 \), I choose \( \delta_{jt} = \delta_{jt}(\theta_2) \) to ensure that the mean valuation components satisfy a market share constraint.

2. **Step 2:** To recover the linear parameters, \( \theta_1 \), we estimate the following regression using 2SLS/GMM:

\[
\hat{\delta}_{jt} = x_{jt}'\beta + \xi_j + \xi_{u(j)t} + v_{jt}
\]

where we use instruments for the endogenous \( x_{jt} \)'s. The method of moments estimator of \( \theta_1 \) solves the sample analogues of the following moments:

\[
\mathbb{E}[\mathbf{Z}'(\delta - \mathbf{X}'\beta)] = 0
\]
where $\mathbf{Z}$ is a matrix of $M$ instruments.

### B.1 Interactions

Note that in order for the procedure to work, we need consistent estimation of the $\delta_{jt}$’s, which are the mean valuation parameters. When constructing the interaction terms, care must be taken to ensure that the $\delta_{jt}$’s accurately reflect mean valuation and not the value of the omitted group.

In the estimation, I created indicators for each group (2-digit industry) as follows. Index sectoral groups by $d = 1, \ldots, D, D+1$, and let the last group, $D+1$, denote the omitted sector group. Define $D_{id}$ as an indicator for whether firm $i$ belongs to industrial sector $d$. Then, define:

$$
D_{id} = \bar{D}_{id} - \bar{D}_{id} = \begin{cases}
1 - \frac{1}{N} \sum_{i=1}^{N} D_{id} & \text{i is in group } d \\
-\frac{1}{N} \sum_{i=1}^{N} D_{id} & \text{else}
\end{cases}
$$

This just amounts to demeaning the group indicators. To see why this works, it is helpful to consider a linear model. For plants in the included group $d$, the expected value of an outcome variable $y_{ijt}$ is given by:

$$
\mathbb{E}[y_{ijt} | x, i \in d] = \delta_{jt} + \sum_{k=1}^{K} (\pi_{k,1} \mathbb{E}[D_{i1} | i \in d] + \ldots + \pi_{k,D} \mathbb{E}[D_{iD} | i \in d]) x_k
$$

$$
= \delta_{jt} + \sum_{k=1}^{K} (\pi_{k,d} - \pi_{k,1} \mu_1 - \ldots - \pi_{k,D} \mu_D) x_k
$$

$$
= \delta_{jt} + \sum_{k=1}^{K} (\pi_{k,d} - \mu' \pi_k) x_k
$$

where $\pi_k = (\pi_{k,1}, \pi_{k,2}, \ldots, \pi_{k,D})$ is a $(D \times 1)$ vector of coefficients on the included sectoral interaction terms for variable $k$, and $\mu = (\mu_1, \mu_2, \ldots, \mu_D)$ is a $(D \times 1)$ vector collecting the probabilities that firms are members of each group. Hence, to uncover mean parameters for included sector group $d$, we simply add the mean parameters $\beta$ to the interaction term $\pi_{k,d}$, then subtract $\mu' \pi_k$.

For the omitted group $D+1$, note that in expectation, $D_{id} = -\mu_d$ for all included groups, $d \neq D$, so we have:

$$
\mathbb{E}[y_{ijt} | x, d = D + 1] = \delta_{jt} - \sum_{k=1}^{K} (\mu' \pi_k) x_k
$$

So, to uncover the mean parameters for the omitted group, we subtract $\mu' \pi_k$ from the mean parameters, $\beta$.

The goal of this exercise is not to estimate parameters on the demeaned interaction terms, $\pi_k$, but to instead estimate parameters for each industry:

$$
\gamma_{kd} = \begin{cases}
\beta + \pi_{kd} - \mu' \pi_k & d \in \{1, \ldots, D\} \\
\beta - \mu' \pi_k & d = D + 1
\end{cases}
$$

To construct these parameters and perform inference on the $\gamma$’s, we make use of the so-called Delta method. Specifically, we will show later that the estimated parameters, $\hat{\beta}_k = (\hat{\beta}_k, \pi_{k,1}, \ldots, \pi_{k,D-1})'$,
are asymptotically normal:

\[ \sqrt{N}(\beta_k - \beta_k) \xrightarrow{d} N(0, V) \]

Define:

\[
\mathbf{R}_{(D \times D)} = \begin{bmatrix}
1 & (1 - \mu_1) & -\mu_2 & \cdots & -\mu_{D-1} \\
1 & -\mu_1 & (1 - \mu_2) & \cdots & -\mu_{D-1} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
1 & -\mu_1 & -\mu_2 & \cdots & (1 - \mu_{D-1}) \\
1 & -\mu_1 & -\mu_2 & \cdots & -\mu_{D-1}
\end{bmatrix}
\]

It is easy to see that \( \mathbf{R} \hat{\beta}_k = \hat{\gamma}_k \), the vector of mean utilities plus sectoral group parameters, which are the estimates we care about.

### B.2 Details: Step 1

Let \( j(s) = (j(1), j(2), \ldots, j(N_s)) \) denote a sequence of choices for firms \( i = 1, \ldots, N_s \) in sector \( s \). Since we take the same draws for each sector, the unconditional probability of observing a sequence of choices, \( \mathbf{s} \), for firms in sector \( s \) is given by:

\[
P_j(s) = \int \prod_{i=1}^{N_s} \left( \frac{\exp\{\delta_{j(i)} + \sum_{k=1}^{K} x_{j(i),t}^k (\sigma_k v_{ks} + \pi_{k1} D_{i1} + \ldots + \pi_{kD} D_{iD})\}}{1 + \sum_{m=1}^{L} \exp\{\delta_{m1} + \sum_{k=1}^{K} x_{m1}^k (\sigma_k v_{ks} + \pi_{k1} D_{i1} + \ldots + \pi_{kD} D_{iD})\}} \right) dF(v_s)
\]

where \( F(v_s) = F(v_{1s}, \ldots, v_{Ks}) \) is the joint CDF of the distribution of the unobserved components. This integral is not computed analytically, but is instead approximated by simulation. For each industry, we draw \( r = 1, \ldots, R \) values of \( v_s \), and each vector of draws is denoted by \( v_s^r = (v_{1s1}^r, \ldots, v_{Ks1}^r) \). In practice, we take \( R = 100 \) Halton sequence draws from a standard normal distribution for each element of the vector. We then approximate each sector’s sequence of choice probabilities by the following:

\[
\tilde{P}_j(s) = \frac{1}{R} \sum_{r=1}^{R} \prod_{i=1}^{N_s} \left( \frac{\exp\{\delta_{j(i)} + \sum_{k=1}^{K} x_{j(i),t}^k (\sigma_k v_{ks} + \pi_{k1} D_{i1} + \ldots + \pi_{kD} D_{iD})\}}{1 + \sum_{m=1}^{L} \exp\{\delta_{m1} + \sum_{k=1}^{K} x_{m1}^k (\sigma_k v_{ks} + \pi_{k1} D_{i1} + \ldots + \pi_{kD} D_{iD})\}} \right)
\]

where \( \text{PROD}^r_{j(s)} \) is the probability of a sequence of choices conditional on vectors of draws \( v_s^r \) for each variable.

The simulated log-likelihood function is formed in the usual way:

\[
SLL(\theta_2, \delta(\theta_2)) = \sum_{s=1}^{S} \ln \tilde{P}_j^*(s)(\theta_2, \delta(\theta_2))
\]

where \( j^*(s) \) denotes the vector of location choices that were actually chosen by firms in sector \( s \).

Note that the number of individuals choosing at time period \( t \), and the choice set of locations at time period \( t \), \( J_t \), varies over time. I’m estimating the choice model on the sample of new firms each year, and not all locations are chosen each period, which is why the size of choice sets and the number of firms change each year.

I maximize the simulated likelihood function over \( \theta_2 = (\pi', \sigma')' \), but at each iteration, I first
calculate the predicted market shares:

$$\widehat{S}_{jt}(\theta, \delta) = \frac{1}{N_t R} \sum_{i=1}^{N_t} \sum_{r=1}^{R} \frac{\exp \{ \cdot \} \{ \cdot \}} {1 + \sum_{m=1}^{M} \exp \{ \cdot \} \{ \cdot \}}$$

Then, I solve for the $\delta_j$'s that equate actual market shares with predicted shares, using the standard BLP contraction mapping:

$$\delta_{jt}^{H+1} = \delta_{jt}^H + \ln S_{jt} - \ln \widehat{S}_{jt}(\theta, \delta)$$

The contraction mapping reduces the dimensionality of the parameter space considerably, but this creates some additional complications when computing the gradient.

Since we estimate $\theta_2$ and $\delta_{jt}$ conditional on $\theta_2$, we have to be careful when computing the score of the likelihood function with respect to $\theta_2$. We need to account for the fact that changing $\theta_d$ also changes the $\delta_j$'s:

$$\frac{dSLL(\theta_2, \delta(\theta_2))}{d\theta_2} = \frac{\partial SLL}{\partial \theta_2} \bigg|_1 + \frac{\partial SLL}{\partial \delta} \bigg|_2 \cdot \frac{\partial \delta}{\partial \theta_2} \bigg|_3$$

To simplify exposition in the discussion that follows, I'm going to subsume all of the interaction terms in one vector. Let $X_{ijt}$ denote the $(1 \times (K \times D))$ vector of choice characteristics interacted with demographic characteristics (and demeaned) that each individual $i$ faces when choosing location $j$ at time $t$:

$$X_{ijt} \equiv [(x_{ijt}^1 D_{i1}, ..., x_{ijt}^1 D_{iD}), (x_{ijt}^2 D_{i1}, ..., x_{ijt}^2 D_{iD}), ..., (x_{ijt}^K D_{i1}, ..., x_{ijt}^K D_{iD})]$$

This notation lets us write the following:

$$\Pi X_{ijt} = \sum_{k=1}^{K} x_{ijt}^k (\pi_{k1} D_{i1} + ... + \pi_{kD} D_{iD})$$

We can also do the same thing for the choice characteristics interacted with the simulation draws:

$$V_{ijt}^s \equiv [x_{ijt}^1 v_{i1}^s, x_{ijt}^2 v_{i1}^s, ..., x_{ijt}^K v_{i1}^s]$$

This is a $(1 \times K)$ vector, unique for each sector $s$ and year $t$.

### B.2.1 Gradient, First Term

The first term of the gradient is straightforward to compute:

$$\frac{\partial SLL}{\partial \theta_2} = \sum_{s=1}^{S} \frac{1}{P_{j^*(s)}} \left[ \frac{1}{R} \sum_{r=1}^{R} \left\{ \text{PROD}_{j^*(s)}^r \cdot \frac{\partial \ln \text{PROD}_{j^*(s)}^r}{\partial \theta_2} \right\} \right]$$

$^51$Note that here, we make use of this fact:

$$\frac{\partial y}{\partial x} = y \frac{\partial \ln y}{\partial x}$$

This helps us to evaluate the derivative of the product of probabilities.
For the $((K \times D) \times 1)$ vector of demographic parameters, $\Pi$, the derivative of the log of the product of the simulated choice probabilities for sector $s$ and simulation $r$ is given by:

$$\frac{\partial \ln PROD^r_{\mathbf{j}^*(s)}}{\partial \Pi} = \sum_{i=1}^{N_s} \left( X_{ij(i)^*t} \sum_{k=1}^{J_i} \left( \frac{\exp\{r_{ikt}\}}{1 + \sum_t \exp\{r_{ikt}\}} \right) X_{ikt} \right)$$

Similarly, for the random coefficients portion, we have:

$$\frac{\partial \ln PROD^r_{\mathbf{j}^*(s)}}{\partial \Sigma} = \sum_{i=1}^{N_s} \left( V_{ij(i)^*t} \sum_{k=1}^{J_i} \left( \frac{\exp\{r_{ikt}\}}{1 + \sum_t \exp\{r_{ikt}\}} \right) V_{ikt} \right)$$

To compute $\partial SLL/\partial \theta_2$, we first compute the partial of the log product of the simulated choice probabilities for each sector $s$ and simulation $r$. We then interact this with $PROD^r_{\mathbf{j}^*(s)}$, then take averages over the simulations. Finally, we divide by $\bar{P}^r_{\mathbf{j}^*(s)}$ and then sum across sectors.

**B.2.2 Gradient, Second Term**

The second term in the gradient is similar to the first:

$$\frac{\partial SLL}{\partial \delta} = \sum_{s=1}^{S} \frac{1}{\bar{P}^r_{\mathbf{j}^*(s)}} \left[ \frac{1}{R} \sum_{r=1}^{R} \left\{ PROD^r_{\mathbf{j}^*(s)} \cdot \frac{\partial \ln PROD^r_{\mathbf{j}^*(s)}}{\partial \delta} \right\} \right]$$

The derivative of the log of the product of the simulated choice probabilities for sector $s$ and simulation $r$ with respect to $\delta$ is given by:

$$\frac{\partial \ln PROD^r_{\mathbf{j}^*(s)}}{\partial \delta} = \sum_{i=1}^{N_s} \frac{\partial \ln P^r_{ijt}}{\partial \delta}$$

where $P^r_{ijt}$ is the conditional logit choice probability, given by an expression similar to \([25]\). To compute this derivative, it is helpful to introduce some more notation. Let $D_{ijt}$ be an indicator equal to 1 if firm $i$ chose location $j$ at time $t$ and zero otherwise. This derivative is equal to the following:

$$\frac{\partial \ln P^r_{ijt}}{\partial \delta} = \begin{cases} 
D_{ijt} - P^r_{ijt} & \text{if } i \text{ chooses at time } t \\
0 & \text{if } i \text{ chooses at time } s \neq t
\end{cases}$$

It is helpful to compute this derivative year-by-year. For a given year $t$, we first compute $\partial \ln P^r_{ijt}/\partial \delta$. We then sum this across all individuals in the sector to obtain $\partial \ln PROD^r_{\mathbf{j}^*(s)}/\partial \delta$. We interact this with $PROD^r_{\mathbf{j}^*(s)}$ and average across simulations, then take averages across sectors.

**B.2.3 Gradient, Third Term**

To obtain an expression for $\partial \delta/\partial \theta_2$, we proceed by remembering that $\delta$ is implicitly defined by $\theta_2$ as the solution to:

$$S_{jt} - \hat{S}_{jt}(\theta_2, \delta) = 0$$

Taking derivatives with respect to $\theta_2$, using the chain-rule, and rearranging, we have:

$$0 = \frac{d\hat{S}_{jt}}{d\theta_2} = \frac{\partial \hat{S}_{jt}}{\partial \theta_2} + \frac{\partial \hat{S}_{jt}}{\partial \delta} \cdot \frac{\partial \delta}{\partial \theta_2}$$
\[
\frac{\partial \delta}{\partial \theta_2} = \left( \frac{\partial \hat{S}_{jt}}{\partial \delta} \right)^{-1} \frac{\partial \hat{S}_{jt}}{\partial \theta_2}
\]

Note that \(\partial \hat{S}_{jt}/\partial \delta\) is a \((N_a \times N_a)\) matrix, and \(\partial \hat{S}_{jt}/\partial \theta\) is a \((N_a \times K)\) matrix.

**B.2.4 Gradient, Third Term, Part (A)**

Let \(\hat{S} = \left( \hat{S}_{11}, ..., \hat{S}_{J_T} \right)\) denote the \((N_a \times 1)\) vector of market shares. Although \(\partial \hat{S}/\partial \delta\) is a large \((N_a \times N_a)\) matrix, fortunately many of its elements are zeros, because:

\[
\frac{\partial \hat{S}_{jt}}{\partial \delta_{ks}} = 0 \text{ if } t \neq s
\]

Hence, the matrix is block diagonal. To compute this matrix, define \(\tilde{P}_{ijt}\) to be the average simulated choice probability for firm \(i\):

\[
\tilde{P}_{ijt} = \frac{1}{R} \sum_{r=1}^{R} \frac{\exp \{ r_{ijt} \}}{1 + \sum_{t} \exp \{ r_{ilt} \}}
\]

Then, a typical element of this matrix of derivatives is given by:

\[
\frac{\partial \hat{S}_{jt}}{\partial \delta} = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{\partial \tilde{P}_{ijt}}{\partial \delta_{jt}} = \frac{1}{N_t} \sum_{i=1}^{N_t} \sum_{r=1}^{R} \left\{ P_{ijt}^s D_{ijt} - P_{ijt}^r \sum_{k=1}^{J_t} P_{ikt}^r D_{ijt} \right\}
\]

The full matrix, \(\partial \hat{S}/\partial \delta\), is an \((N_a \times N_a)\) matrix of derivatives. The computation of this portion of the gradient is also done year-by-year because of the block-diagonal structure.

**B.2.5 Gradient, Third Term, Part (B)**

To form \(\partial \hat{S}_{jt}/\partial \theta_2\), the \((N_a \times K)\) matrix of partial derivatives, note that we have:

\[
\frac{\partial \hat{S}_{jt}}{\partial \theta_2} = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{\partial \tilde{P}_{ijt}}{\partial \theta_2}
\]

For the demographic parameters, we have:

\[
\frac{\partial \tilde{P}_{ijt}}{\partial \Pi} = \frac{1}{R} \sum_{r=1}^{R} \left\{ P_{ijt}^r X_{ijt} - P_{ijt}^r \sum_{k=1}^{J_t} P_{ikt}^r X_{ikt} \right\}
\]

For the choice characteristics interacted with the simulation draws, we have:

\[
\frac{\partial \tilde{P}_{ijt}}{\partial \Sigma} = \frac{1}{R} \sum_{r=1}^{R} \left\{ P_{ijt}^r V_{ijt}^r - P_{ijt}^r \sum_{k=1}^{J_t} P_{ikt}^r V_{ikt}^r \right\}
\]
To compute this term, we first compute $\frac{\partial P_{ijt}}{\partial \Pi}$ and $\frac{\partial P_{ijt}}{\partial \Sigma}$ for each individual. We then average this over all individuals who faced a choice situation with location $j$ at time $t$.

## B.3 Standard Errors

To get appropriate standard errors, we characterize the estimation procedure as a two-step estimator and use asymptotic GMM approximations, stacking the moments from each step. For the non-linear parameters, $\theta_d$, the method of moments estimator sets the sum of the scores of the log-likelihood equal to zero. Let $W_{ijt}$ collect all variables used in the first step (i.e. choice and time indicators, interactions of choice characteristics with firm characteristics). The method of moments estimator solves the following sample moment condition:

$$\Psi_1(\theta_2, \delta(\theta_2)) = LL_\theta(\theta_2, \delta(\theta_2)) = 0$$

To allow for clustered standard errors at the region level (Arellano 1987), the second sample moment is the following:

$$\Psi_2(\delta(\theta_2), \beta) = \sum_{r=1}^{R} \tilde{Z}_r \left( \delta_r(\theta_2) - \tilde{X}_r \beta \right)$$

where $\tilde{Z}_r$ denotes a vector that stacks the history of demeaned instruments for region $r$, and $\tilde{X}_r$ and $\delta_r(\theta_2)$ are defined similarly. Define $\theta \equiv (\theta_d', \beta)'$ to be a vector collecting all of the parameters estimated directly in the model. Estimating $\theta$ with GMM, we have the usual asymptotic results:

$$\sqrt{N} \left( \hat{\theta}_{GMM} - \theta_0 \right) \xrightarrow{d} N(0, V_0)$$

where

$$V_0 = \left( G_0' C_0 G_0 \right)^{-1} G_0' C_0 A_0 C_0 G_0 \left( G_0' C_0 G_0 \right)^{-1}$$

and we have:

$$A_0 = \mathbb{E}_N \left[ \begin{array}{cc} \Psi_1 \Psi_1' & \Psi_1 \Psi_2' \\ \Psi_2 \Psi_1' & \Psi_2 \Psi_2' \end{array} \right]$$

and

$$G_0 = \mathbb{E} \left[ \begin{array}{cc} \partial \Psi_1 / \partial \theta_2 & \partial \Psi_1 / \partial \beta \\ \partial \Psi_2 / \partial \theta_2 & \partial \Psi_2 / \partial \beta \end{array} \right]$$

and $C_0$ is a weighting matrix, set to $I$ because of the 2-step nature of the computation.\(^{52}\)

Note that $A_0$ is easily computable. As for $G_0$, note that the upper right term in the matrix, $\partial \Psi_1 / \partial \beta$, is zero. Moreover, the upper left term in the matrix, $\partial \Psi_1 / \partial \theta_2$, is just the Hessian of the log likelihood function, $H(\theta_2)$, which is returned in the estimation procedure. The bottom right term, $\partial \Psi_2 / \partial \beta$, is just $-\sum_{r=1}^{R} \tilde{Z}_r' \tilde{X}_r$.

The only term that is challenging is the bottom left term:

$$\frac{\partial \Psi_2}{\partial \theta_d} = \sum_{r=1}^{R} \tilde{Z}_r' \left( \frac{\partial \delta_r(\theta_2)}{\partial \theta_2} \right)$$

However, we solved for the $\partial \delta(\theta_2)/\partial \theta_2$ matrix above in computing the third term of the gradient.

\(^{52}\)Since I am not using the optimal GMM weight matrix, this procedure is inefficient.
(parts A and B). So, we have:

$$
\mathbf{\hat{G}} = \begin{bmatrix}
\sum_{r=1}^{R} \mathbf{Z}_r \left( \frac{\partial \delta_r(\theta_2)}{\partial \theta_2} \right) & 0 \\
\sum_{r=1}^{R} \mathbf{Z}_r' \mathbf{X}_r'
\end{bmatrix}
$$