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# Consumer Search and Firm Location: Theory and Evidence from the Garment Sector in Uganda

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Anna Vitali*

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**Abstract**

This paper studies the role of consumer information frictions in driving firms' location choices within cities. I develop a quantitative equilibrium model in which imperfectly informed consumers prefer searching in high-density locations to minimize the cost of gathering information. When choosing location, firms trade-off consumers' preferences for agglomeration, fiercer competition induced by spatial proximity, and lower production costs from supply-side externalities. I estimate the model using bespoke data that I collected from garment firms in Kampala. I combine transaction data (to estimate demand), customer data (to shed light on search) and mystery shoppers data (to measures quality). I find that information frictions lead to substantial agglomeration and limit the ability of high-quality firms to attract customers, allowing lower-quality competitors to survive. Counterfactual scenarios show that the introduction of an e-commerce platform induces a large share of firms to disperse, while also causing customers to shift to high-quality businesses. By contrast, commonly adopted decongestion policies that discourage central clusters without solving information frictions disproportionately harm high-quality firms by increasing consumers' costs of finding high-quality products.

**Key words**: Firm location, consumer search, information frictions, low-income cities
**JEL codes**: R30, R32, D12, O12

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# 1 Introduction

Economic activity in cities is spatially concentrated, with firms in the same sector clustering nearby. Quantitative models of the internal structure of cities have focused on the role of production externalities in influencing firm location and agglomeration preferences.[1] In low-income countries, however, cities are predominantly consumption driven, with the majority of firms operating in the non-tradable sector (Gollin et al., 2016). For these firms, access to customers is a crucial driver of economic performance. How do customers search for products, and what are the consequences of their search behavior for the spatial distribution of firms within cities? The answers to these questions can shed light on the demand-side constraints that prevent high-productivity, high-quality firms from attracting customers, contributing to large resource misallocation and overall low productivity in low-income countries (Hsieh and Klenow, 2009; Bloom et al., 2010).

In this paper, I study the role of consumer information frictions for the location choice and the performance of garment firms in Kampala, Uganda. When consumers are imperfectly informed about the variety of goods sold in the market, they are forced to visit firms in person to learn about product characteristics and availability. This is particularly true in low-income settings, where both customers and firms have limited access to information technology. Since travel to in-person visits is costly, consumers will favor spatially concentrated firms that let them minimize the cost of gathering information. On the one hand, this preference for agglomeration generates demand-side externalities, incentivizing firms to locate near competitors to attract larger pools of uninformed customers.[2] On the other hand, agglomeration also intensifies firm congestion and spatial competition. The trade-off between agglomeration to attract customers vs. business-stealing congestion can have first order effects on the spatial distribution of economic activity and the competitiveness of markets, with implications for the welfare repercussions of urban policies.

To study this trade-off, I collect data from garment firms and their customers in Kampala and document novel facts about consumers' search behavior and firms' choice of location in a low-income setting. I use insights from the data to inform the structure of an equilibrium model of consumer search and firm location in which information frictions, standard production externalities, and economies of scale in transport are key sources of agglomeration. I estimate

[1] Ahlfeldt et al. (2015); Allen et al. (2015); Monte et al. (2018); Dingel and Tintelnot (2020); Owens III et al. (2020)

[2] Examples of theoretical models that incorporate demand externalities arising from agglomeration include Stahl (1982), Wolinsky (1983), Dudey (1990), Fischer and Harrington Jr (1996), Bester (1998), Arentze et al. (2005) and Konishi (2005).

the model to quantify the impact of information frictions and evaluate the effects of urban policies on firm location, profits and consumer welfare.

There are three key take-aways from my analysis. First, demand externalities that arise from information frictions contribute to a substantial share of the observed firm agglomeration. Second, by preventing consumers from comparing all products available in the market, information frictions limit the ability of high-quality firms to attract customers, thus favoring the survival of lower-quality competitors. Third, urban policies that discourage agglomeration without addressing information frictions disproportionately harm high-quality firms. This is because the higher spatial dispersion induced by these policies increases consumers' search costs, preventing them from choosing the best products in the market.

The data for this study comes from a new survey of 600 garment firms and their customers in Kampala. Firms were randomly sampled from an initial census of more than 2,400 establishments across the city. The data collection consisted of three parts: (i) a firm survey, (ii) a customer survey, and (iii) a mystery shoppers exercise. As part of the firm survey, business owners were required to keep a record of all the firm's transactions for a period of three days. These records are rarely available for small, informal businesses in low-income countries, but are essential for estimating demand. 600 customers were randomly sampled from the transaction records to participate in a survey aimed at building a comprehensive picture of how consumers search for products in this setting. Finally, in the mystery shoppers exercise, interviewers posed as customers and purchased the same garment from all firms in the sample. This provided information on the price charged by firms for the same product, as well as on the quality of the product, which was rated by an expert in the garment sector.

I document three empirical patterns about consumers' search behavior and firms' choice of location that motivate the structure of the model. First, customers' transport costs to the central, denser part of the city - the *core* - are almost three times higher than the costs of travelling to the *periphery*. This is because the majority of customers live in residential areas outside the city center. However, once in the core, customers visit 22% more firms prior to purchasing, in line with the marginal cost of gathering information about products being lower in high-density areas. Second, customers purchasing products in the core buy larger quantities and pay lower unit transport costs on average relative to the periphery. This suggests that transport costs are fixed, making sourcing from further locations more feasible for customers buying in bulk. Third, despite having fewer customers, firms in the core serve a higher share of retailers buying products in bulk. As a results, they make double the daily revenues of firms in the periphery on average.

I build a model that accounts for these patterns by incorporating information frictions, transport costs, and heterogeneous consumers (small vs. bulk buyers) in a discrete choice model of demand. Prior to searching, consumers do not know their preferences over varieties - for instance, they may know that they want to buy a specific item (a skirt, a dress, a shirt etc.), but may be unsure about the color, the material or the style that they prefer until they visit the firm and see the product in person. To do so, they must pay a transport cost to the firm, which is a function of the distance between the customer and the business, but not of the quantity purchased. Once in a location, the marginal cost of visiting a store is decreasing in the density of firms. Since high-density locations are further away from residential areas, consumers trade off larger transport costs to denser locations, with lower within-location search costs. This trade-off is less severe for customers buying in bulk, who benefit from economies of scale in transport and are therefore more likely to purchase products from spatially concentrated firms.

Firms are heterogeneous in terms of quality, owner's commuting distance and preferences over locations, and offer differentiated products. They choose location simultaneously in a static game of incomplete information. Once in a location, they decide what combination of land, internal labor and outsourced labor to employ in production, and compete in a Nash-Bertrand pricing game. An increase in the number of businesses operating in a location impacts the firm's variable profits, and hence the choice of location in three ways: (i) it attracts a larger number of customers to the location - the *market-size* effect; (ii) it intensifies the price competition within the location - the *market-share* effect; (iii) it attracts suppliers of external labor, thus lowering the marginal cost of labor - the *supply-side* externality. The trade-off between market-size and market-share effects is heterogeneous for high and low-quality firms. As the size of the agglomeration increases, high-quality businesses capture a larger share of the additional customers attracted to the location and therefore benefit disproportionately from locating in areas with a high concentration of firms.

I estimate the model using collected data from Ugandan firms and their customers. First, I combine firm transaction data with price and quality data from the mystery shoppers exercise to estimate demand. A feature of my data is that, for each transaction, I observe the location where the customer travelled from, as well as whether the buyer is a final customer or a retailer. This allows separately identifying elasticities with respect to distance and firm density. Second, I feed the estimated demand into the firm's production function and use survey data on wages, rents, land and labor employed by firms to identify the supply-side parameters. Finally, I combine data on the residence of firm owners with estimates of firms' expected variable profits across locations to recover the elasticity of profits with respect to commuting distance. This last step requires structurally estimating a static, simultaneous move game of location and pricing with a large number of firms and locations.

I use the estimated parameters to consider how equilibrium outcomes would change in the absence of information frictions. I find that eliminating information frictions would induce 8.2% of firms to relocate outside the core. Because the majority of firms that would move to the periphery are high-quality, this would cause a 41% drop in the share of sales concentrated in the core. By allowing customers to observe and compare all products in the market, removing information frictions would enhance firm competition and lead to a 14% and an 18% decrease in prices and profits respectively. These averages mask substantial heterogeneity across high and low-quality firms. High-quality businesses would gain considerable market share and experience a 17% increase in profits. By contrast, at the new equilibrium, 37% of low-quality businesses would make losses and be better off exiting the market. Overall, eliminating information frictions would lead to an 11% increase in customer welfare, driven by lower prices and access to a larger number of product varieties.

I use the model to consider two sets of counterfactual policies: (i) the introduction of an e-commerce platform, and (ii) urban policies aimed at decongesting Kampala city center. In the e-commerce counterfactual, I assume that customers can observe all product varieties prior to purchasing *and* pay a flat fee to get products delivered to their location. This second aspect eliminates the geographical element of consumer search. With respect to the baseline scenario, the platform leads to a 39% reduction in the number of firms operating in the core, driven by high-quality businesses relocating in the periphery. By eliminating information frictions, the policy harms low-quality firms, whose profits drop by more than half, while it leads to a 27% increase in the profits of high-quality businesses.

Policies that relocate firms in space without addressing information frictions can backfire. I study the effect of two measures: imposing a cap to the number of firms allowed to operate in the core, and banning motorcycle-taxis from the central part of the city. In the former case, firm profits unambiguously decline as caps are imposed.[3] High-quality firms experience the largest losses, as the higher spatial dispersion of firms makes it more costly for consumers to compare products across different locations. Final customers, who do not benefit from economies of scale in transport, gain from firms relocating closer to residential areas. By contrast, caps have a negative impact on the welfare of customers buying products in bulk,

[3]This result is consistent with findings from Bassi et al. (2022a), which show that, in the Ugandan context, (i) firms benefit from locating near larger roads, as it improves customer visibility; (ii) a policy that randomly disperses firms in space would lead to a substantial reduction in firm profits. Even taking into consideration workers' life expectancy gains from lower pollution, the authors show that the policy would have an overall negative surplus.

as the variety of products they can observe within the same location declines. In the latter policy experiment, banning motorcycle-taxis from the center of the city reduces the profits of firms in the core, but increases those of businesses in the periphery. Although these effects lead 10% of firms to relocate outside the core, the impact on consumer welfare is negligible.

Agglomeration economies arising from sharing of suppliers, labor market pooling and knowledge spillovers have been extensively studied as drivers of firm co-location in space (Duranton and Puga, 2004; Rosenthal and Strange, 2004; Ellison et al., 2010; Combes and Gobillon, 2015). Starting from the seminal work of Fujita and Ogawa (1982), production externalities have been incorporated into spatial equilibrium models that have highlighted their role as key determinants of the internal structure of cities (Lucas and Rossi-Hansberg, 2002; Ahlfeldt et al., 2015; Allen et al., 2015; Monte et al., 2018; Dingel and Tintelnot, 2020; Owens III et al., 2020). In these models, the demand structure is such that a rise in the number of firms in a location either does not affect, or increases price competition among agglomerated firms. While allowing for traditional supply-side externalities, the contribution of this paper is to introduce demand externalities that can soften competition among spatially concentrated firms. Quantifying this channel is important to accurately measure the welfare effects of agglomeration.[4]

To model demand-side externalities, this paper builds on the industrial organization literature on consumer search with limited information about product characteristics (Hortaçsu and Syverson, 2004; Hong and Shum, 2006; Goeree, 2008; De los Santos et al., 2012). In particular, two recent studies by Murry and Zhou (2020) and Moraga-González et al. (2022) show that when consumers must travel to uncover information about products, spatial clustering can lower price elasticity and increase the market power of co-located businesses. I take this literature to a very different context and add to it by endogenizing firms' choice of location. In doing so, I incorporate an explicit model of consumer demand with spatial differentiation, price competition, demand and supply-side externalities in a model of firm entry and location (Bresnahan and Reiss, 1991; Mazzeo, 2002; Seim, 2006; Jia, 2008; Ciliberto and Tamer, 2009; Zhu and Singh, 2009; Vitorino, 2012; Datta and Sudhir, 2013). While entry models typically do not distinguish between demand and cost parameters and estimate the net effect of firm entry on profits, the richness of the model and the data in this study allows making this distinction. This is key to be able to quantify the effect of information frictions on firm location.

[4]Demand externalities in the model arise from consumers visiting firms in person to uncover information about products. This feature of the model relates to recent evidence from the urban literature showing that travel to consume is common within cities and has important implications for the spatial dispersion of economic activity (Agarwal et al., 2017; Davis et al., 2019; Miyauchi et al., 2021).

Finally, this paper contributes to a growing literature documenting the impact of information frictions on domestic and international trade flows (Arkolakis, 2010; Allen, 2014; Steinwender, 2018; Startz, 2021). This type of frictions can generate substantial inefficiencies in the formation of buyer-seller relationships, leading to the survival of low productivity businesses (Atkin et al., 2017; Jensen and Miller, 2018) and generating excess price dispersion in the market (Jensen, 2007; Aker, 2010; Goyal, 2010). I contribute to this literature by using demand-driven agglomeration to infer the size of consumers' information frictions within a city. I then estimate the impact of these frictions on prices and on the profitability of firms offering products that are heterogeneous in terms of quality.

The paper is structured as follows. Section 2 introduces the setting of the study and the data. In Section 3, I document key facts about firms' choice of location and consumers' search behavior. I use this empirical evidence to motivate the structure of the model, which is presented in Section 4. Section 5 describes the estimation procedure and discusses the identification of the model parameters. Section 6 summarizes the results of the estimation, which are used to construct counterfactual scenarios in Section 7. Section 8 concludes, summarizing the key findings from the paper and outlining potential avenues for future research.

# 2 Setting and Data

## 2.1 Kampala garment sector

The setting of this study is the garment sector in Kampala. Kampala is the administrative capital and economic hub of Uganda, hosting 29% of all business establishments and contributing to 60% of the country GDP (KCCA, 2019). Panel A of Figure 1 plots the location of all formal and informal firms operating in the city. In Kampala, economic activity is heavily concentrated on a small area at the heart of city, with 40% of all establishments operating within 2 km from the central business district.[5] Within the central area, firms are clustered by sector. Panel B of Figure 1 shows the location of all the establishments operating in the central area for the top 5 Ugandan manufacturing sectors.[6] In the figure, each dot is a firm, and each color a four digit ISIC sector. The color pattern clearly shows that firms spatially sort according to their sector, with different areas of the city center hosting different industries.

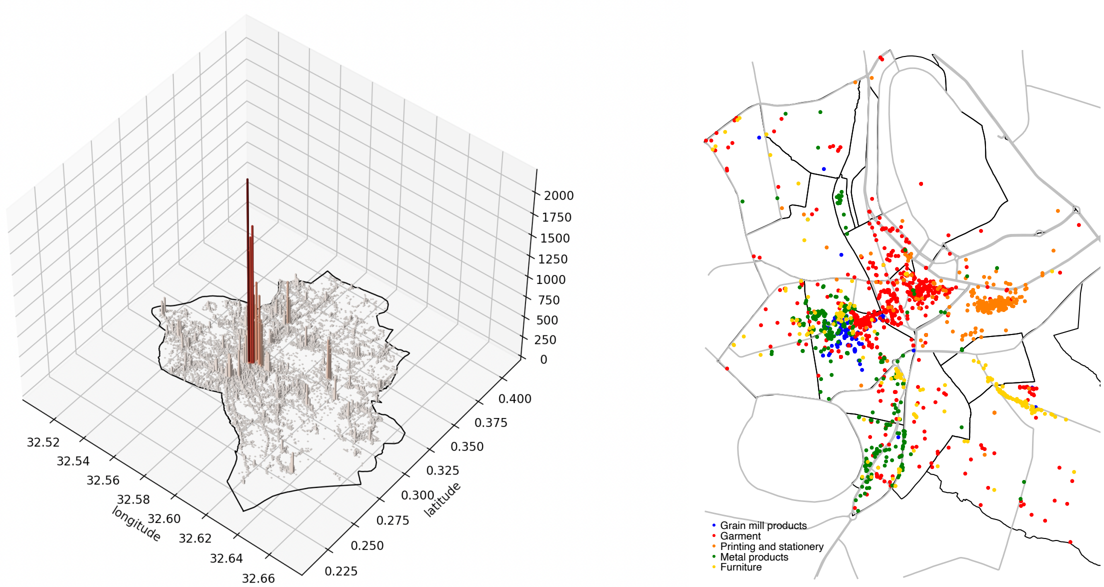
[5] For comparison, respectively 25% and 11% of firms in London and Los Angeles operate within 2 km of the central business district (author's calculations using CDRC 2021, County Business Patterns 2019).

[6] The top 5 manufacturing sectors are defined in terms of number of firms.

The focus of this study is the garment sector. Garment is one of Uganda key manufacturing industries: it accounts for 42% of all Ugandan manufacturing firms (43% of the manufacturing firms in Kampala), and employs 15% of the manufacturing labor force. Despite its size, the sector is highly fragmented: 77% of businesses consist of a single, self-employed individual, and 84% have an annual turnover below \$2,000.[7] The choice of sector for the study was driven by two elements. First, the garment sector exhibits strong spatial clustering (Panel B of Figure 1), constituting an ideal setting for studying agglomeration forces. Second, garment firms produce goods that are differentiated both horizontally and vertically. Horizontally, because firms produce different styles of garments.[8] Vertically, because tailors possess different levels of skills and use inputs of various quality. Information frictions are more likely to emerge when consumers must acquire information on a number of product characteristics, making the garment sector a good setting to study demand-side externalities that arise from consumer search.

**Figure 1: Spatial distribution of firms in Kampala**

PANEL A: All firms PANEL B: Top 5 manufacturing sectors




**Notes**: Data is from 2010 Ugandan Census of business establishments, which covers the universe of formal and informal firms in Uganda. Panel A shows he distribution of all firms within the city of Kampala, with the height of the bar indicating the number of firms located within a specific area. Panel B zooms in on the central part of the city and shows the location of all firms in the five manufacturing sectors with the highest number of establishments in Uganda. On the map, each dot is a firm and each color a four digit ISIC sector.

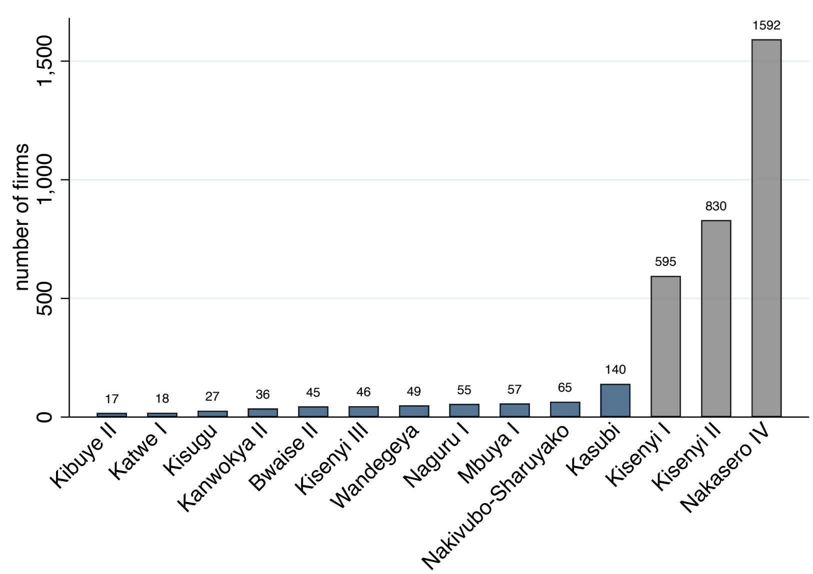
[7]These characteristics are by no mean specific to the garment sector. Excluding garment, the median manufacturing firm in Uganda has no employees and has an annual turnover below \$2,000.

[8]Figure A1 provides an example of this by showing the typical dress sold by four firms in the sample

## 2.2 Data

**Firm sampling:** The data for this study comes from an original survey of 600 garment firms and their customers. Firms were selected from an initial listing of garment businesses across 14 randomly selected parishes in Kampala.[9] Parish selection was stratified by firm density, measured as the average number of firms per square-km operating in the parish using data from the latest Census of Business Establishments conducted by the Uganda Bureau of Statistics in 2010. The aim of the stratification was to include the areas with the highest concentration of firms and to have some variation in density across parishes outside of the central part of the city. Parishes with less than 10 tailoring firms were dropped from the sample. The remaining parishes were assigned to four strata: (i) 0-49, (ii) 50-99, (iii) 100-300, (iv) more than 300 firms per square-km. I randomly selected 4 parishes in stratum (i), 5 in stratum (ii), 3 in stratum (iii) and 2 in stratum (iv) to be part of the study. Appendix figure A2 shows the location of the selected parishes next to a map of the density of garment firms across all Kampala. Although the study only covered 14 out of the 96 parishes in the city, in 2010 68% of all garment firms in Kampala were operating in one of the sampled parish.

**Figure 2: Number of firms in selected parishes**




**Notes**: Data is from the census of garment firms. Figure 2 shows the number of garment firms in each of the selected parishes. Parishes in the periphery are in blue, while parishes in the core are in gray.

Interviewers conducted a door-to-door, in-person listing of all the garment firms in the

[9] In Uganda, the parish is the second lowest administrative unit. Kampala has a total of 96 parishes, with an average parish size of 2.03 square-km.

selected parishes, enumerating a total of 2,407 firms.[10] Figure 3 plots the number of firms per parish using data from the listing. In line with previous census data, three parishes at the center of town host a number of firms that is substantially larger than any other parish in the sample. For the rest of the paper, I refer to these parishes as the *core* of the city and call the remaining parishes the *periphery*. From the initial listing, I randomly selected approximately 300 firms in the core and 300 firms in the periphery to participate in the survey. Compliance was high at 89% and not statistically different across core and periphery, resulting in a final sample of 601 firms. All results in the paper are weighted to reflect the sampling strategy.

**Customer sampling:** The list of potential customers was compiled using two data sources. First, interviewers had to list all the customers that purchased products from the firm during the interview. Second, firms were asked to record their transactions for the three days immediately after the survey. For each transaction, firms recorded the name and contacts of the customer, as well as information on whether the customer buying a product was a *final* customer - an individual making a purchase for herself or her household, or a *retail* customer - an individual making a purchase for her firm. Overall, the details of a 1,510 customers (64% final and 36% retailers) were collected from 385 firms.[11] From this list, 581 customers were randomly selected to take part in the survey. The selection was stratified by firm location (core vs. periphery) and type of customer (final vs. business) to ensure a sufficient coverage of both customer types across the two locations.

**Survey design:** The data collection was designed with two key objectives in mind: understanding what drives the demand for a firm's products and shedding light on the determinants of firms' choice of location. Three data sources contributed to the first objective: transaction data, a customer survey, and a mystery shopper exercise. The firm survey focused on the second objective.

Transaction data provided information on the outcome of the search process. It was collected by asking owners to keep a written record of all the firms' transactions for the three days after the survey.[12] A total of 2,848 transactions were recorded, with information on the type (e.g. a dress, t-shirt, trousers, skirt), the quantity and the price at which the product was

[10] In the two denser parishes, Nakasero IV and Kisenyi II, interviewers only enumerated one every two parish they encountered in their random walk. All estimates are weighted to account for this sampling strategy.

[11] 36% of firms, equally distributed across core and periphery, did not provide information about any of their customers. Whether a customer was listed or not is uncorrelated with firm revenues and number of employees at baseline, but is positively correlated with the average weekly number of customers.

[12] Firm owners were provided a monetary incentive to keep transaction records. 88% of firms provided records of their transaction. Attrition was uncorrelated with firm location, number of employees, monthly revenues, firm age, and total number of weekly customers.

sold, the type of customer making the purchase - a final customer or a retailer - and the location where the customer travelled from.

The customer survey was designed to complement transaction data by providing a comprehensive picture of how customers search for products. To this end, the survey included detailed questions on how consumers decide where to look for a firm and which business to buy products from once in a location.

The mystery shoppers exercise consisted in commissioning the same garment to all firms in the sample, with the aim of collecting accurate information on prices and product quality. Firms were commissioned a dress, the most common garment in this setting, designed by an expert tailor to have characteristics that would allow testing for tailors' skills. Interviewers posed as customers, and were trained to follow a script to commission the dress (Appendix E1). Firms were provided with fabric,[13] an accurate description and, upon request, a photo of the product. The quality of the products was then rated by an expert tailor according to detailed evaluation criteria (Appendix E2).

The firm survey focused on the second objective of the data collection: understanding the drivers of firms' choice of location. On top of standard firm-level information such as number of employees, revenues, profits and firm owner's characteristics, the survey included a set of questions on the firm's location history and the reasons that motivated the owner's initial and subsequent relocation choices. Detailed data was also collected on the firm's production process with the objective of investigating the potential sources of supply-side externalities.

# 3 Firm Location and Consumer Search in Kampala

In this section, I use the collected data to provide evidence on firm location choice and consumer search in Kampala. The section is divided in two parts. The first part shows summary statistics on the drivers of firms' location decision and of consumers' choice of where to search for products. The second part presents four facts about the relationship between firm density, consumer search and firm production which are consistent with the presence of quantitatively important demand and supply-side externalities in this setting.

[13] In this setting, it is very common for customers to provide fabric to firms. Of the customers that took part in the survey, 77% reported providing firm with the material in their last purchase.

## 3.1 Comparing Firms in Core and Periphery

**Firms in core vs. periphery.** Table 1 shows summary statistics on firms, split by the type of location in which they operate. In line with the general picture of Ugandan garment sector, businesses are small: the average firm has no employees, owns three machines/tools - typically, a sewing machine, a pair of scissors and a flat iron - and operates on a 3 square-meter surface. Despite their small size, firms have been in the market for 8 years on average and have monthly revenues of $167, almost three times the Ugandan monthly GDP per-capita ($60). Given their size, these businesses are a hybrid between a manufacturer and a retailer. Typically, production and sale are carried out by the same person in the same location, which makes demand-related considerations particularly important for the choice of location.

**Table 1: Summary statistics**

| | **All** | **Core** | **Periphery** | **P-value** |
|---|---|---|---|---|
| Number of workers | 1.319 | 1.250 | 1.701 | {.000} |
| | [1.000] | | | |
| Number of machines | 3.674 | 3.573 | 4.224 | {.002} |
| | [3.000] | | | |
| Size of premises ($m^2$) | 3.005 | 2.652 | 4.952 | {.000} |
| | [2.000] | | | |
| Years of operation | 8.001 | 7.974 | 8.151 | {.814} |
| | [5.000] | | | |
| Monthly revenues (USD) | 167.039 | 179.402 | 100.611 | {.000} |
| | [100.442] | | | |
| Rent per square-meter (USD) | 19.459 | 20.847 | 11.717 | {.000} |
| | [14.147] | | | |
| Monthly commuting cost (USD) | 36.642 | 39.817 | 19.564 | {.000} |
| | [40.743] | | | |
| Number of observations | 601 | 302 | 299 | |

**Note:** Data is from the baseline survey of garment firms. The table reports means, medians in square brackets, and p-values from a t-test of equality of means in core and periphery in curly brackets. All estimates are weighted to be representative of the universe of garment firms in the sampled parishes.

Firms in the core and in the periphery differ on a number of dimensions. The average monthly revenues of firms in the core are 78% higher than the revenues of firms in the periphery. Despite this, firms in the core employ less inputs: they have 36% less workers, use 18% fewer machines and operate on premises that are half the size of those of businesses in the periphery.[14] There are two obvious forces deterring businesses from locating in the core: higher commuting and rental costs. The median firm in the periphery has no commuting costs, while firm owners in the core spend 22% of their monthly revenues in commuting. Similarly, rental prices in the core are approximately double the rents in the periphery.

**Firm mobility.** A key question for understanding location decisions is how mobile firms are over time. The data suggests that firms' location choice is very persistent. Table A1 shows that 54% of firms in the sample have never moved from their initial location. 23% moved into different premises, but remained within the core, or within the periphery. Only 5% and 3% of firms report relocating from the periphery to the core and vice versa.[15]

**Drivers of initial location decision.** How do firms make their initial location decision? To answer, I asked firms two sets of questions: (i) what were the main constraints the owner faced when setting up the business, and (ii) what were the reasons that affected the initial choice of location. The answers to both questions point towards demand being a key driver of firm location. Finding customers is by far the most common set-up constraint, with 73% of firms mentioning it. In comparison, access to finance, which has been widely studied as a potential barrier to starting a business, was only reported by 53% of firms. The third most common constraint are transport costs, mentioned by 11.4% of businesses, suggesting that commuting distance to work plays a role in owners' decision of where to locate the firm.[16]

Figure 2 shows the answers to the second question. Specifically, it shows: in light blue, the share of firms in the core mentioning the corresponding reason as a driver of their initial location decision; in gray, the same share, but for firms located in the periphery. The blue rectangles represent the difference between the share of firms in the core and the periphery mentioning a given reason, with the corresponding 95% confidence interval. Two things emerge clearly from this graph. The primary reason why firms locate in the core is to have access to customers. Almost 60% of businesses say that their decisions has been driven by the large number of customers shopping in the core. Second, standard agglomeration economies such as proximity to input and machine suppliers and access to potential employees also play a role in firms' decision to operate in the core, but they appear to be second order.

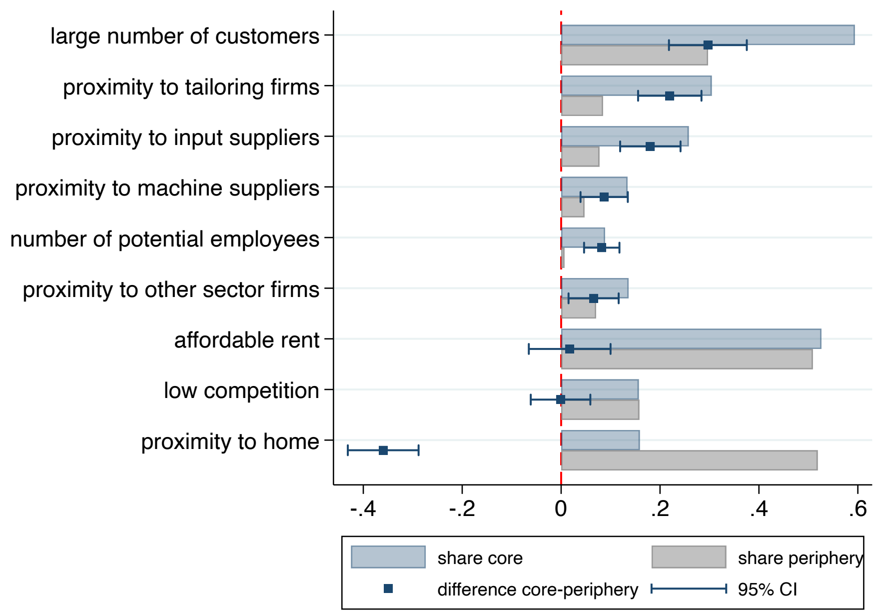
[14] In the next section I discuss how the presence of supply-side externalities could explain this pattern.

[15] The remaining 14% of firms relocated from outside Kampala. Of these, 6% moved into the core, and 8% into the periphery.

[16] Other set-up constraints are, in order of importance, high taxes/license fees (10%), finding suppliers (9.9%), lack of managerial ability (8.1%), high competition (7.1%), lack of space (6.1%), accessing machines (4.9%) and high cost of premises (4.8%).

Affordable rent is an equally important determinant of firm location for businesses in the core and in the periphery. Although this may be surprising given rental prices in the core are much higher than in the periphery, firms in the central location are able to operate on much smaller premises and, as a consequence, total rental costs are similar across firms operating in the two types of location. The only reason motivating firms to remain in the periphery is proximity to home (52% vs. 16%), which suggests that commuting cost are a key congestion force.

**Figure 2: Reasons for Locating in Core/Periphery**




**Notes**: Data is from the baseline survey of garment firms. The blue bars in Figure 2 show the share of firms in the core reporting the reason indicated on the left as a driver of their initial choice of location. The gray bars show the same statistic, but for firms operating in the periphery. The blue rectangles show the difference between the share of firms in the core and the share of firms in the periphery reporting a given reason, with the bar indicating the 95% confidence interval.

## 3.2 Consumer Search in Kampala

The aim of the customer survey was to collect information on how consumers search for products. To this end, customers were asked detailed questions about their purchasing history.[17] For each firm with whom the customer interacted, data was collected on the way in which the customer initially found the firm, the reason why she searched a particular area, the travel cost to the firm, and the number of firms visited while searching. To limit recall bias, similar questions were asked about a hypothetical scenario in which the customer had to search for a new firm.

[17] Business customers were asked about their purchasing history over the last month, while final customers were asked about the last 3 months.

**The majority of search is through walk-ins.** Table 2 shows the methods employed by customers to find a new firm. Walk-ins are the most common search method, with 54% and 56% of final and retail customers respectively reporting it. This is followed by asking family members or friends for recommendations, with 43% of customers saying they would use this method to find a new supplier. Interestingly, the number of firms visited by customers who receive a recommendation prior to purchasing is not statistically different from the number of firms visited by individuals who search randomly. This suggests that, although recommendations are common, customers still engage in independent search before buying a product. Consistent with previous findings from the literature (Cai and Szeidl, 2018), business customers are more likely to rely on other firms to find a new supplier. Only a few customers (8% and 4% among final and business) mention they would search on internet, suggesting that access to accurate information about businesses is particularly difficult in this context.

**Table 2: Way in which customers would search for firms**

| | % of final customers | % of retail customers |
|---|---|---|
| Walk into any firm | 53.5 | 55.8 |
| Ask friends/family members | 43.9 | 42.4 |
| Ask other garment firm | 14.5 | 33.8 |
| Ask firm in different sector | 6.9 | 11.9 |
| Look on the internet | 7.9 | 4.0 |

**Note:** Data is from the baseline survey of customers. Table 2 reports the percentage of final and retail customers who reported they would be using the method indicated in the first column in the hypothetical scenario in which they had to search for a new firm.

**Reasons for searching core vs. periphery.** Respondents were asked in which part of Kampala they would look for a new garment firm and why. Figure 3 shows the reported reasons, separately for customers who said they would search for a firm in the core and the periphery. The structure of the figure is analogous to Figure 2. Large number of tailors and varieties (55% of customers), firms' reputation of being good quality (58%) and proximity to workplace (45%) are the main reasons why customers search for products in the core. In relative terms, the first two reasons play a bigger role in explaining why customers prefer the core to the periphery.[18] Workers' beliefs about quality are in line with the data from the mystery shoppers exercise, which shows that the average quality of good sold in the core is 0.185 standard deviation higher than in the periphery (p-value = 0.039). Figure A3 shows

[18]Trip chaining, namely the tendency to make purchases from different firms in one trip, does not play a big role in this context: only 15% of customers report typically buying from more than one firm when shopping for garment.

that his difference is entirely driven by the tales of the distribution: the lowest quality firms in the economy remain in the periphery, while businesses that produce the highest-quality goods are more likely to select into the core. Similarly to firms, the overwhelming majority of customers who search in the periphery do so to remain close to home and save in transport costs (64%).

**Figure 3: Reasons for Searching in Core/Periphery**


**Notes**: Data is from the survey of customers. In Figure 3 the blue bars show, among customers who indicated they would prefer to search for a new firm in the core, the share reporting the reason on the left as a driver of their choice of location. The gray bars show the same statistic, but for customers who indicated they would prefer to search for a firm in the periphery. The blue rectangles show the difference between the share of customers searching the core and the share of customers searching the periphery reporting a given reason, with the bar indicating the 95% confidence interval.

## 3.3 Sources of demand and supply-side externalities

In this section, I present four facts about the relationship between firm density, consumer search and firm production, which are suggestive of the presence of quantitatively important demand and supply-side externalities. These facts are used to guide the structure of the model.

**Fact 1: Customers incur larger transport costs to travel to the core. However, once in the core they visit more firms prior to purchasing.**

93% of transactions in this setting occur in person, with the average transport cost corresponding to 9% of the transaction value. Transport costs to a firm in the core are almost three times as high as the costs of travelling to the periphery ($1.28 vs. $0.48). This is without considering the opportunity cost of time. On average, the length of a one way trip to the core and the periphery is 34 and 17 minutes respectively.[19] However, once in the core, customers visit 22% more firms prior to buying a product than customers who search in the periphery. This is consistent with (i) consumers possessing imperfect information about products and having to search prior to purchasing; (ii) search costs being lower within locations that have a larger concentration of firms.

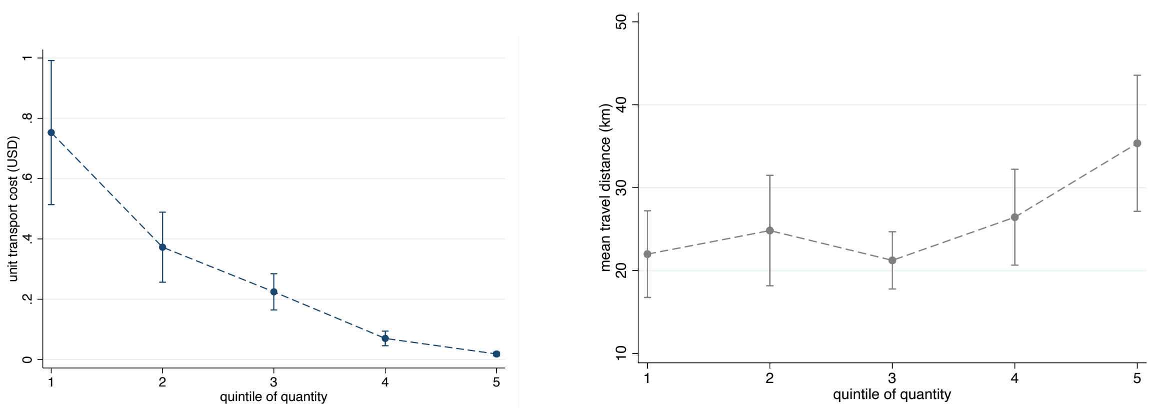
**Fact 2: Economies of scale in travel costs allow customers buying in bulk to source from further locations**

Figure 4 uses data from the customer survey to plot mean travel cost and travel time by quintile of quantity purchased. The figure shows that there is a negative relationship between quantity purchased and unit transport cost to the location where the transaction takes place (Panel A). For the lowest quintile, average transport costs to the firm correspond to 32% of the transaction value. For the highest quintile, they only amount to 5.5% of the transaction value. This pattern is observed despite the fact that customers buying larger quantities travel further (Panel B).

**Figure 4: Unit transport cost and travel time, by quantity quintile**

PANEL A: Unit transport cost

PANEL B: Travel time




**Notes**: Data is from the survey of customers. Panel A plots the average unit transport costs (total transport costs divided by the quantity of goods purchased in a given transaction) and the corresponding 95% confidence intervals for each quintile of the distribution of purchases quantities. Panel B shows average travel distance in kilometers and correpsonding confidence intervals by quintile of the distribution of the purchased quantities.

Overall, this evidence suggests that transport costs are fixed and generate economies of scale in transport. This finding is not unique to this setting. For instance, Grant and Startz (2021)

[19] For final customers, costs to the core are higher because the majority of the population lives outside the center of the city (Figure A4). Similarly, the majority of business customers that buy from firms in the core come from outside Kampala.

find evidence of economies of scale in transport in Nigerian wholesale and retail sector. The idea is simple: customers only find travelling to further locations convenient if the higher transport cost is traded-off with benefits (lower price, better styles, etc.) gained over a large number of items. Final customers, who typically buy fewer units, may find it optimal to pay a higher price or acquire a less preferred variety in the periphery and save the cost of a trip to the core. The opposite is true for retailers, who typically buy products in bulk.

**Table 3: Transaction characteristics, by type of location**

| | (1)<br>Daily revenues (USD) | (2)<br>Number of daily customers | (3)<br>Share of retail customers | (4)<br>Transaction Value (USD) | (5)<br>Quantity | (6)<br>Unit price (USD) |
|---|---|---|---|---|---|---|
| **Panel A: No Controls** | | | | | | |
| Core | 9.336*** | -0.163** | 0.446*** | 8.497*** | 12.23*** | 1.848*** |
| | (2.340) | (0.0799) | (0.0294) | (0.932) | (1.125) | (0.326) |
| **Panel B: Product FEs** | | | | | | |
| Core | | | | 4.277*** | 14.80*** | -0.079 |
| | | | | (0.860) | (1.422) | (0.243) |
| **Panel C: Quality** | | | | | | |
| Core | | | | 4.289*** | 14.35*** | -0.215 |
| | | | | (0.923) | (1.493) | (0.243) |
| Quality score | | | | 1.489*** | -1.936** | 0.836*** |
| | | | | (0.571) | (0.781) | (0.183) |
| Mean \| Periphery | 7.423 | 0.980 | 0.102 | 6.763 | 3.628 | 3.136 |
| N. Observations | 546 | 546 | 512 | 2,726 | 2,726 | 2,726 |

**Note**: * $p < .10$, ** $p < .05$, *** $p < .01$. Data is from transactions records and the mystery shoppers exercise (for quality scores). In Columns 1 to 3, the unit of observation is the firm. In Columns 4 to 6, it is the transaction. Panel A of Table 3 shows the results from a regression of the outcomes on a dummy equal to one for firms in the core, without any additional control. Panel B adds products type fixed effects, and Panel C additionally controls for quality scores. In Column 6, all regressions control for quantity purchased in the transaction. The mean value of the outcome in the periphery is indicated at the foot of the table.

### Fact 3: Firms in the core serve fewer, but larger customers, who grant them larger revenues

Table 3 reports the results from regressions of a number of transaction characteristics on a dummy for whether the firm operates in the core. Columns 1 and 2 show that firms in the core have more than double the daily revenues of businesses in the periphery, despite serving 18% fewer customers. Larger revenues are driven by firms in the core serving a higher share of retailers (Column 3: 58% vs. 10% in the periphery). As a result of the different customer composition, for the same type of product, the average transaction size is 65% larger in the core (Column 4, Panel B). This is driven by customers in the core purchasing larger quantities of the same product and not by higher prices (Columns 5 and 6). For instance, the median customer in the periphery - a final customer - buys one unit, while the median customer in the core - a retailer - purchases five units of the same product (mean: 3.6 and 16 units).

The difference in purchased quantities is not explained by customers buying different types of products or by differences in quality across locations. In fact, the coefficient on the core dummy in Column 5 barely changes with the inclusion of product type fixed effect (Panel B) and the product quality score obtained from the mystery shoppers exercise (Panel C)[20].

**Fact 4: Firms in the Core are more likely to outsource intermediate tasks**

Data from the firm survey shows that outsourcing is very common in the Ugandan garment sector, with 40% of the production being carried out by external workers.[21] The most commonly outsourced tasks are overlocking (50% of firms), making buttonholes (20%) and ironing (13%). This type of firm-to-firm interactions are comparable to the machines rental market studied by Bassi et al. (2022b) in Ugandan carpentry sector, which provide firms with a workaround for the market imperfections that prevent investments in machines and allow firms to mechanize. Similar constraints are likely to apply to the garment sector.[22]

Panel A of Table 4 shows summary statistics on outsourcing separately for firms located in the core and the periphery. On average, firms in the core: (i) employ more workers in the production; (ii) are 14 percentage points (24%) more likely to employ at least one external worker; (iii) outsource a larger share of their production to external workers (42% vs. 32% in the periphery). The fact that outsourcing is more common in the core is consistent with firms in the core employing less workers, owning less assets and operating on smaller premises than firms in the periphery.

Differences in outsourcing across core and periphery arise because suppliers of intermediate

[20] Notice that quality score and prices come from two different sources. The quality score is from the mystery shoppers exercise, while prices are from transaction data. The fact that the score is positively correlated not only with the price of the dress acquired for the mystery shopper exercise, but with firm prices from transaction data suggests that this measure is a good reflection of the overall quality of products sold by the firm.

[21] The firm survey included detailed question about the production process of a specific garment. Firm owners were asked: (i) how many workers were involved in the production of a typical garment and, (ii) of those, how many were employed by the firm and how many are hired externally to perform a specific task. The share of outsourced production is calculated as the ratio of external to total workers.

[22] Machines rental is not very common in the garment sector. The data shows that only 8% of businesses in the periphery and 10% in the core rent any machine. A possible explanation for the different behavior is that while carpentry is characterized by decreasing returns, the garment sector is likely to have increasing returns from specialization, which makes outsourcing a better strategy for organizing production.

tasks are also geographically concentrated in the core. For instance, more than 95% of task providers in the core are located within a 5 minutes walking distance from the firm, compared to only 56% in the periphery (Table 4, Panel B). Proximity to suppliers reduces both transport and information frictions. It reduces transport costs by limiting the opportunity cost of bringing and picking up products from suppliers. At the same time, it lowers the cost of monitoring suppliers, which can be substantial in contexts with weak contractual enforcement. The ability of firms to outsource tasks at a lower cost can be an important source of production externalities arising from agglomeration.

**Table 4: Outsourcing**

| | Core | Periphery | P-value |
|---|---|---|---|
| **PANEL A: Outsourcing** | | | |
| Total number of workers | 2.240 | 1.927 | [0.000] |
| Any external worker | 0.726 | 0.583 | [0.000] |
| Share of external workers | 0.418 | 0.324 | [0.000] |
| **PANEL B: Distance from Suppliers** | | | |
| Within 5 minutes | 0.954 | 0.557 | [0.000] |
| Between 5 and 15 minutes | 0.040 | 0.188 | [0.000] |
| More than 15 minutes | 0.005 | 0.257 | [0.000] |

**Note**: Data is from the baseline survey of garment firms. Table 4 shows means and p-values from a t-test of equality of means across core and periphery, controlling for product type fixed effects. Panel A shows the total number of workers employed in the production of the most typical product sold by the firm, the share of firms that employ at least one external worker, and the total share of external workers employed in production. Panel B shows the average walking distance to the majority of external workers employed by the firm.

# 4 Model

In this section, I present a model of consumer search and firm location in the presence of information frictions. The key mechanisms in the model are guided by the evidence presented in Section 3. In short, uninformed consumers prefer to search for goods in locations with a high spatial concentration of firms, where they can observe a larger variety of products at a lower search cost. Since denser locations are further away from residential areas, this force is particularly strong for consumers buying in bulk, who benefit from economies of scale in transport. Combined, access to product information and economies of scale in transport generate demand-side externalities. On the production side, firms that operate within denser locations can outsource production to external suppliers at a lower cost. This reduces firms' marginal costs, generating a standard supply-side externality. The congestion forces that push firms towards the periphery are price competition, larger transport costs and higher factor prices in concentrated locations.

I build the quantitative framework in three steps. First, I develop a discrete choice model of demand that embeds imperfect information and economies of scale in transport. I show how these two mechanisms can lead to demand for a firm's products being higher in locations with a larger number of competitors. Second, I model firms' price and inputs choices explicitly, allowing businesses to hire external labor to carry out parts of the production. Finally, I study how agglomeration and congestion forces affect firms' initial location decision, which I model as a static game of incomplete information.

## 4.1 Setup

The economy consists of a set of locations $l = \{1, 2, ..., N\}$ and features a discrete number of firms[23] and consumers: $J$ and $I$. *Firms* are single-product, produce differentiated goods and have idiosyncratic preferences over locations. They decide: (i) where to locate; (ii) what price to charge; (iii) what combination of land, internal labour and outsourced labor to employ. *Consumers* only purchase one type of good, but are heterogeneous in the quantity demanded of a given good $q$. They are exogenously distributed across locations and have idiosyncratic preferences over products and idiosyncratic search costs across locations. They choose: (i) which location to search; (ii) within the chosen location, what product to buy. All interactions between firms and consumers occur in person.

The model is static. This assumption is justified by evidence in the data that suggests that firms' and consumers' choices are persistent,[24] and by the need of making the computation of a spatial equilibrium with many locations and firms tractable. The theoretical framework should therefore be seen as modelling the formation of firm-customer matches and firm location decisions that persist over time.

[23] I do not model firms' entry in the market. For estimation, this is equivalent to explicitly modelling entry, with an entry cost that is calibrated to make the number of entrants predicted by the model equal to the number of firms in the data, as in Seim (2006). However, the key difference is that in this setting the number of firms is kept fixed in the counterfactuals.

[24] In Section 3, I discussed firm mobility and showed evidence of the firm's location decision being persistent. Among consumers, the average length of firm-customer relationships is 2 years and 10 months. In addition, the most common reason customers report for terminating previous relationship is firm closure or relocation. This suggests that, once they find a good match, consumers keep buying products from the same supplier. In Appendix F I test this assumption by adding a second period to the model.

## 4.2 Demand

**Utility.** The utility of consumer $i$ buying $q$ units of product $j$ in location $l$ is given by:

$$u_{ijl}^{q} = \Big(\beta \mathbf{x}_j + \xi_j + (1-\sigma)\varepsilon_{ij}\Big) q^{\theta} - \alpha p_{jl} q - C_{il} \tag{1}$$

where $\mathbf{x}_j$ is a vector of observable product characteristics, $\xi_j$ incorporates product $j$'s unobservable characteristics, and $\varepsilon_{ij}$ is an idiosyncratic match value, which consumers only observe upon visiting a firm. This includes for example the style of a garment (color, cut, fit, etc.), which enters utility according to consumers' specific tastes. I assume $\varepsilon$ is distributed as a standard type-I extreme value, with $\sigma \in [0,1]$ governing the variability of the taste shocks within a location. $p_{jl}$ and $q$ are respectively the price and the quantity demanded of a given good. The quantity demanded is heterogeneous across consumers and treated as an exogenous consumer type.

**Search cost.** $C_{il}$ is the search cost consumers pay to visit location $l$ and gather information about products. Crucially, the quantity purchased by a consumer does not affect search costs, which embeds the idea of this type of costs being fixed. I specify the search cost as:

$$C_{il} = \tau_1 g(||z_i - z_l||) + \tau_2 \frac{N_l}{ar_l} + \omega_{il} \tag{2}$$

$\tau_1 g(||z_i - z_l||)$ represents the transport cost to the firm, which is a function of the distance between the consumer location and the firm location. $\frac{N_l}{ar_l}$ is the number of firms per square-kilometer within the location, with $ar_l$ representing the area of the location in square-kilometers. This term allows for consumers to face additional firm-specific search costs once in a location. $\omega_{il}$ is an individual-location specific idiosyncratic search cost, which could capture for example random information that consumers receive from other individuals about a specific location. I assume $\omega$ is distributed according to a standard type-I extreme value distribution.

**Timing.** The timing of the consumer choice is the following:

1. Before searching, consumers observe all products and locations characteristics - including the spatial distribution of firms - but do not observe the match-specific value $\varepsilon$. Given this information, they choose which location to visit.

2. Upon paying the search cost, consumers observe the match value $\varepsilon$ for all firms operating in the selected location and buy the product that yields the highest utility.

Prior to searching, consumers have the outside option of not buying any products in the sampled locations. However, once in a location, consumers do not have an outside option and must buy one of the products. I normalize the utility of the outside option $u_0$ to zero for final customers, but allow retail customers to have a different outside option, which I estimate.

**Consumer location choice.** Consumers choose to search the location that maximizes their expected utility $V_{il}^q$. Given the assumption on the distribution of $\varepsilon$, the expected utility takes the following form:

$$V_{il}^q = E_\varepsilon \left[ \max_{j \in l} u_{ijl}^q \right] = q^\theta (1-\sigma) \ln \left( \sum_{j=1}^{N_l} \exp \left( \frac{\delta_{jl}^q}{1-\sigma} \right) \right) - C_{il} + \gamma \tag{3}$$

where $\delta_{jl}^q = \beta \mathbf{x}_j - \alpha p_{jl} q^{1-\theta} + \xi_j$ denotes the mean utility from product $j$ for consumers of type $q$, $N_l$ is the number of firms in location $l$ and $\gamma$ is the Euler constant.

There are two things worth noticing about this expression. First, a location with more firms is, all else equal, more attractive to consumers. This can be seen from the summation in equation (3) being increasing in the number of firms operating in a location at a given set of prices. The reason why consumers prefer larger locations is that they can observe more draws of the idiosyncratic match value $\varepsilon$ or, intuitively, more varieties of the same product. Hence, in expectation, they have a higher probability of finding a product with the desired characteristics.[25] This is the source of the demand-side agglomeration in the model, which I refer to as the *market-size* effect. The positive effect of agglomeration on demand is however mitigated by search costs being higher in locations that have a larger number of firms ($\frac{N_l}{ar_l}$).

Second, the agglomeration force is stronger: (i) the larger the quantity $q$ bought by the consumer; (ii) the higher the dispersion of firm-specific taste shocks within a location (lower $\sigma$). Agglomeration is stronger for consumers buying in bulk because they benefit from finding a better match over all the units of products that they buy. In addition, a lower $\sigma$ implies a lower similarity among products sold in the same location. From the point of view of the customer, this increases the value of having an additional product in the location.

Let $\mathbf{L} = \{l_1, l_2, ..., l_J\}$ denote the J x 1 vector of firm locations and let $\mathbf{p} = \{p_{1l_1}, p_{2l_2}, ..., p_{Jl_J}\}$ denote the J x 1 vector of prices, with $l_j$ and $p_{jl_j}$ respectively indicating the location and the price charged by firm $j$ in the chosen location. For simplicity, from now on I omit the subscript $j$ when referring the firm location $l_j$. The share of type-$q$ customers from location $i$ buying products in location $l$ is given by the following expression:

[25] This is a well known property of variants of logit discrete choice models (see Anderson et al. (1992)).

$$s^q_{il}(\mathbf{L},\mathbf{p}) = Pr(V^q_{il} \geq V^q_{il'} \,\forall\, l' \neq l)$$

$$= \frac{\left( \sum_{j=1}^{N_l} \exp(\frac{\delta^q_{jl}}{1-\sigma}) \right)^{q^\theta(1-\sigma)} \exp(-\tau_1 g(||z_i - z_l||) - \tau_2 \frac{N_l}{ar_l})}{\exp(u^q_0) + \sum_{k=1}^{N} \left[ \left( \sum_{h=1}^{N_h} \exp(\frac{\delta^q_{hk}}{1-\sigma}) \right)^{q^\theta(1-\sigma)} \exp(-\tau_1 g(||z_i - z_k||) - \tau_2 \frac{N_k}{ar_k}) \right]} \tag{4}$$

This expression summarizes the elements affecting firm competition *across* locations. The first term at the numerator reflects the market-size effect: by offering a larger number of varieties, locations with a higher number of firms attract a higher share of customers. In line with the earlier discussion, the agglomeration force is stronger for customers buying in bulk, and the lower the substitutability of products sold in a location. Firm-specific search costs $(\tau_2 \frac{N_k}{ar_k})$ reduce the relative attractiveness of large locations by increasing the cost of acquiring information where there are more firms. Finally, the share of customers visiting location $l$ is increasing in the quality of products sold in the location ($\mathbf{x}_j$ and $\xi_j$), and decreasing in prices ($p_{jl}$) and in the travel distance to the location ($||z_i - z_l||$).

**Conditional firm choice.** Conditional on searching location $l$, the share of type-$q$ consumers buying products from firm $j$ is:

$$s^q_{j|l}(\mathbf{p}_l) = Pr(u^q_{ijl} \geq u^q_{ij'l} \,\forall\, j' \neq j \; in \; l) = \frac{\exp(\frac{\delta^q_{jl}}{1-\sigma})}{\sum_{h=1}^{N_l} \exp(\frac{\delta^q_{hl}}{1-\sigma})} \tag{5}$$

This second expression reflects firm competition *within* a location. Notice that, all else equal, the share of customers purchasing products from firm $j$ is decreasing in the number of firms operating in the location. This is intuitive, as the presence of an additional firm means that the customers visiting the location have an additional alternative they can choose. I refer to this effect as the *market-share* effect. Firms with a higher mean utility $\delta_{jl}$, namely firms offering higher quality products and charging lower prices, have a higher share of customers and are less affected by within-location competition.

**Unconditional firm choice.** Overall, equations (4) and (5) show that, at a given set of prices, the presence of an additional firm has two effects on the demand for a firm products: (i) it attracts customers to the location by increasing the number of available varieties (*market-size effect*); (ii) it increases search costs and intensifies competition within a location (*market-share effect*). These two effects are combined in the unconditional demand for firm $j$'s products, which is the product of equations (4) and (5):

$$s^q_{ijl}(\mathbf{L},\mathbf{p}) = s^q_{il}(\mathbf{L},\mathbf{p}) \times s^q_{j|l}(\mathbf{p}_l) =$$

$$= \frac{\exp(\frac{\delta^q_{jl}}{1-\sigma})\Bigg(\sum_{j'=1}^{N_l}\exp(\frac{\delta^q_{j'l}}{1-\sigma})\Bigg)^{q^\theta(1-\sigma)-1}\exp(-\tau_1 g(||z_i - z_l||) - \tau_2\frac{N_l}{ar_l})}{\exp(u^q_0) + \sum_{k=1}^{N}\Bigg[\Bigg(\sum_{h=1}^{N_h}\exp(\frac{\delta^q_{hk}}{1-\sigma})\Bigg)^{q^\theta(1-\sigma)}\exp(-\tau_1 g(||z_i - z_k||) - \tau_2\frac{N_l}{ar_l})\Bigg]} \tag{6}$$

The overall impact of the number of firms $N_l$ on demand depends on the relative strength of the market-size and the market-share effects. To illustrate this, I temporarily assume that mean utility is constant across firms within the same location ($\delta^q_{jl} = \bar{\delta}^q_l$)[26] and set $\tau_2 = 0$. In Appendix B1 I show that, under these assumptions, the marginal effect of an additional firm on the unconditional demand from type-$q$ consumers is given by the following expression:

$$\frac{\partial s^q_{ijl}}{\partial N_l} = s^q_{il}{s^q_{j|l}}^2\Bigg(q^\theta(1-\sigma)(1-s^q_{il}) - 1\Bigg) \tag{7}$$

***Proposition:*** If $\delta^q_{jl} = \bar{\delta}^q_l\ \forall\ j \in l$ *and* $\forall\ l$, and if $\tau_2 = 0$, $s^q_{ijl}$ is increasing in $N_l$ if and only if $s^q_{il} < 1 - \frac{1}{q^\theta(1-\sigma)}$.

The proof follows simple algebra.

The market-size effect is more likely to outweigh the market-share effect: (i) the higher the quantity purchased $q$,[27] (ii) the lower the similarity of taste-shocks $\sigma$, and (iii) the lower the share of customers purchasing products in the location $s^q_{il}$. Although the marginal effect of an additional firm is non-monotonic in $s^q_{il}$, it eventually becomes negative as this share increases. Intuitively, if a location is already attractive - because it hosts a large number of firms, offers high-quality products at low prices, or because it is geographically close to consumers - then an additional firm only changes the relative attractiveness of the location by a small margin.[28]

The last thing to notice about equation (7) is that the marginal effect of an additional firm is increasing in absolute value in $s^q_{j|l}$. As a result, firms with a higher mean utility (see equation (5)) benefit the most from the agglomeration force, but are also harmed the most by competition if the term in parenthesis is negative. This has important implications in

[26] This is not without loss of generality, as it implies that prices do not vary with the number of firms. However, I defer the discussion of prices to Section 4.3.

[27] Notice that the inequality never holds for $q = 1$, as in this case the right hand-side of the inequality becomes negative.

[28] At the limit, if all firms operate within the same location (ignoring consumers' outside option) Equation (6) reduces to Equation (5), and the agglomeration effect is null.

terms of *selection*. If $\frac{\partial s^q_{ijl}}{\partial N_l} > 0$, we should expect a larger share of high-quality firms selecting into larger locations. The opposite is true if the sign of the inequality is reversed.

Aggregating over all consumer types, the overall demand for firm $j$ in location $l$ is:

$$Q_{jl}(\mathbf{L},\mathbf{p}) = \int q s^q_{ijl}(\mathbf{L},\mathbf{p}) dF(q, z) \tag{8}$$

where $dF(\cdot)$ is the exogenous joint distribution of customer types and origin.

## 4.3 Supply

### 4.3.1 Production and outsourcing

Firms produce output using labor $\ell$ and land $h$ according to the following Cobb-Douglas, constant-returns to scale production function:

$$f(h, \ell) = A_l \ell^\delta h^{1-\delta} \tag{9}$$

I assume that all firms are equally productive, but allow locations to have heterogeneous productivity, for example due to different amenities. Labor is a composite input produced by combining a continuum of perfectly complementary tasks $t$: $\ell = min\{x(t)|t \in [0, 1]\}$. This is a plausible assumption for the garment sector, where the production is organized in sequential steps.[29] Tasks can be produced internally or be outsourced: $x(t) = \frac{l_I}{a(Z)} + l_E$, where $l_I$ and $l_E$ denote internal and external labor respectively, and $Z$ is the share of internally produced tasks.

Producing a task externally requires one unit of labor. The external technology is provided by a continuum of perfectly competitive intermediate tasks providers[30] who sell labor at marginal cost $w$, where $w$ the is market wage for both internal and external labor. Procuring an external task requires firms to pay an additional cost (e.g. for transport and/or monitoring) that depends on the number of garment firms operating in the location, $T(N_l) > 1$. The cost of one unit of external labor is therefore $wT(N_L)$. In the presence of agglomeration economies related to the sharing of suppliers, this cost will be decreasing in the number of firms in the location: $dT/dN_l < 0$.

Producing a task internally requires $a(Z)$ units of labor. I assume that, as firms internalize more tasks, their productivity decreases: $a'(Z) > 0$. Intuitively, this could be interpreted as

[29]Typically, these steps are: designing, sampling, laying, marking, cutting, stitching, checking, finishing, pressing and packaging.

[30]Intermediate task providers are distinct from garment firms and do not enter my sample.

firms moving away from their core competency (Eckel and Neary, 2010), or as a consequence of learning-by-doing. At the optimal level of outsourcing $Z^*$, the firm is indifferent between using internal or external labor to produce a task. This occurs at the threshold $a(Z^*) = T(N_l)$.

**Proposition**: If $dT/dN_l < 0$, as $N_l$ increases, $Z^*$ decreases and firms outsource a larger share of production to suppliers of external tasks.

Because of the Leontief technology in tasks production, the input quantities must satisfy: $\frac{l_I}{a(z)} = l_E = \ell$. The marginal cost of producing tasks internally and externally is therefore the same and equal to $wT(N_l)$. Firms will choose how much labor and land to employ in production to maximize:

$$\max_{h,\ell} \pi_{jl}(h,\ell) = \max_{h,\ell} p_{jl} A_l h^{1-\delta} \ell^{\delta} - rh - wT(N_l)\ell \tag{10}$$
$$\text{s.t. } Q_{jl} = A_l h^{1-\delta} \ell^{\delta}$$

where $Q_{jl}$ is the demand for a firm's product. Given firms' optimal choice of land and labor, marginal costs are given by the following expression:

$$c_l = \frac{1}{A_l} \left( \frac{wT(N_l)}{\delta} \right)^{\delta} \left( \frac{r}{1-\delta} \right)^{1-\delta} \tag{11}$$

Notice that this expression is constant for all firms in a given location and decreasing in $N_l$ if the cost of outsourcing $T(N_l)$ decreases with the number of firms operating in a location. This is the microfoundation of the supply-side externality that generates agglomeration economies in the model.

### 4.3.2 Prices

Conditional on their location choice and on the spatial distribution of other garment businesses, firms play a static Nash-Betrand pricing game by simultaneously setting the price of their product. They choose prices to maximize variable profits:

$$\pi_{jl}(\mathbf{L},\mathbf{p}) = \Big( p_{jl} - c_l \Big) Q_{jl}(\mathbf{L},\mathbf{p}) \tag{12}$$

Optimal prices are implicitly given by the expression below, where I omit the arguments $\mathbf{L}$ and $\mathbf{P}$ (see Appendix B2 for a derivation):

$$p^*_{jl} = c_l + \frac{1-\sigma}{\alpha} \left( \frac{\int q s^q_{ijl} dF(q,z)}{\int q s^q_{ijl} [q^{-\theta} + s^q_{j|l}((1-\sigma)(1-s_{il}) - q^{-\theta})] dF(q,z)} \right) \tag{13}$$

In Appendix B3 I show that the net effect of agglomeration on prices is ambiguous and depends on the relative strength of three forces. First, marginal costs decrease in the number of firms in a location due to cheaper outsourcing, leading to lower prices. Second, within-location competition pushes prices downwards via the market-share effect. Finally, demand-side externalities arising from the market-size effect soften competition and push prices upwards.

The system of best response equations can be written as:

$$\mathbf{p} = \mathbf{c} - \Lambda(\mathbf{p})^{-1}Q(\mathbf{p}) \tag{14}$$

where $\Lambda$ is the $J \times J$ matrix of price derivatives (Berry, 1994). A Nash-Bertrand equilibrium of this game is a vector $\mathbf{p}^*$ that solves (14). In AppendixB4, I follow Mizuno (2003) to derive the conditions for the existence and uniqueness of a price equilibrium. Due to the presence of externalities, when the market-size effect is strong the uniqueness of an equilibrium is not guaranteed.

## 4.4 Location

I model firms' choice of location as a static game of *incomplete information* in which firms owners simultaneously choose where to locate their business. Firms can only enter one location, and so the set of choice alternatives for firm $j$ is $l_j \in \{1, 2, ..., N\}$. Owners choose location to maximize the following profit function:

$$\Pi_{jl}(\mathbf{L},\mathbf{p}) = \pi_{jl}(\mathbf{L},\mathbf{p}) - \tau_3 g(||z_j - z_l||) - e_{jl} \tag{15}$$

where $\pi_{jl}(\mathbf{L},\mathbf{p})$ are the firm's variable profits in location $l$ as expressed in equation (12) and $\mathbf{L} = (l_j, \boldsymbol{l}_{-j})$, with $\boldsymbol{l}_{-j}$ being the vector of actions of all firms other than $j$. To enter a location, owners must pay a commuting cost ($\tau_3 g(||z_j - z_l||)$) which depends on the distance between the owner's residence/workplace and the firm.[31] While it is standard in the urban literature to incorporate commuting costs in the employee's choice of workplace, these do not typically enter the firm location problem. Including commuting costs in this context is important for two reasons: first, they constitute a sizeable share of the firm's costs, as discussed in Section 3. Second, 80.1% of the labor force in low-income countries is self-employed.[32] For these individuals, the choice of workplace coincides with the choice of where to locate the business.

Finally, $e_{jl}$ is an idiosyncratic entry or set-up cost, which is firm specific and is private

[31]When I estimate the model, I consider distance from the customer's residence for final customers and distance from workplace for retailers.

[32]For comparison, the corresponding figure is 77% for Uganda and 6.1% for the United States.

information to the firm. Incomplete information guarantees the existence of an equilibrium of the entry game Doraszelski and Satterthwaite (2010) and is more realistic in a context in which information frictions are large.

**Externalities:** Demand and supply-side externalities enter the firm's choice of location via their effect on variable profits. To illustrate this, I assume that there is an continuum of firms and take the total derivative of profits with respect to the number of firms in a location at the optimal prices $\mathbf{p}^*$:

$$\frac{d\Pi_{jl}(\mathbf{L},\mathbf{p}^*)}{dN_l} = \frac{d\pi_{jl}(\mathbf{L},\mathbf{p}^*)}{dN_l} = \underbrace{(p^*_{jl} - c_l)\frac{\partial Q_{jl}(\mathbf{L},\mathbf{p}^*)}{\partial N_l}}_{\text{demand externality}} - \underbrace{\frac{\partial c_l}{\partial N_l} Q_{jl}(\mathbf{L},\mathbf{p}^*)}_{\text{supply externality}} \tag{16}$$

The sign of $\frac{\partial Q_{jl}}{\partial N_l}$ depends on the relative magnitude of the market-size and market-share effects: if the former prevails, firms face higher demand in larger locations and have a demand-side incentive to agglomerate. The sign of $\frac{\partial c_{jl}}{\partial N_l}$ depends on the effect of $N_l$ on outsourcing costs $T(N_l)$. Cheaper outsourcing in locations with a larger number of firms lowers marginal costs, generating a supply-side externality. Notice that, although I do not model the land market explicitly, in the data firms pay higher rental costs in geographically concentrated locations. Therefore, marginal costs may overall be higher in areas with a higher density of firms.

**Bayesian Nash equilibrium:** Since firms have imperfect information about the profitability of other businesses, they choose location based on their expected profits: $E_{\mathbf{e}_{-j}}[\Pi_{jl}]$, where $\mathbf{e}_{-j}$ is the matrix of unobserved shocks for firms other than $j$. I assume that shocks $e$ are iid across firms and locations, and are distributed according to a type-1 extreme value with scale parameter $\mu$, which is known to all firms. By the independence of private information, a firm's expected profits from entering location $l$ can be expressed as:

$$E_{\mathbf{e}_{-j}}[\Pi_{jl}(e_{jl})] = \int \pi_{jl}(l_j, \boldsymbol{l}_{-j}|\mathbf{e}_{-j}) \prod_{h\neq j} dG(e_h) - \tau_3 g(||z_j - z_l||) + e_{jl} \tag{17}$$

Firms' expected profits from location $l$ can be rewritten in terms of *Conditional Choice Probabilities* (CCPs). Let $\mathbf{P}^a \equiv \{P_j(l_j|\boldsymbol{l}_{-j}) : j \in J; l_j \in N; \boldsymbol{l}_{-j} \in N^{J-1}\}$ be the vector of conditional choice probabilities associated with a given a set of strategy functions $a = \{l_j(\boldsymbol{l}_{-j}, \mathbf{e}_j) : j \in J\}$. Firms' expected profits, which I denote by $\bar{\Pi}^a_{jl}$, can be rewritten as a function of this vector:

$$\bar{\Pi}^a_{jl}(e_{jl}) = \sum_{\boldsymbol{l}_{-j}} \left( \pi_{jl}(l_j, \boldsymbol{l}_{-j}) \prod_{h\neq j} P^a_h(l_h) \right) - \tau_3 g(||z_j - z_l||) + e_{jl} \tag{18}$$

where the summation is taken over all the possible combinations of the actions of firms other than $j$, with the number of combinations being equal to $N^{J-1}$.

***Definition***: A *Bayesian Nash Equilibrium* (BNE) is a set of strategy functions $a^* = \{l_j^*(\boldsymbol{l}_{-j}, \mathbf{e}_j) : j \in J\}$, such that for any firm $j \in J$ and any $e_{jl} \in R^{J \times L}$, $l_j^*(\boldsymbol{l}_{-j}, \mathbf{e}_j) = \arg\max_l \{\bar{\Pi}_{jl}^{a}{}^*(e_{jl})\}$

Let $\mathbf{P}^*$ be the vector of CCPs associated with $a^*$. Given the assumption on the distribution of the $e$ shocks, the Bayesian Nash equilibrium can be characterized as the fixed point of the best response mapping:

$$\Psi_j(l_j|\mathbf{P}^*) = \frac{\exp\left(\left(\sum_{\boldsymbol{l}_{-j}} \pi_{jl}(l_j, \boldsymbol{l}_{-j}, J) \prod_{h\neq j} P_h^*(l_h) - \tau_3 g(||z_j - z_l||)\right)/\mu\right)}{\sum_{k=0}^{N} \exp\left(\left(\sum_{\boldsymbol{l}_{-j}} \pi_{jk}(k_j, \boldsymbol{l}_{-j}, J) \prod_{h\neq j} P_h^*(l_h) - \tau_3 g(||z_j - z_k||)\right)/\mu\right)} \tag{19}$$

***Proposition***: The location game has at least one equilibrium.

Given the assumption on the distribution of private information, the best response probability functions (equation (19)) are well defined and continuous in the compact set of players' choice probabilities. Hence, by Brouwer's fixed point theorem, there exists at least one equilibrium. However, as it is common in entry games, the equilibrium might not be unique.

# 5 Estimation

To quantify demand and supply-side externalities, I structurally estimate the model. The estimation is carried out in three steps. First, taking firm location and production choices as given, I combine transaction data and data from the mystery shoppers exercise to estimate the demand parameters $\boldsymbol{\theta_1} = \{\alpha, \beta, \sigma, \theta, \tau_1, \tau_2\}$ via maximum likelihood. Second, given the estimated demand parameters and data on wages and rents across locations, I simulate firms' choice of land and labor. I estimate firms' production function and supply-side externality parameters $\boldsymbol{\theta_2} = \{\delta, A_l, T(N_l)\}$ using a simulated method of moments approach. Finally, I use the Rust's Nested Fixed Point algorithm (Rust, 1987) applied to a static setting to estimate the remaining commuting cost parameter $\boldsymbol{\theta_3} = \{\tau_3\}$ for the entry game.

An important aspect of the estimation is the assignment of firms to locations. In the baseline estimation, I assume that a location corresponds to a parish, but consider parishes in the core to be one location. I justify this choice in Appendix C.

## 5.1 First Step: Demand parameters

I use firm transaction data to estimate demand via weighted exogenous sampling maximum likelihood (Manski and Lerman, 1977). Taking firm location and prices as given, the log-likelihood function takes the following form:

$$\ln L(\boldsymbol{\theta_1}|\mathbf{L},\mathbf{p}) = \sum_{i,q,j,l} w_j \times I_{iqjl} \times \ln s^q_{ijl}(\mathbf{L},\mathbf{p}) \tag{20}$$

where $s^q_{ijl}$ is the probability that a consumer of type $q$ from location $i$ purchases products from firm $j$ in location $l$, which is expressed by equation (6). $w_j$ are sampling weights and $I_{iqjl}$ is an indicator for whether a consumer of a given type purchases a product from firm $j$. The parameters to be estimated are $\boldsymbol{\theta_1} = \{\alpha, \beta, \sigma, \theta, \tau_1, \tau_2\}$.

What is key about my dataset is that it contains information about the location where the customer travelled from, as well as the type of customer - final or retailer - making the purchase. The former provides information on the distance between customer and firm $||z_i - z_l||$. I assume that distance enters utility linearly and calculate it as the driving time between the centroids of the customer and the firm parish. One drawback of the data is that customer location is missing for around 19% of transactions. For an additional 16% the firm reported the name of the district, but not the exact parish where the customer travelled from. For these observations customer location is imputed. Appendix D1 provides a detailed description of the imputation procedure.

The customer type maps directly into the quantity purchased. In line with my data, I assume that there are only two types of customers in the economy: final customers and retailers. I assume that final customers always buy one unit of the purchased good ($q_f = 1$).[33] By contrast, retailers buy ten units ($q^r = 10$), the median transaction size for this type of consumers in the data. As previously mentioned, final customers' outside option is normalized to zero ($u^f_0 = 0$), while retailers' outside option $u^r_0$ is estimated within the likelihood (details in Appendix D2).

When estimating the model, I face a trade-off between adding heterogeneity on the firm side and keeping the estimation of the entry game computationally feasible. This is because the state space for the latter grows exponentially as the number of firm types increases. Therefore, I assume that firms only differ along one observable dimension: product quality. Specifically, I assume that firms are either *high* or *low* quality.[34] I choose this dimension

[33] 59% of final customers in the transaction data buy one unit of good. 94% buy less than five units.

[34] To assign firm types, I use data from the mystery shoppers exercise. Specifically, I assign firms with a

for two reasons: first, quality is by far the most important characteristic customers consider when searching for products.[35] Second, mystery shoppers data show a strong correlation between prices and product quality.[36] Including quality in the demand estimation is therefore important for the unbiasedness of the price coefficient. This point is discussed in more detail in the identification subsection.

### 5.1.1 Identification

In this section I provide a discussion of the model identification. I start with the identification of mean utility parameters $\{\alpha, \beta\}$ and discuss in detail how I address price endogeneity. I then discuss the identification of parameters governing the agglomeration/competition trade-off $\{\sigma, \theta\}$ and of the search parameters $\{\tau_1, \tau_2\}$.

**Mean utility parameters.** Intuitively, mean utility parameters $\alpha$ and $\beta$ are identified from variation in within-location market shares across firms with different prices and product quality. I allow the coefficient on product quality $\beta$ to differ for final and retail customers. Variation in the share of final and retail customers buying products from high and low-quality firms that operate within the same location separately identify the two coefficients.

**Price endogeneity.** An important implication of the assumption that firms only differ in terms of quality is that there is no unobserved firm heterogeneity ($\xi_j = 0$). This can be a concern for the estimation of the price coefficient $\alpha$, as it implies that, conditional on quality, there are no omitted variables that simultaneously explain variation in firm prices and demand. To mitigate this concern, I construct the log-likelihood using prices from the mystery shoppers exercise instead of transaction data. Reassuringly, mystery shoppers prices are strongly correlated with prices from transaction data. Table A2 shows that, controlling for product quality and type of product sold, a unit dollar increase in mystery shoppers prices is associated with a \$1.08 increase in transaction prices (p-value$<$0.001). However, the exogeneity of mystery shoppers prices is more plausible than that of transaction prices. By construction, mystery shoppers purchased identical products from all firms. Interviewers were also trained to follow a script to ensure a similar interaction with firms and were provided with clear instructions on how to bargain for prices, which is a common practice in this setting (see Appendix E for details).

This is of course not sufficient to ensure that there is no residual unobserved heterogeneity

quality score above average to be high quality, and firms with a score below average to be low quality.

[35] 87% of customers mention product quality as an important characteristics to consider while searching for firms. This is follower by good customer care and timely delivery, mentioned by 58% and 40% of customers.

[36] A one standard deviation increase in the quality score is associated with an 8% increase in price.

that is correlated with both prices and demand. To further test this assumption, I rely on additional data collected by mystery shoppers. In Table A3, I show the results from a regression of mystery shoppers prices on the quality score and a number of variables potentially correlated with both demand and prices. Quality is strongly correlated with prices: a one standard deviation increase in the quality score is associated with a 4.7% increase in price. Additional measures of the quality of customer care and store appearances, the timely delivery of products, and firms' advertising efforts do not significantly explain prices. The only variable that has a significant effect on prices is a 0 to 10 score of the cleanliness of the business premises. As a robustness check, in Appendix F I re-estimate demand allowing for unobserved heterogeneity and show that the estimated price coefficient does not substantially change. Overall, this evidence supports the plausibility of the exogeneity of mystery shoppers prices once quality is controlled for.

**Agglomeration/competition trade-off.** Broadly speaking, $\sigma$ governs the correlation of product taste shocks within the same location: the larger the $\sigma$, the lower the dispersion of taste shocks and the higher the competition among firms in the same location.[37] The identification $\sigma$ is similar to that of the nesting coefficient in nested logit models. Importantly, this parameter is not separately identified from the variance of the search cost shock $\omega$, which is therefore normalized to one (Ben-Akiva et al., 1985). The identification then relies on variation in the share of same type, similarly distant customers buying from firms that operate in locations of different sizes. To illustrate this, I assume without loss of generality that all firms have the same mean utility $\delta^q_{jl} = 0 \; \forall j, l$, and let the search parameters $\tau_1$ and $\tau_2$ be equal to zero. Under these assumptions, the share of *final* customers purchasing from firm $j$ in location $l$ is given by:

$$s^f_{ijl} = \frac{N_l^{-\sigma}}{1 + \sum_{k=1}^{N} \left( N_k^{1-\sigma} \right)} \tag{21}$$

It is straightforward to see that $\sigma$ is pinned down by variation in market shares across locations with different numbers of firms. Notice that when $\sigma = 0$ (minimum within-location competition) equation (21) reduces to $s^f_{ijl} = \frac{1}{1+\sum_{k=1}^{N} N_l}$: all firms have the same share of customers, independently of how many other firms operate within the same location. When $\sigma = 1$ (maximum within-location competition), $s^f_{ijl} = \frac{1}{N_l}$: all that matters for firm demand is the number of businesses operating in the same location.

To discuss the identification of $\theta$, I maintain the same assumptions and look at the share of *retail* customers purchasing from firm $j$ in location $l$:

[37] This is what Berry and Waldfogel (1999) refer to as the *business stealing* effect.

$$s^r_{ijl} = \frac{N_l^{q^\theta(1-\sigma)-1}}{\exp(u_{i0})^r + \sum_{k=1}^N \left(N_k^{q^\theta(1-\sigma)}\right)} \tag{22}$$

Given $\sigma$, $\theta$ is identified by variation in the share of retail customers purchasing from firms that operate in locations with different $N_l$.

**Identification of search parameters.** The remaining parameters to identify are those governing demand elasticity to travel distance ($\tau_1$) and firm density within a location ($\tau_2$). Variation in the share of same type customers who buy products from locations that have a similar inclusive value $IV^q_l = \sum_{j=1}^{N_l} \exp(\frac{\delta^q_{jl}}{1-\sigma})$, but differ in distance from customers and firm density identifies $\tau_1$ and $\tau_2$ respectively. Notice that the identification of the former is allowed by the availability of data on buyers' origin.

## 5.2 Second Step: Supply parameters

Exploiting data on rents, wages, labor and land from the firm survey, I estimate the supply-side parameters via simulated method of moments. These include the production function parameters $\delta$ and $A_l$, and the supply-side externality $T(N_l)$. I simulate firms' choice of labor and land given demand and the factor prices observed in the data:

$$h^*_{jl} = \frac{Q_{jl}}{A_l}\left(\frac{(1-\delta)w_l T(N_l)}{\delta r_l}\right)^{\delta} \quad \ell^*_{jl} = \frac{Q_{jl}}{A_l}\left(\frac{\delta r_l}{(1-\delta)w_l T(N_l)}\right)^{1-\delta} \tag{23}$$

Since the goods market must clear, the quantity produced by firms in equilibrium must be equal to demand. I therefore construct the demand for a firm's product using the parameters estimated in the first step, and plug it into the firm optimal choice of land and labor. I take rents and wages from the data. Although I do not explicitly model land and labor markets, I allow rents to be parish specific and wages to differ across core and periphery. Finally, I assume that the externality takes the following functional form: $T(N_l) = 1 + N_l^T$. This parametrization is akin to an iceberg transport cost and captures the idea that firms in denser areas are geographically closer to suppliers of intermediate inputs.

The targeted moments are the mean number of workers, including firm owner and external employees, the mean size of the business premises, and the mean ratio of workers to business premises in each of the locations. Given rents and wages, the variation in ratios of land to labor *across* different locations pins down the supply side externality: $\frac{\ell^*_{jl}/h^*_{jl}}{\ell^*_{hk}/h^*_{hk}} = \frac{r_l w_k T(N_k)}{r_k w_l T(N_l)}$. When $T$ is known, the ratio of labor to land *within* locations identifies $\delta$. Finally, given demand, the values of mean land and labor identify the productivity parameter $A_l$ for the different locations.

### 5.3 Third Step: Location parameters

The estimation of the commuting parameter $\tau_3$ follows Rust's (1987) Nested Fixed Point (NFXP) algorithm.[38] A fixed point of the NFXP is a pair $\{\boldsymbol{\theta}_3^*, \mathbf{P}^*\}$ that satisfies:

(i) $\boldsymbol{\theta}_3^* = \arg\max_{\boldsymbol{\theta}_3} \sum_j \sum_l \ln \Psi_j(l|\mathbf{P}^*, \boldsymbol{\theta}_\mathbf{3}) I_{lj}$

(ii) $\mathbf{P}^* = \Psi(\mathbf{P}^*, \boldsymbol{\theta}_3^*)$

where $I_{lj}$ is an indicator function for firm $j$ being located in $l$ and $\Psi(\mathbf{P}^*, \boldsymbol{\theta}_3)$ is given by equation (19). For this part of the estimation, I consider garment firms in the entire city of Kampala and not only those operating in sampled parishes.[39] However, I consider the location decision of owners from outside Kampala as exogenous.[40] The biggest challenge for the computation of the NPL fixed point are the memory requirements associated with the size of the state space. In the model, the computation of the best response function in (19) requires computing variable profits for $N \times J \times N^{J-1}$ possible states, where $N$ is the number of parishes where a firm owner can choose to locate its business and $J$ is the total number of firms. In my setting, there are 96 locations and 3,742 firms, which makes the computation very clearly unfeasible. To reduce the state space, I need to make assumptions about firms' choice sets, heterogeneity and the information firms have about other businesses.

**Choice set**: Firm owners' location is taken exogenously from the data. I assume owners' can only choose to locate their business in the parish where they reside or in the core, which reduces the number of locations from which a firm can choose from 96 to 2. This choice is supported by the data. First, proximity to home is by far the main reason why owners prefer the core to the periphery (Figure 2). Second, among owners operating in the periphery, 50% have their business in the same parish where they live.

**Firm heterogeneity:** As previously mentioned, I assume that firms are either high or low quality. Reducing the number of types reduces the state space dramatically. This is because what matters for computing firms' variable profits is the number of firms of a given type

[38] The location parameter $\mu$ is not identified, and is therefore normalized to 0.75 of a standard deviation of firms' variable profits.

[39] This is because, with the demand and supply parameters at hand, the only data required to compute firms' best responses in the entry game ($\Psi(\mathbf{P}, \boldsymbol{\theta}_3)$) are the number garment firms operating in a parish, the number of firm owners born in a parish, factor prices and productivity.

[40] 1,195 out of 2,496 firms operating in the core are from outside Kampala. I do not model the entry decision of these firms and assume they stay in the core regardless of other firms' behaviour.

operating in each parish and not their identity. However, firms also differ in the location where the owner resides. So, even with high and low quality firms only, the model would feature 192 types of firms. If firms were uniformly distributed across types, the size of the state space would be approximately $2 \times 192 \times 18^{192}$, which is of the order of magnitude of $10^{243}$. Again, computation with such a large state space is unfeasible.

**Information:** The last assumption I make for the tractability of the problem is about the information firms have about other businesses. I assume that firms know the total number of high and low-quality firms in the economy, but have no information about where other owners come from. When making their location decision, they assume that other owners are uniformly distributed across the 93 parishes outside the core and that these parishes are identical in terms of factor prices, productivity and distance from customers.[41] This reduces the size of the state space to approximately 33 million.

To obtain firm $j$'s best response function $\Psi_j(l|\mathbf{P}, \boldsymbol{\theta_3})$, I need to compute variable profits $\pi_{jl}(l_j, \mathbf{n}_k)$ for all possible configurations $k$ of other firms' actions. Notice this is only a function of the firm's location $l_j$ and the number of high and low-quality firms (other than $j$) in core and periphery in each configuration ($\mathbf{n}_k$). This still requires computing the Nash Bertrand equilibrium of the price game in each of these configurations. Although it is feasible in terms of memory space, the computation would be very time consuming. Following Aguirregabiria and Vicentini (2016), I compute variable profits only for a subset $S$ of the actual state space[42] and use interpolation to approximate variable profits for configurations outside this set. I use the following interpolation function:

$$\Gamma_{jl}(\mathbf{n}_k) = \begin{cases} \pi_{jl}(l_j, \mathbf{n}_k) & \text{if k} \in \text{S} \\ \gamma_{0l}^T + \gamma_{1l}^T n_{Lk} + \gamma_{2l}^T n_{Lk}^2 + \gamma_{3l}^T n_{Hk} + \gamma_{4l}^T n_{Hk}^2 + \gamma_{5l}^T n_{Lk} n_{Hk} + & \\ \quad + \gamma_{6l}^T n_{Lk}^2 n_{Hk} + \gamma_{7l}^T n_{Lk} n_{Hk}^2 & \text{if k} \notin \text{S} \end{cases} \tag{24}$$

where $n_{Lk}$ and $n_{Hk}$ are respectively the number of low and high-quality firms in the core in configuration $k$, and $T \in \{L, H\}$ is the type of firm $j$. The $\gamma$ parameters are obtained by running an OLS regressions of variable profits on the explanatory variables for the values of $\mathbf{n}_k$ in $S$. The fit of the regression for the set of points in subset $S$ is shown in Figure A5. With

[41] I assume that this representative parish has factor prices and productivity equal to the average value across the periphery parishes in sample. Distance from customers in a given parish is computed as the average distance between the centroid of that parish and all other periphery parishes in Kampala.

[42] $S = \{\mathbf{n}_1, \mathbf{n}_2, ..., \mathbf{n}_S\}$, with $\mathbf{n}_k$ a vector containing the number of high and low-quality firms operating in the core and the periphery in a particular configuration. I randomly choose the grid points in $S$ from a uniform distribution over $\{1, 2, ..., n_l\} \times \{1, 2, ..., n_h\}$, where $n_l$ and $n_h$ are respectively the total number of low and high-quality firms in the economy. The size of the subset is 10% of the size of the total state space.

the variable profits at hand, I can use Rust (1987) iterative algorithm to find the NFXP fixed point. The estimation routine consists in first solving the fixed point mapping in Equation (19) at an initial guess of the parameter $\boldsymbol{\theta}_3$. Once the fixed point probabilities are obtained, they feed into the log-likelihood $\mathcal{L}(\mathbf{P}^0) = \sum_j \sum_l \ln \Psi_j(l|\mathbf{P}^0, \boldsymbol{\theta}_3) I_{lj}$, which is maximized with respect to $\boldsymbol{\theta}_3$. This procedure is repeated until both probabilities and parameters converge.

# 6 Model Estimates and Fit

Table 5 shows the results from the estimation separately for demand, supply and location parameters. Panel A reports estimates of the demand parameters. Estimated coefficients are of the expected sign: the price coefficient is negative, while the quality coefficient is positive and more than three times larger for retailers relative to final customers. $\sigma$ and $\theta$ are key drivers of the competition vs. agglomeration effect. A necessary condition for the market-size effect to outweigh the market-share effect is that $q^\theta > \frac{1}{1-\sigma}$. The parameter estimates show that this is satisfied for retail customers ($q_r^\theta = 2.07$, $\frac{1}{1-\sigma} = 1.49$), while, by construction, it does not hold for final customers ($q_f^\theta = 1$).

Both travel and firm-specific search cost parameters $\tau_1$ and $\tau_2$ are negative. The magnitude of the former implies that, on average, final customers' transport costs correspond to 14.4% of the transaction value. For retail customers, the corresponding figure is 1.5%, in line with the presence of economies of scale in transport. Across all customers, average transport costs correspond to 7.5% of the transaction value, which is close to the percentage observed in the data (9%). The negative sign of $\tau_2$ implies that customers must pay additional firm-specific search costs once in the location. This cost is economically meaningful for final customers shopping in the core: it corresponds to 4.2% of the value of transactions and to around one third of the average transport cost. For retail customers, who make larger transaction, this additional cost is negligible (less than 0.1% of the transaction value). As a result of the trade-off between product variety and transport/search costs, it is primarily retail customers who purchase products in the core.

To test the fit of the demand model, Panel A of Figure A6 shows the estimated and predicted share of customers by parish. The prediction traces the data quite closely, suggesting that the model captures the key determinants of demand. If anything, the estimated share of customers purchasing goods in the core is underpredicted by the model. This could be due to additional amenities that customers benefit from in the core,[43] which I am unable

[43] For example due to cross-sector trip chaining, as documented by Myauchi et al (2021) for Tokyo and Oh and Seo (2022) for Seoul.

to separately identify using my data. Panel B of Figure A6 shows the share of customers purchasing from a given firm within a location ($s_{j|l}$ in the model). Comparing conditional shares tests more closely whether the variation induced by prices and quality is able to explain the allocation of customers across firms within the same location. Overall, the estimated shares follow the trend in the data, but there is a considerable amount of noise. This is not surprising considering theere is limited firm heterogeneity in the model.

**Table 5: Parameter estimates**

| | Parameter | Estimate | Std Error |
|---|---|---|---|
| **PANEL A: Demand** | | | |
| Price (USD) | $\alpha$ | -0.064 | (0.016) |
| Quality final customers | $\beta_f$ | 0.205 | (0.083) |
| Quality retail customers | $\beta_r$ | 0.724 | (0.377) |
| Taste shocks correlation | $\sigma$ | 0.329 | (0.210) |
| Quantity multiplier | $\theta$ | 0.316 | (0.083) |
| Travel cost | $\tau_1$ | -0.139 | (0.016) |
| Within location search cost | $\tau_2$ | -0.0004 | (0.0004) |
| **PANEL B: Supply** | | | |
| Labor share | $\delta$ | 0.651 | (0.030) |
| Outsourcing cost | T | -0.521 | (2.170) |
| Productivity Core | $A_{core}$ | 18.122 | (3.035) |
| Productivity Periphery (mean) | $A_{per}$ | 10.045 | (2.647) |
| **PANEL C: Location** | | | |
| Commuting cost | $\tau_3$ | -5.046 | |

**Note**: Table 5 shows point estimates and standard errors for the model parameters. Standard errors are bootstrapped using 100 bootstrapped samples.

Panel B shows the results of the supply-side estimation and Table A4 reports the data and simulated moments for goodness of fit. The cost of outsourcing is decreasing in the number of firms operating in the same location, in line with the presence of supply-side externalities. The magnitude of the estimate implies that the cost of procuring intermediate tasks ($T(N_l)$) decreases by 20% moving from the smallest parish in the sample to the core. In addition, firms are on average more productive in the core, as shown by the relative size of the productivity parameter $A_l$. This could be a reflection of firms in the core having access to better infrastructures or more productive inputs. However, Table A5 shows that there is a large variation in productivity across parishes in the periphery, with $A$ ranging from

3 to 24. This is reassuring because it means that higher productivity is not systematically related to a larger number of firms. In turn, it suggests that there are no additional supply-side externalities or selection of better firms into larger locations which can explain residual variation in firm productivity across parishes.

The last panel of Table 5 shows the estimated commuting cost parameter. The magnitude of the estimate implies that commuting costs correspond to 17% of firms' average variable profits in equilibrium. The Bayesian Nash Equilibrium associated with this estimate sees 30.5% of low-quality firms and 46% high quality firms choosing to locate in the Core. This is in line with the data, where the corresponding figures are 32.6% and 48.5%. The result indicates that high quality firms are more likely to select into the core and is consistent with consumers reporting to prefer the core due to firms' reputation of being better quality (Figure 3). Positive selection is driven by two elements in the model: first, high quality firms benefit most from demand-side externalities. This is in line with equation (7), which shows stronger effects for firms with larger within-location shares. Second, retail customers value quality the most and, regardless of quality, they are more likely to search for products in larger locations. This generates a complementarity between customer preferences and firm location, inducing high-quality firms to locate their business in the core.

**Robustness**: I test the robustness of the estimates by (i) re-estimating demand allowing for price endogeneity and using instrumental variables for prices to identify $\alpha$; and (ii) re-estimating demand and supply using an alternative definition of locations, in which the three parishes in the core are considered separate locations. Details and results are provided in Appendix F. I find that parameter estimates only change slightly in these alternative estimations. In addition, I test the assumption of the model being static by adding a second period to the model and allowing customers to buy from a different firm (in the same or a different location) after observing the taste shocks for products sold in the location visited in the first period. I find that even if customers were allowed to change seller, 83% would choose to go back to firm they bought products from in the first period.

# 7 Counterfactuals

In this section, I use the estimated model parameters to consider two sets of counterfactuals. First, I consider how equilibrium outcomes would change in the absence of information frictions, and study the effects of introducing an e-commerce platform that alleviates both information frictions and transport costs. Second, I evaluate the impact of two different policies aimed at decongesting the central area of Kampala.

## 7.1 Reducing search frictions

The first counterfactual studies the effect of shutting down information frictions. This exercise is not meant to simulate a real-world policy, but rather to give a sense of the importance of these types of frictions for equilibrium outcomes and welfare. Under the *no information frictions* scenario, I assume that customers can observe all product characteristics prior to purchasing, but must travel to the firm in person to complete the purchase. I then construct a second counterfactual that simulates the introduction of an e-commerce platform reducing both information frictions *and* transport costs.

**No information frictions:** I study the impact of eliminating information frictions by setting the idiosyncratic search cost $\omega_l$ to be equal to zero. Under this scenario, customers can observe and compare product varieties across all locations prior to purchasing. However, transactions are still conducted in person: to purchase the product customers must pay a transport cost to the location, as well as a firm-specific within-location search cost.[44] In Appendix B5, I derive demand and optimal prices for this scenario. I re-compute variable profits using the new demand system and find the BNE by searching for the fixed point to the system of best response functions given by equation (19). Since the model could feature multiple equilibria, I search for fixed points starting from different initial beliefs.[45] All searches lead to the same equilibrium, which suggests it is unique.

The results from this exercise are presented in Table 6. The first column shows the share of firms in the core, average prices, profits and consumer welfare[46] in the baseline scenario with both information frictions and transport costs. The second column shows the same statistics in the counterfactual with no information frictions. Eliminating information frictions reduces the share of firms operating in the core by 8.1%. This change masks a big shift in the composition of firms across core and periphery. While in the baseline scenario the majority of firms operating in the core are of high quality (60%), when frictions are removed it is primarily low-quality firms that choose to locate in the core, with the share of high-quality businesses dropping to 42%. The reason for these heterogeneous effects is that, as discussed in Section 4.2, high-quality firms are less affected by the within-location competition and hence benefit the most from agglomeration when consumers are imperfectly informed. Due to this shift in firm composition, the removal of information frictions leads to a 41% drop in

[44] With complete information, this search cost could be seen as the cost of finding the firm once in a location.

[45] These include beliefs that all firms locate either in the core or the periphery, or that one type of firm locate in the core, and the other type in the periphery.

[46] As it is standard in discrete choice models (Small and Rosen, 1981), consumer welfare is calculated as the expected maximum value of consumer's utility divided by the price coefficient: $E_{\varepsilon,\omega}(\max_j U^q_{ijl})/\alpha$

the share of sales concentrated in the core.

When information frictions are eliminated, prices and firm profits decrease by 14% and 18% on average. Lower prices, combined with access to a large number of varieties, increase consumer welfare by 11%. The impact on profits is heterogeneous across firms. High-quality businesses experience a 17.5% increase in firm profits, while the profits of low-quality firms drop by more 60%. This is because consumers are only able to compare product varieties within the same location when variety is uncovered upon visiting a firm. Once frictions are removed, consumers can compare the varieties sold by firms across all locations before visiting any location, which enhances competition and harms low-quality firms disproportionately.

**Table 6: Profits and welfare in counterfactual scenarios**

| | **Baseline** | **No information frictions** | **E-commerce** |
|---|---|---|---|
| Share of firms in core | 0.365 | 0.335 | 0.222 |
| Share of high-quality in core | 0.460 | 0.313 | 0.098 |
| Share of low-quality in core | 0.305 | 0.349 | 0.300 |
| Share of sales in core | 0.382 | 0.222 | 0.065 |
| | | | |
| Average price | 20.44 | 17.52 | 17.38 |
| Average profits | 476.0 | 391.0 | 411.3 |
| Average consumer welfare | 19.22 | 21.31 | 32.80 |

**Notes**: Table 6 shows firm location, prices, profits and consumer welfare in the baseline version of the model and the three counterfactual scenarios.

In Appendix G, I present an extension to the model in which firms are allowed to enter and exit the market. The scope of this extension is to recover firms' entry costs and assess what share of the businesses currently operating in the economy would find it profitable to entry and exit under different counterfactual scenarios. Given the current number of firms in the market, 37% of low-quality businesses would make negative profits and benefit from exiting the market once information frictions are removed. By contrast, an additional 20% of high-quality firms would find it profitable to enter. Although computing the number of businesses that would be operating in the market at the new equilibrium is beyond the scope of this exercise, these numbers suggest that with the elimination of information frictions (i) the total number of firms in the economy would decrease, (ii) the composition of firms would shift, leading to a larger share of high-quality firms in the market.

**E-commerce platform:** For the second counterfactual, I assume that customers can observe all varieties on an e-commerce platform (no information frictions) and pay a flat fee to get products delivered to their location. The goal of this exercise is to simulate the creation of an online platform where firms can sell their products. I calibrate the delivery fee to the fee charged by Jumia, Ugandan main online shopping website, which is approximately 1.58$ and the same for all locations within the city. The results of this counterfactual are presented in the last column of Table 6.

The creation of an e-commerce platform for garment firms reduces the share of firms and sales concentrated in the core by 39% and 83% respectively. The magnitude of these changes shows that the geographical centrality of the core, which makes it an easy location to reach from consumers across all Kampala, is a key driver of agglomeration. The reduction in the share of businesses in the core is driven by a relocation of high-quality firms, while the distribution of low-quality firms across locations only changes slightly with respect to the baseline scenario. Average prices and profits decrease on average, with heterogeneous effects on low and high-quality firms (-64% and +27%). As a result of no information frictions and lower product transport costs, consumer welfare increases by 70%. Overall, these results indicate that the introduction of an e-commerce platform would have large positive effects, with high-quality firms gaining market share over lower-quality businesses, the share of firms in the core sharply decreasing, and consumers benefiting from a large raise in welfare.

## 7.2 Decongestion policies

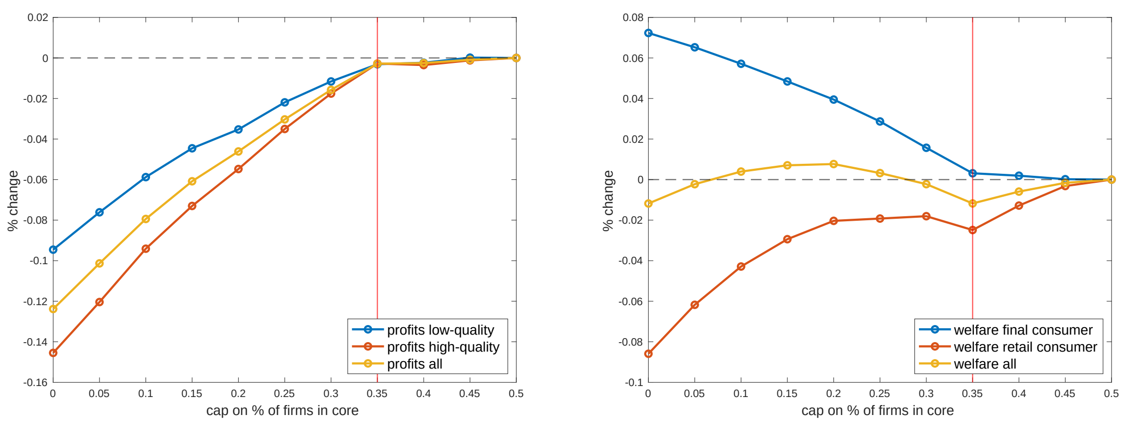
Firm agglomeration comes at a high cost in terms of travel time and congestion. In Kampala, travel time is estimated to be 13.5% of the city GDP plus an additional 4.2% considering congestion (Baertsch, 2020). This led governments across Africa to introduce policies aimed at relocating informal businesses outside of city centers and reducing traffic congestion. I simulate the impact of two types of urban policies that are currently being discussed in Uganda. The first one is the introduction of a cap to the number of firms allowed to operate in the core, paired with the eviction of firms in excess. The second one is the creation of a congestion zone in Kampala city center, where motorcycle taxis (boda-bodas), which cover 42% of city daily trips (KCCA, 2016), are banned.

**Firm caps:** I study the effect of limiting the percentage of firms that can operate in the core to a range between 0 and 50% of firm owners.[47] I assume that the same cap applies to both low and high-quality firms across all parishes. Figure 5 plots changes in average firm profits and consumer welfare with respect to the baseline scenario. The red vertical line at 35% indicates the point at which the cap only becomes binding for high-quality firms. At 50% the cap is no longer binding for any type of firm, so the equilibrium in the market goes back to the baseline scenario.

Panel A of Figure 5 shows that firm profits unambiguously decline as caps are imposed, as decongestion policies prevent firms from exploiting demand-side externalities that arise from search frictions. When no firm is allowed to operate in the core, average profits decline by 12%. The negative impact gets smaller as caps become less strict. This pattern holds for both high and low-quality firms, with the former experiencing a larger decline in profits from the introduction of caps.

**Figure 5: Changes in profits and welfare with caps**

PANEL A: Change in firm profits PANEL B: Change in consumer welfare




**Notes**: Figure 5 plots changes in firm profits (Panel A) and consumer welfare (Panel B) with respect to the baseline model as a function of the size of the cap. The size of the cap is measured as the share of firms allowed to operate in the core. The red vertical line at 0.35 indicates the point where the cap only becomes binding for low-quality firms.

The impact of caps on average consumer welfare is muted, ranging between -1% and +1%. However, Panel B shows that these effects mask a substantial reallocation of welfare from retailers to final consumers. Final consumers benefit from the introduction of caps, with welfare increasing by 7.2% as firms are banned from the core. By contrast, the welfare of retail customers declines by 8.6%. The effect is stronger for stricter caps and flattens out as caps

[47] I still consider the choice of firms outside Kampala as exogenous, and assume that they are not affected by the cap.

become less stringent.[48] The reason for these heterogeneous effects is that final consumers, who do not enjoy economies of scale in transport, would benefit from firms relocating outside the core and closer to residential areas. Retail customers, who benefit disproportionately from access to variety, would instead prefer to have as many firms as possible concentrated within the same location and would therefore be harmed by decongestion policies.

**Boda-boda ban:** In the final counterfactual, I analyze the implication of a policy banning motorcycle taxis (boda-bodas) from the core. The main reason why people use boda-bodas in Kampala, and particularly within the central part of the city, is to avoid congestion. To simulate the ban, I exploit the fact that Google maps in Uganda provides directions and driving time separately for cars and motorcycles (Figure A8). Differences in driving time between these two transport modes typically reflect the ability of two-wheelers to avoid traffic. I use the average difference in travel time between cars and motorcycles across locations in the the central district of Kampala to calibrate the increase in transport cost, which I apply to both customers and firm owners commuting to the core.[49]

The ban induces 9.8% of firms to relocate outside the core, with a stronger effect among high-quality businesses (12.7%). In Kampala, the ban is strongly opposed by firms operating in the core, who believe that it would lead to a reduction in footfall and therefore to a decrease in firms' profits. My estimates confirm this intuition: as a result of the ban, the profits of firms remaining in the core drop by 3.6%. However, businesses in the periphery gain from this measure, with profits increasing by 3.3%. Since the majority of firms operate outside the core, overall the policy leads to a 1% increase in average firm profits. The impact on consumer welfare is negligible (0.3%), but does not account for the potential benefits that consumers and workers might have from reduced decongestion and pollution.[50]

[48] As caps get closer to the baseline equilibrium, they only become binding for high-quality firms, thus altering the composition of businesses across locations.

[49] For firm owners, I use the change in average travel time on a Wednesday morning at 9am (+6.8%). For customers, I take the difference in travel time on a Saturday at 9am (+5.2%). In doing so, I implicitly assume that car driving time would not be affected by the ban. Although this is a strong assumption, the impact of banning boda-bodas on congestion, and hence driving times, is ex-ante ambiguous. On the one hand, boda-bodas are known not to be very respectful of the rules of the road. Banning them from the most crowded part of the city could reduce congestion by allowing traffic to flow more easily. In addition, if effective at reducing the number of people travelling to the core, they would reduce overall congestion. On the other hand, individuals that would have otherwise travelled to the core by boda-boda will have to use a different transport mode: a car or a minibus. If these means of transport create more congestion per passenger than motorcycles, overall congestion will increase.

[50] For instance, Bassi et al. (2022a) show that by locating next to busy roads searching for customer visibility, they expose workers to substantial pollution. In addition, the counterfactual also neglects potential interactions with the impact the policy would have on the behavior of firms and consumers in other sectors, as well as the effects that the policy would have on motor-cycle taxis.

# 8 Conclusion

Limited information on product characteristics can generate benefits from agglomeration for firms operating in cities. This paper offers a case study that highlights the importance of considering demand-side externalities when modelling firms' choice of location. Using novel data from a representative sample of garment firms and their customers in Kampala, I study the consequences of demand-driven agglomeration on heterogeneous firms and consumers.

There are two key take-aways from this paper. First, information frictions have a sizeable impact on firm agglomeration, with important implications for the profitability of firms and consumer welfare. In particular, results from this study show that information frictions limit the ability of high-quality firms to attract customers and expand, favoring the survival of low-quality firms in the market. A large body of literature has focused on the supply-side constraints that prevent small firms in low-income countries from growing (see Woodruff (2018) for a review). This paper suggests that demand-side constraints, which have been largely unexplored, may play an equally important role.

Second, by increasing consumers' costs of gathering information, policies aimed at reducing agglomeration penalize high-quality firms. At the same time, they reallocate welfare from retailers to final consumers, who benefit from firms being more spatially disperse and closer to residential areas. This result suggests that firm agglomeration may create an incentive for intermediaries - retailers in this setting - to operate in the market. Studying the linkages between firms' choice of location and intermediaries' entry decision is an interesting avenue for future research.

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# Appendix A: Additional Figures and Tables

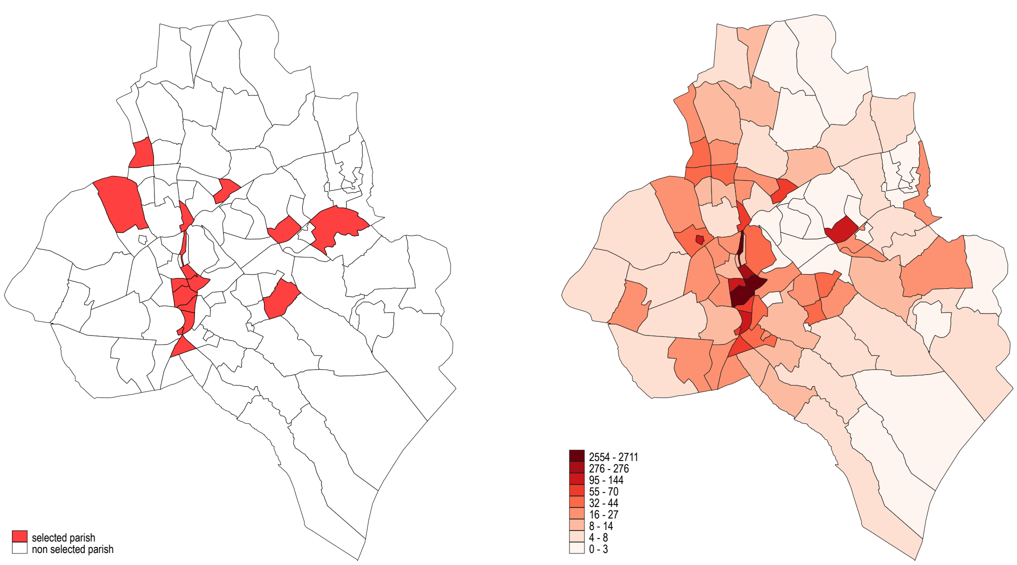
## A1 Figures

### Figure A1: Typical dresses

### Figure A2: Selected locations

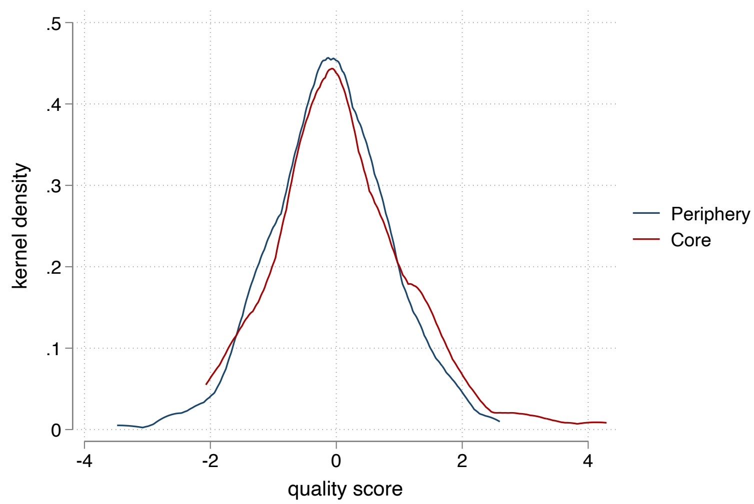
PANEL A: Selected Parishes

PANEL B: Garment firms per square-km



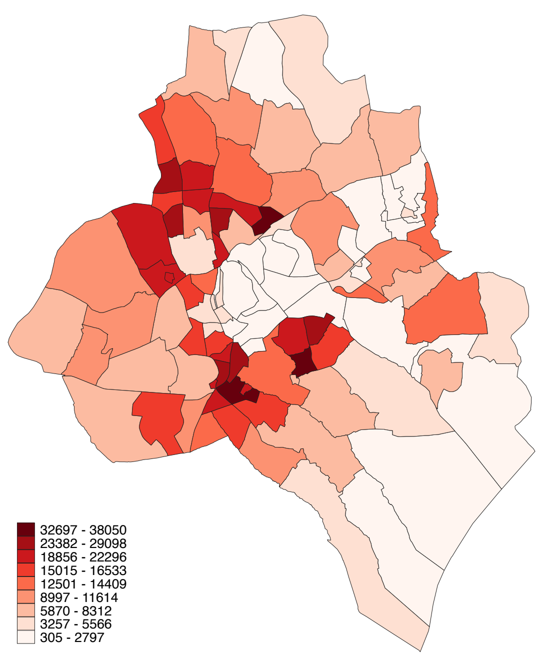

Source: 2010 Census of Business Establishments

## Figure A3: Product quality distribution in core and periphery




**Note:** The figure shows the kernel density estimate of the distribution of quality scores from the mystery shoppers exercise separately for firms in the core and the periphery.

## Figure A4: Kampala population




**Note:** The figure shows the number of inhabitants per square-km for the 96 Kampala parishes. Data is from 2014 National Population and Housing Census.

**Figure A5: Profits from full model estimation vs. OLS prediction**

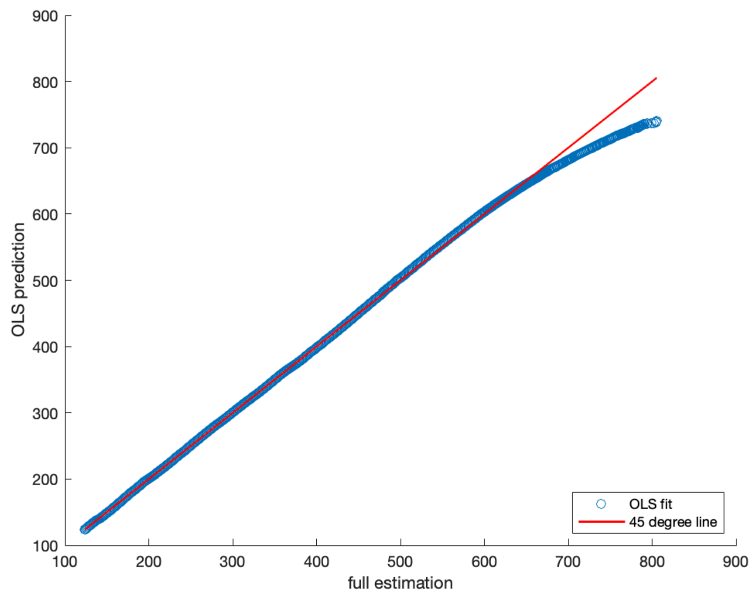
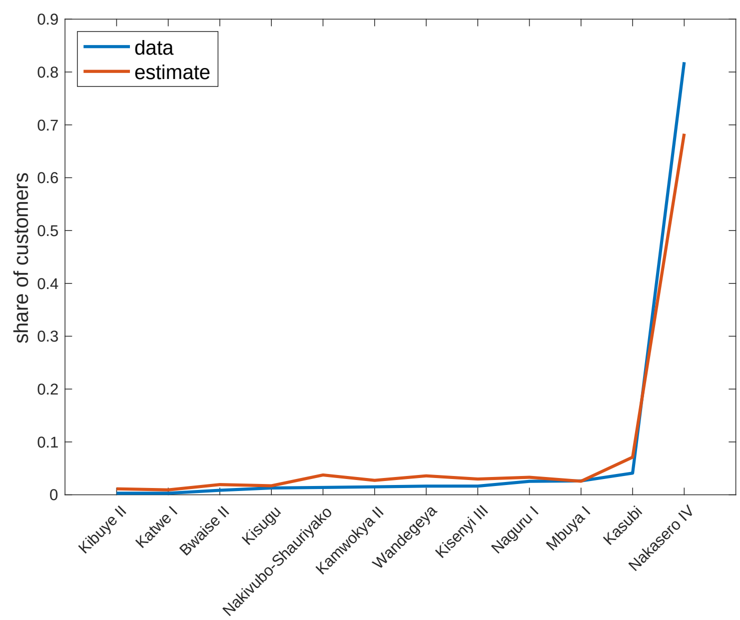
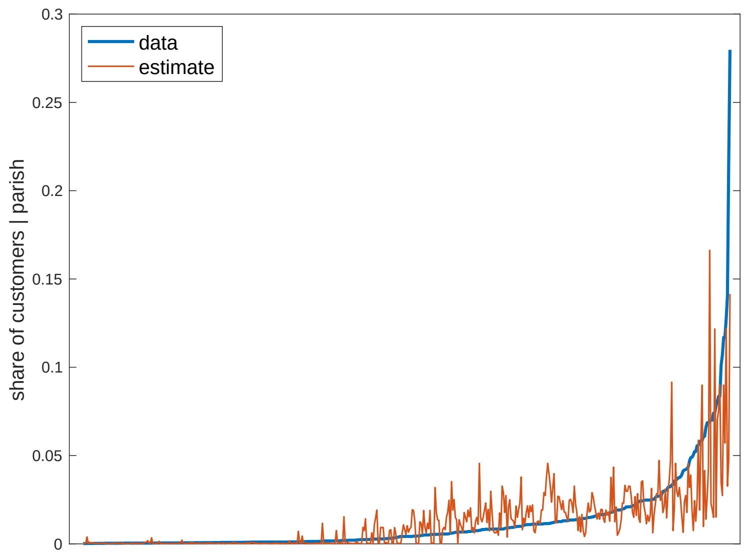



**Figure A6: Observed and predicted shares of customers**

PANEL A: Location shares



PANEL B: Within location firm shares




## Figure A7: Share of final and retail customers in each parish

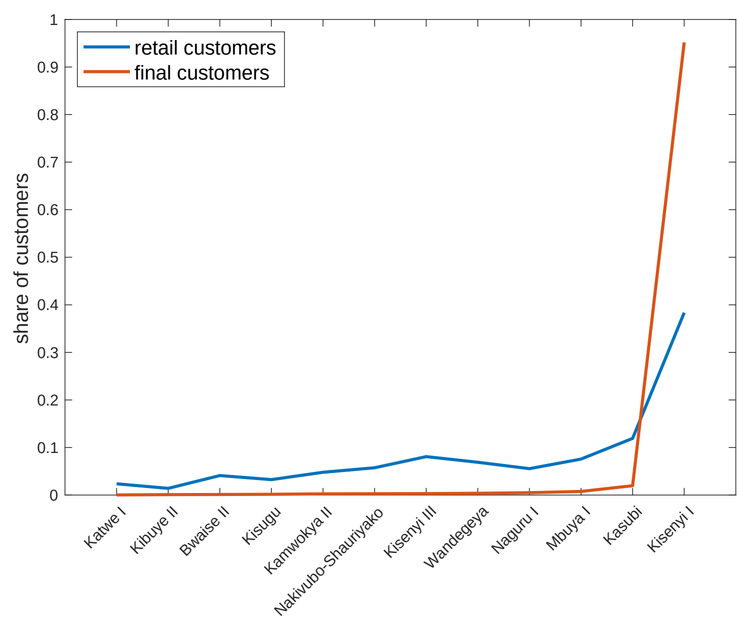
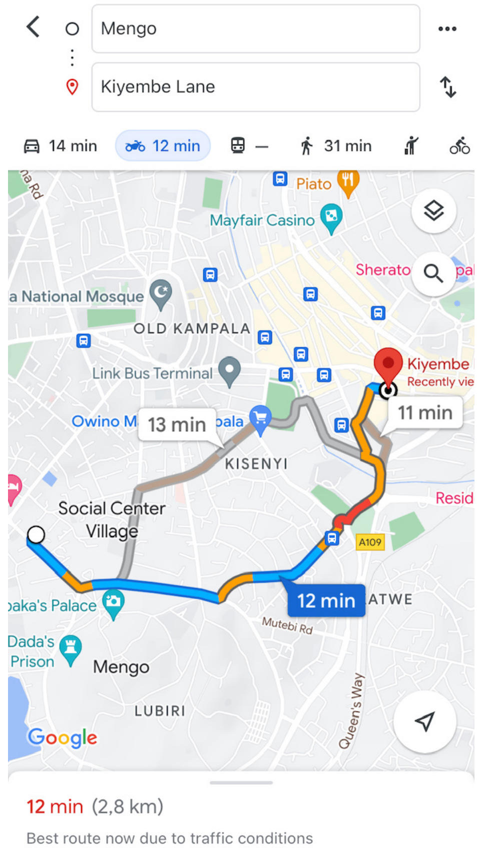


Figure A8: Example of Google Maps travel time by car and motorcycle



## A2 Tables

### Table A1: Relocation

| | % of firms |
|---|---|
| **No Relocation** | |
| Never relocated | 54.4 |
| **Relocation to Core** | |
| Periphery to core | 5.32 |
| Outside Kampala to core | 6.16 |
| Relocated within core | 11.3 |
| **Relocation to Periphery** | |
| Core to periphery | 2.83 |
| Outside Kampala to periphery | 7.82 |
| Relocated within periphery | 12.1 |

### Table A2: Correlation between transaction and mystery shopper prices

| | (1) | (2) | (3) |
|---|---|---|---|
| | | Transaction price | |
| Mystery shoppers price | 0.925*** | 0.808*** | 1.077*** |
| | (0.122) | (0.100) | (0.065) |
| Quality score | | | 0.461*** |
| | | | (0.111) |
| Product FEs | | ✓ | ✓ |
| Number of Observations | 2,571 | 2,571 | 2,541 |

**Notes**: Robust standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

**Table A3: Correlates of Mystery Shoppers prices**

| | (1) |
|---|---|
| | Price (USD) |
| Quality score | 0.241*** |
| | (0.0761) |
| Customer care (0-10 rating) | 0.0533 |
| | (0.0678) |
| Greeted upon entering the firm | -0.249 |
| | (0.460) |
| Given undivided attention | 0.268 |
| | (0.354) |
| Pleasant closing comment | -0.451 |
| | (0.395) |
| Tidiness of premises (0-10 rating) | -0.0475 |
| | (0.0656) |
| Cleanliness of premises (0-10 rating) | 0.164** |
| | (0.0741) |
| Product ready by delivery date | -0.202 |
| | (0.199) |
| Offered something to come back | 0.543 |
| | (0.515) |
| Told to advertise firm | 0.147 |
| | (0.279) |
| Shopper FEs | ✓ |
| Parish FEs | ✓ |
| Average price (USD) | 5.579 |
| Number of Obs | 529 |

Standard errors clustered at the parish level in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

## Table A4: Supply estimation data and simulated moments

| **Parish** | | Land ($h$) | Labor ($\ell$) |
|---|---|---|---|
| Bwaise II | *Data* | *6.050* | *1.931* |
| | Sim | 5.890 | 2.333 |
| Kamwokya II | *Data* | *5.450* | *1.650* |
| | Sim | 5.466 | 1.594 |
| Kasubi | *Data* | *5.003* | *2.246* |
| | Sim | 4.736 | 2.711 |
| Katwe I | *Data* | *1.750* | *1.500* |
| | Sim | 1.989 | 1.045 |
| Kibuye II | *Data* | *2.857* | *2.429* |
| | Sim | 2.671 | 2.619 |
| Kisenyi III | *Data* | *3.450* | *2.450* |
| | Sim | 3.823 | 0.948 |
| Kisugu | *Data* | *7.750* | *1.938* |
| | Sim | 7.347 | 2.943 |
| Mbuya I | *Data* | *9.394* | *2.314* |
| | Sim | 9.194 | 2.941 |
| Naguru I | *Data* | *3.862* | *2.353* |
| | Sim | 4.192 | 1.224 |
| Core | *Data* | *2.671* | *2.321* |
| | Sim | 2.808 | 2.167 |
| Nakivubo-Shauriyako | *Data* | *4.533* | *2.467* |
| | Sim | 3.282 | 3.606 |
| Wandegeya | *Data* | *2.478* | *2.696* |
| | Sim | 2.217 | 2.896 |

**Notes**: Robust standard errors in parentheses. $^{*}$ $p < .10$, $^{**}$ $p < .05$, $^{***}$ $p < .01$

**Table A5: Estimates of parish-specific productivity parameter**

| **Parish** | **Productivity** ($A_l$) |
|---|---|
| **Core** | 18.12 |
| **Periphery** | |
| Bwaise II | 5.541 |
| Kamwokya II | 9.636 |
| Kasubi | 8.400 |
| Katwe I | 24.47 |
| Kibuye II | 7.596 |
| Kisenyi III | 19.08 |
| Kisugu | 4.096 |
| Mbuya I | 2.652 |
| Naguru I | 9.164 |
| Nakivubo-Shauriyako | 5.806 |
| Wandegeya | 14.05 |

# Appendix B: Proofs and Derivations

## B1 Demand and number of firms

Under the assumption that mean utility is constant across firms in the same location, equation (5) can be rewritten as:

$$s^q_{ijl}(\mathbf{L},\mathbf{p}) = \frac{\exp(\frac{\bar{\delta}^q_l}{1-\sigma})\left(N_l \exp(\frac{\bar{\delta}^q_l}{1-\sigma})\right)^{q^\theta(1-\sigma)-1} \exp(-\tau_1 g(||z_i - z_l||))}{1 + \sum_{k=1}^L \left[\left(N_h \exp(\frac{\bar{\delta}^q_k}{1-\sigma})\right)^{q^\theta(1-\sigma)} \exp(-\tau_1 g(||z_i - z_k||))\right]} \tag{A.1}$$

Let $\Gamma$ denote the denominator $1+\sum_{k=1}^L \left[\left(N_h \exp(\frac{\bar{\delta}^q_k}{1-\sigma})\right)^{q^\theta(1-\sigma)} \exp(-\tau_1 g(||z_i - z_k||))\right]$. Then:

$$\begin{aligned}
\frac{ds^q_{ijl}}{dN_l} = \frac{1}{\Gamma^2}\Bigg[ & \exp\left(\frac{2\bar{\delta}^q_l}{1-\sigma}\right)(q^\theta(1-\sigma)-1)\left(N_l \exp(\frac{\bar{\delta}^q_l}{1-\sigma})\right)^{q^\theta(1-\sigma)-2} \exp(-\tau_1 g(||z_i - z_l||))\Gamma \\
& - \exp\left(\frac{2\bar{\delta}^q_l}{1-\sigma}\right) q(1-\sigma)\left(N_l \exp(\frac{\bar{\delta}^q_l}{1-\sigma})\right)^{2q^\theta(1-\sigma)-2} \exp(-2\tau_1 g(||z_i - z_l||))\Bigg] \\
& = (q^\theta(1-\sigma)-1)s^q_{ijl}s^q_{j|l} - q^\theta(1-\sigma){s^q_{ijl}}^2 \\
& = s^q_{ijl}s^q_{j|l}\left(q^\theta(1-\sigma)(1-s_{il})-1\right)
\end{aligned} \tag{A.2}$$

where the last expression can be derived by rewriting $s_{ijl}$ as the product of $s_{il}$ and $s_{ij|l}$.

## B2 Derivation of optimal prices

The FOC for firms' optimal prices are:

$$p_{jl}(\mathbf{p},\mathbf{J}) = c_l - \frac{Q_{ijl}(\mathbf{p},\mathbf{J})}{\partial Q_{ijl}(\mathbf{p},\mathbf{J})/\partial p_{jl}} = c_l - \frac{\int q_i s^q_{ijl}(\mathbf{p},\mathbf{J}) dF(q,z)}{\int q_i \frac{\partial s^q_{ijl}(\mathbf{p},\mathbf{J})}{\partial p_{jl}} dF(q,z)} \tag{A.3}$$

Omitting the arguments $(\mathbf{p},\mathbf{J})$ from now on, the derivative within the integral in the denominator is equal to:

$$\frac{\partial s^q_{ijl}}{\partial p_{jl}} = \frac{\partial s^q_{il}}{\partial p_{jl}} s^q_{j|l} + s^q_{il}\frac{\partial s^q_{j|l}}{\partial p_{jl}} \tag{A.4}$$

where, $\frac{\partial s_{il}^q}{\partial p_{jl}} = -\alpha q s_{ijl}^q(1 - s_{il}^q)$ and $\frac{\partial s_{j|l}^q}{\partial p_{jl}} = -\frac{\alpha q^{1-\theta}}{1-\sigma} s_{j|l}^q(1 - s_{j|l}^q)$. Putting everything together, the expression above becomes:

$$\frac{\partial s_{ijl}^q}{\partial p_{jl}} = -\frac{\alpha}{1-\sigma} q s_{ijl}^q \left[ q^{-\theta} + s_{j|l}^q((1-\sigma)(1-s_{il}^q) - q^{-\theta}) \right] \tag{A.5}$$

where the terms in square brackets is greater than zero. Plugging this into equation (A.4), the expression for optimal prices becoms:

$$p_{jl}^* = c_l + \frac{1-\sigma}{\alpha} \left( \frac{\int q s_{ijl}^q dF(q,z)}{\int q s_{ijl}^q [q^{-\theta} + s_{j|l}^q((1-\sigma)(1-s_{il}^q) - q^{-\theta})] dF(q,z)} \right) \tag{A.6}$$

## B3 Optimal prices and number of firms

Without loss of generality, I show how prices change in response to the number of firms operating in a location when firms face a single type of consumers. For ease of notation, I omit the exponent $q$. Optimal prices under this assumption are simply:

$$p_{jl}^* = c_l + \left( \frac{1-\sigma}{\alpha[q^{-\theta} + s_{j|l}^q((1-\sigma)(1-s_{il}^q) - q^{-\theta})]} \right) \tag{A.7}$$

Taking the total derivative of equation (A.7) with respect to the number of firms operating in the the location:

$$\frac{\partial p_{jl}^*}{\partial N_l} = \frac{\partial c_l}{\partial N_l} + \frac{d}{dN_l} \left( \frac{1-\sigma}{\alpha[q^{-\theta} + s_{j|l}^q((1-\sigma)(1-s_{il}^q) - q^{-\theta})]} \right) \tag{A.8}$$

Let $\tilde{S} = q^{-\theta} + s_{j|l}^q((1-\sigma)(1-s_{il}^q) - q^{-\theta})$. The derivative of this term with respect to the number of firms in the same location is:

$$\frac{d\tilde{S}}{dN_l} = \left( \frac{\partial s_{j|l}^q}{\partial p_{jl}^*} \frac{\partial p_{jl}^*}{\partial N_l} + \frac{\partial s_{j|l}^q}{\partial N_l} \right) ((1-\sigma)(1-s_{il}^q) - q^{-\theta}) - \left( \frac{\partial s_{il}^q}{\partial p_{jl}^*} \frac{\partial p_{jl}^*}{\partial N_l} + \frac{\partial s_{il}^q}{\partial N_l} \right) s_{j|l}^q (1-\sigma) \tag{A.9}$$

Plugging this expression into equation (A.8) and rearranging:

$$\begin{aligned} &\frac{\partial p_{jl}^*}{\partial N_l} \left[ 1 + \frac{1-\sigma}{\alpha \tilde{S}^2} \left( \frac{\partial s_{j|l}^q}{\partial p_{jl}^*} ((1-\sigma)(1-s_{il}^q) - q^{-\theta}) - \frac{\partial s_{il}^q}{\partial p_{jl}^*} s_{j|l}^q (1-\sigma) \right) \right] \\ &= \frac{\partial c_l}{\partial N_l} - \frac{1-\sigma}{\alpha \tilde{S}^2} \left( \frac{\partial s_{j|l}^q}{\partial N_l} ((1-\sigma)(1-s_{il}^q) - q^{-\theta}) - \frac{\partial s_{il}^q}{\partial N_l} s_{j|l}^q (1-\sigma) \right) \end{aligned} \tag{A.10}$$

We focus on the case in which the agglomeration effect outweighs the competition effect, so that the demand for a firm's product is increasing in the number of firms operating in the same location: $\frac{\partial s^q_{ijl}}{\partial N_l} > 0$[51]. Under this scenario, the term in parenthesis on the right-hand side is negative, as $\frac{\partial s^q_{j|l}}{\partial N_l} < 0$, $\frac{\partial s^q_{il}}{\partial N_l} > 0$ and $q^\theta > \frac{1}{(1-\sigma)(1-s_{il})}$ (see equation (A.2)).

I now focus on the sign of the term in square brackets on the left-hand side:

$$\begin{aligned} &\frac{\alpha}{1-\sigma}\left(q^{-2\theta} + s^{q\,2}_{j|l}((1-\sigma)(1-s^q_{il}) - q^{-\theta})^2 + 2q^{-\theta}s^q_{j|l}((1-\sigma)(1-s^q_{il}) - q^{-\theta})\right) \\ &\quad -\frac{\alpha}{1-\sigma}q^{1-\theta}s^q_{j|l}(1-s^q_{j|l})((1-\sigma)(1-s^q_{il}) - q^{-\theta}) + \alpha q s^{q\,2}_{ijl}(1-s^q_{il})(1-\sigma) \geq 0 \\ \iff &\frac{\alpha}{1-\sigma}s^q_{j|l}((1-\sigma)(1-s^q_{il}) - q^{-\theta})\left(s^q_{j|l}((1-\sigma)(1-s^q_{il}) - q^{-\theta}) + 2q^{-\theta} - q^{1-\theta}(1-s^q_{j|l})\right) \\ &\quad +\alpha q s^{q\,2}_{ijl}(1-s^q_{il})(1-\sigma) \geq 0 \end{aligned} \tag{A.11}$$

A sufficient condition for this term to be positive is that $q < \frac{2}{1-s^q_{j|l}}$. If this condition holds, the sign of $\frac{\partial p^*_{jl}}{\partial N_l}$ depends on the term on the right-hand side of equation (A.10), where $\frac{\partial c_{jl}}{\partial N_l} < 0$ (supply-side externality), and the second term is positive as long as the agglomeration effect outweighs the competition effect (demand-side externality). Whether price increases or decreases in $N_l$ therefore depends on the relative strength of the two externalities.

## B4 Existence and Uniqueness of price equilibrium

I use a result from Mizuno (2003) to find the conditions that guarantee the existence and uniqueness of a Nash-Bertrand equilibrium in the model. Let $D_j(p_j|\mathbf{p}_{-j})$ be the demand for product $j$ in a differentiated products setting, and let $C_j(Q_j)$ be the firm $j$ cost function. Mizuno (2003) proves that the following five conditions are sufficient for the existence of a unique price equilibrium:

(i) $D_j(p_j|\mathbf{p}_{-j})$ is strictly positive and strictly decreasing in $p_j$ on $R^n$,

(ii) $D_j(\mathbf{p}) = D_j(\mathbf{p} + k\mathbf{u}^n)$ for all $k$, where $u$ is the n vector whose elements are all unity,

(iii) $D_j(p^H_j|\mathbf{p}^H_{-j})D_j(p^L_j|\mathbf{p}^L_{-j}) \geq D_j(p^H_j|\mathbf{p}^L_{-j})D_j(p^L_j|\mathbf{p}^H_{-j})$ for $p^H_j \geq p^L_j$ and $\mathbf{p}^H_{-j} \geq \mathbf{p}^L_{-j}$,

(iv) $D_j(p_j|\mathbf{p}_{-j})$ is increasing in $\mathbf{p}_{-j}$ on $R^n$, OR, $C_j(Q_j) = c_jQ_j$, where $c_j \geq 0$

[51] If the competition effect is stronger than the agglomeration effect, then trivially prices are decreasing in the number of firms operating in the location.

It is easy to see that the model satisfies conditions (i), (ii) and (iv). Condition (iii) can be re-written as:

$$\frac{D_j(p_j^H|\mathbf{p}_{-j}^H) - D_j(p_j^L|\mathbf{p}_{-j}^H)}{D_j(p_j^L|\mathbf{p}_{-j}^H)} \geq \frac{D_j(p_j^H|\mathbf{p}_{-j}^L) - D_j(p_j^L|\mathbf{p}_{-j}^L)}{D_j(p_j^L|\mathbf{p}_{-j}^L)} \tag{A.12}$$

which is satisfied if $\frac{\partial D_j(\mathbf{p})}{\partial p_j}/D_j(\mathbf{p})$ is increasing in $p_{-j}$, namely if:

$$\frac{\partial^2 D_j(\mathbf{p})}{\partial p_j \partial p_{-j}} \frac{1}{D_j(\mathbf{p})} - \frac{1}{D_j(\mathbf{p})^2} \frac{\partial D_j(\mathbf{p})}{\partial p_j} \frac{\partial D_j(\mathbf{p})}{\partial p_{-j}} \geq 0 \tag{A.13}$$

I focus again on the case of firms facing one type of consumers and show under what conditions inequality (A.14) is satisfied. With one type of consumers, the demand for firm $j$ operating in location $l$ is $s_{ijl}(\mathbf{L},\mathbf{p})$, where I omit the arguments $\mathbf{L},\mathbf{p}$ from now on. Equation (A.14) becomes:

$$\frac{\partial^2 s_{ijl}}{\partial p_{jl} \partial p_{-j}} - \frac{1}{s_{ijl}} \frac{\partial s_{ijl}}{\partial p_{jl}} \frac{\partial s_{ijl}}{\partial p_{-j}} \geq 0 \tag{A.14}$$

Where the price derivatives are:

$$(i) \;\; \frac{\partial s_{ijl}}{\partial p_{jl}} = -\frac{\alpha q}{1-\sigma} s_{ijl} \left( q^{-\theta} + s_{ij|l}((1-\sigma)(1-s_{il}) - q^{-\theta}) \right) \tag{A.15}$$

$$(ii) \;\; \frac{\partial s_{ijl}}{\partial p_{kl}} = -\frac{\alpha q}{1-\sigma} s_{ijl} s_{k|l}((1-\sigma)(1-s_{il}) - q^{-\theta}) \qquad for\ k \neq j \tag{A.16}$$

$$(iii) \;\; \frac{\partial s_{ijl}}{\partial p_{kh}} = \alpha q s_{ijl} s_{ikh} \qquad for\ k \neq j\ and\ h \neq l \tag{A.17}$$

Notice that, for firm $j$ in location $l$ an increase in the price charged by a different firm in a different location has a positive effect on demand (equation (A.17)). However, the impact of an increase in the price charged by a different firm in the same location is negative if $q^\theta > \frac{1}{(1-\sigma)(1-s_{il})}$ (equation (A.16)). This is because such an increase in prices makes the location less attractive, thus reducing demand. If the agglomeration force is strong, this effect can outweigh the lower within-location competition generated by an increase in the price charged by other firms.

I study the sign (A.14) separately for the effect of a change in the prices charged by firms in the same and in different locations.

### B4.1 Change in price by firms in the same location

I start with the former case. The cross-derivative in equation (A.14) becomes:

$$\frac{\partial^2 s_{ijl}}{\partial p_{jl}\partial p_{kl}} = \left(\frac{\alpha q}{1-\sigma}\right)^2 s_{ijl}s_{k|l}((1-\sigma)(1-s_{il})-q^{-\theta})\Big(q^{-\theta}+s_{ij|l}((1-\sigma)(1-s_{il})-q^{-\theta})\Big)$$
$$-\frac{\alpha q^{1-\theta}}{1-\sigma}s_{ijl}s_{ij|l}s_{ik|l}((1-\sigma)(1-s_{il})-q^{-\theta})-\alpha q s_{ijl}s_{ik|l}(1-\sigma)(1-s_{il}) \tag{A.18}$$

And the second term in the inequality is equal to:

$$\frac{1}{s_{ijl}}\frac{\partial s_{ijl}}{\partial p_{jl}}\frac{\partial s_{ijl}}{\partial p_{kl}} = \left(\frac{\alpha q}{1-\sigma}\right)^2 s_{ijl}s_{k|l}((1-\sigma)(1-s_{il})-q^{-\theta})\Big(q^{-\theta}+s_{ij|l}((1-\sigma)(1-s_{il})-q^{-\theta})\Big) \tag{A.19}$$

Putting together these two expressions, the inequality in (A.14) becomes:

$$\frac{\partial^2 s_{ijl}}{\partial p_{jl}\partial p_{-j}} - \frac{1}{s_{ijl}}\frac{\partial s_{ijl}}{\partial p_{jl}}\frac{\partial s_{ijl}}{\partial p_{-j}} =$$
$$-\frac{\alpha q^{1-\theta}}{1-\sigma}s_{ijl}s_{ij|l}s_{ik|l}((1-\sigma)(1-s_{il})-q^{-\theta})-\alpha q s_{ijl}s_{ik|l}(1-\sigma)(1-s_{il}) \tag{A.20}$$

First, notice that this expression is negative when $q^\theta > \frac{1}{(1-\sigma)(1-s_{il})}$, which is the same condition upon which an increase in the price charged by a firm in the same location decreases the demand for a firm's products. If this condition holds, the existence and uniqueness of a price equilibrium is not guaranteed.

Equation (A.20) is positive, and hence a price equilibrium exists and is unique, if and only if:

$$q^\theta \leq \frac{1}{(1-\sigma)(1-s_{il})\Big(1+q^\theta(1-\sigma)s_{il}\Big)} \tag{A.21}$$

### B4.2 Change in price by firms in a different location

For an increase in the price charged by firms operating in different locations, inequality (A.15) becomes:

$$
\begin{aligned}
&-\frac{(\alpha q)^2}{1-\sigma} s_{ijl} s_{ikh} \left( q^{-\theta} + s_{ij|l}((1-\sigma)(1-s_{il}) - q^{-\theta} - s_{il}) \right) \\
&+\frac{(\alpha q)^2}{1-\sigma} s_{ijl} s_{ikh} \left( q^{-\theta} + s_{ij|l}((1-\sigma)(1-s_{il}) - q^{-\theta}) \right) \geq 0 \\
&\iff \frac{(\alpha q)^2}{1-\sigma} s_{ijl} s_{ikh} s_{il} \geq 0 \qquad \text{(A.22)}
\end{aligned}
$$

which is always true, as the term on the left-hand side is always $\geq 0$.

## B5 Demand in the *no information frictions* counterfactual

In the *no information frictions* counterfactual described in Section 7.1, I assume customers can observe all product varieties at no cost prior to visiting a location ($\omega_l$=0). With this assumption, the demand for firm $j$'s product in location $l$ becomes:

$$
s^q_{ijl}(\mathbf{L},\mathbf{p}) = Pr(u^q_{ijl} \geq u^q_{ihk} \,\forall\, h,k) = \frac{\exp\left( \frac{\delta^q_{jl}}{1-\sigma} - \frac{q^{-\theta}}{1-\sigma}(\tau_1 g(||z_i - z_l||) + \tau_2 \frac{N_l}{ar_l}) \right)}{\exp(u^q_0) + \sum_{k=1}^{N} \sum_{h=1}^{N_h} \exp\left( \frac{\delta^q_{hk}}{1-\sigma} - \frac{q^{-\theta}}{1-\sigma}(\tau_1 g(||z_i - z_k||) + \tau_2 \frac{N_k}{ar_k}) \right)} \qquad \text{(A.23)}
$$

Notice that the number of firms operating in the location $N_l$ enters the numerator negatively (as a it increases search costs) and the denominator positively via the internal summation term. In this expression, there is no *market-size* effect, and having an additional competitor in the same location only decreases the demand for a firm's product via the *market-share* effect. The optimal price charged by the firm to type-$q$ consumers from location $i$ is simply:

$$
p^*_{jl} = c_l + \frac{1-\sigma}{\alpha q^{1-\theta}(1 - s^q_{ijl})} \qquad \text{(A.24)}
$$

where this expression is easily derived from $\frac{\partial s^q_{ijl}}{\partial p_{jl}} = -\frac{\alpha q^{1-\theta}}{1-\sigma} s^q_{ijl}(1 - s^q_{ijl})$ and $p^*_{jl} = c_l - s^q_{ijl} / \frac{\partial s^q_{ijl}}{\partial p_{jl}}$.

# Appendix C: Choice of Locations

On the demand side, the underlying assumption for firms to belong to the same location is that customers who visit it are able to observe the characteristics of all the products sold in that location, but cannot observe products sold by businesses in neighbouring locations. To define the borders of a location, it is therefore important to take into account how far customers are willing to travel to search for products. On the supply-side, firms within the same location have the same production cost, as they benefit from the same amenities, and face the same outsourcing cost.

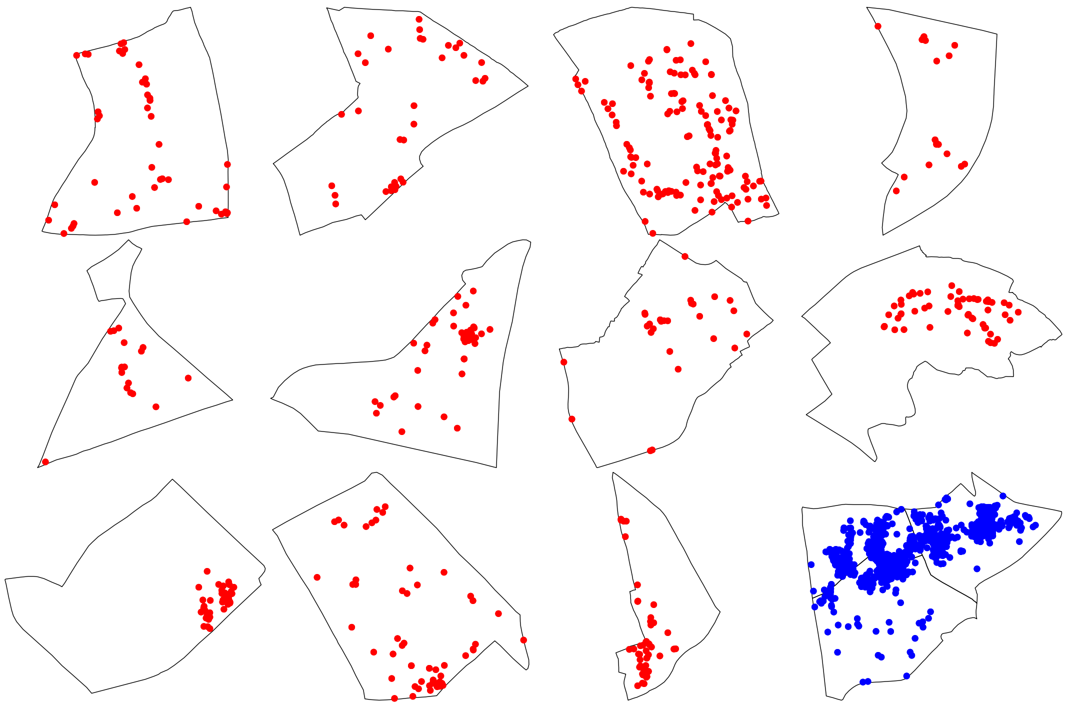
In the baseline estimation a location corresponds to a parish, with the exception of parishes in the core - Kisenyi I, Kisenyi II and Nakasero IV - which I consider one location. This choice takes into consideration the geographical dispersion of firms, which is important for customer search and outsourcing, as well as the political administration to which firms are subject, which can affect firms' production cost.

It is reasonable to assume that, once in a location, individuals in this setting walk around to search for products[52]. Firms that belong to the same location must therefore be of walking distance to one another. The average size of Kampala parishes is 2.03 square-kilometer, which is a reasonable area to walk. In addition, within parishes firms tend to cluster along main roads or in marketplaces (Figure A.C1). This implies that (i) the effective distance customers must walk to visit all firms within the location is lower than the parish area; (ii) clusters tend to be contained within the parish borders, and relatively far from other clusters. This is not true for the core area, where the majority of firms are part of the same cluster located at the border of the three parishes (Figure A.C1 in blue). In fact, Density-Based Spatial Clustering of Applications with Noise algorithms (DBSCAN) with a distance radius above 25 meters generate a unique cluster for the three central parishes.

Although a pure spatial algorithm could be used to generate "search" clusters, it is important to also take into consideration the supply-side of the model. In Uganda, parishes are under the administration of a chief who is responsible for tax collection, the implementation of national and local government policies and, in some instance, the settling of land disputes. All these factors are part of the amenities that firms face in a given location, and likely to affect their productivity.

[52]In the customer survey, 61% of individuals report walking to the location where they purchased a product, 37% report travelling by public transport, and less than 1% drove a car.

**Figure A.C1: Firm Location within Periphery parished and Core**



Considering the trade-off between geographical dispersion and production amenities, the identification of parishes as locations is a reasonable choice. In Appendix F, I conduct a robustness exercise where I consider firms in the core to be separate locations. I also plan to re-estimate the model using a pure spatial algorithm for assigning firms to location to verify the robustness of my finding to alternative definitions.

# Appendix D: Details on data for demand estimation

## D1. Imputation of customers' location

Before describing the imputation procedure, it is important to understand what are the correlates of missing location. Table A.D1 shows the results from a regression of a dummy for missing location on a number of transaction and firm characteristics, controlling for parish (Column 1) and firm fixed effects (Column 2). I consider both transactions for which no information about the location is provided, and transaction for which only the region was recorded as missing.

Reassuringly, Column 1 shows that attrition is uncorrelated with the total amount of the transaction, the number of items purchased, and the firm's average number of daily customers and average daily revenues, suggesting that busier firms are not more likely to omit customers' origin. However, the table shows that location is more likely to be missing for final than for retail customers. A possible explanation is that retail customers are 21% more likely to have had interactions with the firm in the past, increasing the chances that the firm owner is aware of the origin of the customer. In Column 2, I include firm fixed effects to look at variation in reporting within the firm. Once again, I find no significant relationship between size of the transaction and attrition, but find that firms are less likely to report the origin of retail customers. Overall, these results show that, conditional on customer type, transactions for which customer origin is observed are not different from those for which location is missing in terms of observable characteristics. This suggests that they can be safely used to impute missing locations.

**Table A.D1: Correlates of missing location**

| | (1)<br>Missing origin | (2)<br>Missing origin |
|---|---|---|
| Total transaction value (USD) | 0.000 | -0.000 |
| | (0.001) | (0.000) |
| Quantity for customer | 0.000 | -0.000 |
| | (0.000) | (0.000) |
| Retail customer | -0.073* | -0.069*** |
| | (0.034) | (0.023) |
| Average of daily customers | -0.041 | |
| | (0.039) | |
| Average daily revenues (USD) | -0.001 | |
| | (0.001) | |
| Parish FEs | ✓ | |
| Firm FEs | | ✓ |
| Number of Observations | 2,569 | 2,569 |

Standard errors clustered at the parish level in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

I rely on the structure of the model for imputation. Equation (5) shows that, within a location, the share of type $q$ consumers buying products from a given firm is independent of the origin $i$ of the customer. This is because mean utility $\delta_{jl}^{q}$ is independent from the customer's origin. This implies that, conditional on customer type and firm location, the distribution of customers' origin should not differ across transactions for which location is reported, and those for which it is missing in terms. Therefore, I randomly assign customers to locations proportionally to the share of customers origin observed in the data, conditional on customer type and firm location.

## D2. Data for outside option

The estimation of retailers' outside option requires data on the total number of final and retail customers purchasing tailoring products in each parish. For final customers, I constructed this measure using data from the 2020 Ugandan National Panel Survey, which contains information on households' annual consumption of clothing. This information was used to calculate the share of households in Kampala purchasing tailoring products over a three days period (the length of the transaction data), assuming consumption is uniformly distributed over the year. The corresponding number at the parish level was then calculated by multiplying this share by the number of households per parish from 2014 Ugandan Population Census.

For retail customers, total number of customers was constructed combining data from the 2010 Ugandan Census of Business Establishments and the customer survey. Data from the latter shows that on average retail customers purchase products from a firm every 3.5 days. I therefore considered the total number of retailers as the pool of customers. I considered retail customers all firms operating in one of the following sectors: wholesale of textiles, clothing and footwear (ISIC 4641), retail sale of clothing, footwear and leather articles in specialized stores (ISIC 4771) and retail sale via stalls and markets of textiles, clothing and footwear (ISIC 4782). I used the 2010 Census, which includes geo-localized data, to compute the number of firms in these sectors operating in each parish.

# Appendix E: Mystery shoppers material

## E1 Mystery shoppers script

*"Hi, I am looking for someone who can sew for me a short dress for my niece who is 13 years old girl. I got your contact from a friend who recommended you, and so I would like you to make the dress. Specifically, I would like you to reproduce this dress."*

- Show the picture of the garment to be replicated to the tailor.

*"As you can see, the dress has a gathered skirt, a baby collar and puff sleeves finished with elastics. On the back, it should have a long zip, not buttons. I bought some fabric that I would like you to use for this dress."*

- Show the fabric to be used to the garment.

*"Would you be able to do it? These are the measurements for the dress."*

- Show the measurements to the respondent. Do not leave them with him/her.

*"I am going to travel to Soroti in 3 days, and I would need the dress by then, so I can bring it with me. I will leave at [time at which you placed the order]. Would you be able to make it by then?"*

If not: *"Why not? When would be the earliest you can make it?"*

- Accept the time frame given by the respondent as long as it is within the next 2 weeks.

*"At what price would you be willing to sew this dress for me?"*

- Reduce the price by 20%. If the reduced price is above 30,000UgSh, say that 30,000UgSh is the maximum you can offer.

*"Would you be willing to sew it for me for [rounded price]?"*

- Accept whatever price is then given by the respondent, as long as it is below or equal to 30,000UgSh. If not, thank the respondent and leave without buying anything.

*"How much should I give you as a deposit?"*

- Agree to deposit up to 50% of the price if the respondent insists.

*"Can I please have a receipt, so that I can remember how much the balance is? Ok, then I will come and collect it on [earliest day available]. If you happen to finish the dress before, please give me a call at this number [phone number]"*

- Give your phone number to the respondent. Leave the fabric and thank him/her. End of the exercise.

**Figure A.E1: Product commissioned by mystery shoppers**

Photo credit: Mariajose Silva Vargas

## E2 Quality scoring sheet

| BUSINESS ID: | | | | |
|---|---|---|---|---|
| | ASSESMENT CRITERIA | SCORING GUIDE | MAX SCORE | SCORE |
| 1 | DARTS | Dart of 4 ”long by 1”wide | 3 | |
| | | Correctly sewn | 3 | |
| | | Press to the right side | 2 | |
| | | Position of the Dart observed | 2 | |
| 2 | COLLAR | Peter Pan/Baby Collar | 5 | |
| | | Fixed correctly round the neckline | 5 | |
| 3 | SLEEVES | Sleeved Well Gathered | 3 | |
| | | Sleeve Length 8” | 2 | |
| | | Round sleeve 14” | 2 | |
| | | Correctly fixed on Bodice | 3 | |
| 4 | SKIRT | Skirt length 18” | 2 | |
| | | Skirt Equally Gathered | 2 | |
| | | Neatly fixed to Bodice | 2 | |
| | | Correct Seam Allowance | 2 | |
| | | Skirt bottom shaped round | 2 | |
| 5 | ZIP | Zip attached to Centre back seam | 4 | |
| | | Right color of Zip | 3 | |
| | | Right length of Zip | 3 | |
| 6 | SEAM | Right Seam Allowance “Y2-1” | 3 | |
| | | Correctly Pressed | 3 | |
| | | Neatly Finished Edges | 4 | |
| 7 | HEM | Hemmed bottom of Dress | 2 | |
| | | Hem lin-2ins | 1 | |
| | | Hem Neatly sewn | 3 | |
| | | Hem well pressed | 4 | |
| 8 | MEASUREMENTS | Cross Back 15” | 2 | |
| | | Bust - 34” | 2 | |
| | | Waist – 28” | 2 | |
| | | Top to Waist –14” | 2 | |
| | | Full Length – 32” | 2 | |
| 9 | FINISHING | No hanging threads seen | 3 | |
| | | Dress Pressed with no wrinkles seen | 3 | |
| | | No chalk marks | 2 | |
| | | Dress clean | 2 | |
| 10 | PACKAGING | Dress Neatly and Correctly Folded | 5 | |
| | | Packed in Bag | 3 | |
| | | Branded Packaging | 2 | |

# Appendix F: Robustness

## F1 Endogenous prices

To ensure that estimates of price elasticity are not biased by endogeneity, I re-estimate demand using instrumental variables for prices to identify the price coefficient $\alpha$. Given estimates of $\{\sigma, \theta, \tau_1, \tau_2\}$, I can solve for the vector of mean utilities $\delta_{jl}^q$ that matches observed and predicted market shares from the model. Berry (1994) proves that, for discrete choice models satisfying standard regularity conditions, such vector exists.

Mean utilities take the following form: $\delta_{jl}^q = \beta \mathbf{x}_j - \alpha p_{jl} q^{1-\theta} + \xi_j$. Because prices might be endogenous, I instrument for them using (i) a cost-shifter: the average price paid by the firm for one meter of fabric; (ii) a BPL instrument - the share of high-quality firms in the same location (excluding the firm itself). I use transaction prices as output and control for product type fixed effects. The first and second stage of the IV estimation are shown in Table A.F1.

**Table A.F1: Estimate of price coefficient allowing for endogeneity**

| | (1)<br>Transaction price | (2)<br>Delta |
|---|---|---|
| **Panel A: First Stage** | | |
| Cost of fabric (1 meter) | 0.647*** | |
| | (0.192) | |
| Share high-quality firms | 8.383*** | |
| | (2.450) | |
| **Panel B: Second Stage** | | |
| Transaction price | | -0.092** |
| | | (0.038) |
| Product FEs | ✓ | ✓ |
| Number of Observations | 608 | 608 |

**Notes**: Robust standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

In the first stage, the instruments are strong predictors of prices. Contrary to what one would expect from a standard demand model, but consistent with the presence of demand-side externalities in my setting, the share of high-quality firms in the same location has a positive impact on prices. In the second stage, $\alpha$ is equal to $-0.092$, which falls within the confidence interval of the estimated coefficient in the baseline estimation.

## F2 Alternative location definition

I test the robustness of the demand and supply parameters to an alternative definition of locations in the model. In the baseline scenario, a location corresponds to a parish, with the exception of the three parishes in the core - Kisenyi I, Kisenyi II and Nakasero IV - which are considered one location. I re-estimate the model allowing for the three central parishes to be separate locations. The results are presented in Table A.F2 below. The parameters are similar to those in the baseline estimation with one location in the core.

**Table A.F2: Estimated coefficients with separate central parishes**

| | **Parameter** | **Estimate** |
|---|---|---|
| **PANEL A: Demand** | | |
| Price (USD) | $\alpha$ | -0.054 |
| Quality final customers | $\beta_f$ | 0.083 |
| Quality retail customers | $\beta_r$ | 0.761 |
| Taste shocks correlation | $\sigma$ | 0.499 |
| Quantity multiplier | $\theta$ | 0.382 |
| Travel cost | $\tau_1$ | -0.134 |
| Within location search cost | $\tau_2$ | -0.0002 |
| | | |
| **PANEL B: Supply** | | |
| Labor share | $\delta$ | 0.693 |
| Outsourcing cost | T | -1.230 |
| Productivity Core | $A_{core}$ | 16.530 |
| Productivity Periphery (mean) | $A_{per}$ | 13.695 |

## F3 Allowing for dynamics

To model presented in Section 4 is static. Although this is partly justified by the persistence of firm-customer relationships and firm location choices in the data, I conduct a robustness check to test the plausibility of this assumption by adding a second period to the model. In the first period, consumers do not observe any of the match-specific shocks $\varepsilon$ and decide what firms to buy products from as described in Section 4.2. However, upon visiting a location, consumers observe the $\varepsilon$-shocks for all firms operating in the selected location. Hence, in a second period, consumers would have to decide whether to go back to the same location (in which case they would buy from the same firm, as it would still be yielding the highest utility), or visit a different location.

Let $l^{(1)}$ and $j^{(1)}$ be the location and the firm chosen in the first period. In the second period, consumers will choose the location yields the highest expected utility:

$$l^{(2)} = \arg\max_{k \in L} \{u^q_{il^{(1)}j^{(1)}}, \max_{k \neq l^{(1)}} V^q_{ik}\} \tag{A.25}$$

where $V^q_{ik}$ is given by equation (3). I simulate a second period using the estimated parameter and compute the share of customers who would choose to search a different location. I find that only 17% of customers would switch to a different location in a subsequent period, while 83% would go back to the initial firm. This suggests that a static model captures the core of the consumer search process and hence of firm choice of location.

# Appendix G: Model extension with entry

In this section I present an extension to the model that allows for firm entry and exit. Let $E$ be the number of potential entrants, which is finite and known to all firms, and let $J$ be the corresponding number of firms actually entering the market. Potential entrants simultaneously choose whether to enter the market and in which location to place the firm. I assume that firms observe their type (high or low-quality) prior to making the entry decision. To enter, firms must pay an entry cost $EC_j$. If they decide not to enter the market, they make zero profits. Firms' total profits are given by the following expression:

$$\Pi_{jl}(\mathbf{L},\mathbf{p}) = \pi_{jl}(\mathbf{L},\mathbf{p}) - \tau_3 g(||z_j - z_l||) - e_{jl} - EC_j \tag{A.26}$$

In equilibrium, each entrant expects to earn non-negative profits. Given the assumption on the unobserved preference shock $e_{jl}$, one can follow the same steps outlined in Section 4.4 to derive the probability of a firm entering the market:

$$Pr_j(Entry|\boldsymbol{P}^*) = \frac{\sum_{l=0}^{N} \exp\left( \sum_{\boldsymbol{l}_{-j}} \left( \pi_{jl}(l_j, \boldsymbol{l}_{-j}) \prod_{h\neq j} P^*_h(l_h) E(Pr_h(Entry)|\boldsymbol{P}^*) - \tau_3 g(||z_j - z_l||) - EC_j \right)/\mu \right)}{1 + \sum_{k=0}^{N} \exp\left( \sum_{\boldsymbol{l}_{-j}} \left( \pi_{jk}(k_j, \boldsymbol{l}_{-j}) \prod_{h\neq j} P^*_h(l_h) E(Pr_h(Entry)|\boldsymbol{P}^*) - \tau_3 g(||z_j - z_k||) - EC_j \right)/\mu \right)} \tag{A.27}$$

where the term at the numerator is a weighted average of firms' expected profits across all locations[53]. Notice that the expected number of entrants depends on conjectured firm

[53] Notice that when firms are heterogeneous, entry probability does not only depend on the total number of entrants, but also on their identity.

location in equilibrium, which in turn depends on the expected number of entrants. To solve for both entry and location, one should solve for the augmented system of equations (19) and (A.26) for all potential entrants. This is beyond the scope of this paper.

## G1 Estimation of entry costs

Under the assumption that the expected number of entrants is exactly equal to the number of entrants in the data, it is possible to recover firms' entry costs following the approach outlined in Seim (2006). In the model, firms are only heterogeneous in quality and the location where the owner resides. Let $E_{ot}$ be the potential number of owners of type $t = \{H, L\}$ from location $o = \{1, ..., L\}$. The number of actual entrants is given by $J_{ot} = Pr_{ot}(Entry|\boldsymbol{P}^*) \times E_{ot}$, where the probability of entry is given by expression (A.26), conditional on the number of entrants observed in the data. To recover entry costs, one must know the number of potential entrants from each location. I assume that this number is equal to 0.1% of the population and that there is an equal share of low and high-quality type owners in each location (i.e. each parish). Given the conditional choice probabilities associated with firms' equilibrium strategies $\mathbf{P}^*$, which is estimated in the baseline model, it is possible to solve the pair of equations (19) and (A.26) to obtain entry costs. First, notice that entry costs can be expressed as:

$$-\frac{EC_{ot}}{\mu} = \log Pr_{ot}(Entry|\boldsymbol{P}^*, J) - \log(1 - Pr_{ot}(Entry|\boldsymbol{P}^*, J))$$
$$- \log\left[\sum_{k=0}^{N} \exp\left(\left(\sum_{\boldsymbol{l}_{-j}} \pi_{tk}(k_t, \boldsymbol{l}_{-j}, J) \prod_{h \neq j} P_h^*(l_h) - \tau_3 g(||z_o - z_k||)\right)/\mu\right)\right] \tag{A.28}$$

The logarithm of the probability of entry can be re-written as: $\log Pr_{ot}(Entry|\boldsymbol{P}^*, J) = \log J_{ot} - \log E_{ot}$. Plugging this expression into (A.27), I obtain:

$$-EC_{ot} = \mu \times \Bigg\{ \log J_{ot} - \log(E_{ot} - J_{ot})$$
$$- \log\left[\sum_{k=0}^{N} \exp\left(\left(\sum_{\boldsymbol{l}_{-j}} \pi_{tk}(t_j, \boldsymbol{l}_{-j}, J) \prod_{h \neq j} P_h^*(l_h) - \tau_3 g(||z_o - z_k||)\right)/\mu\right)\right]\Bigg\} \tag{A.29}$$

Given the estimated parameters, the number of potential and actual entrants and $\mathbf{P}^*$, entry costs can be directly calculated from (A.28). I estimate average entry costs for low-quality and high-quality firms to $-272.76$ and $-557.50$ respectively. I use entry costs to calculate the share of firms that, *at the current number of firms in the market*, would be making negative profits and hence be better off exiting in the counterfactual scenarios. This is simply given by $(1 - Pr_{ot}(Entry|\boldsymbol{P}^*, J))$.