Flood Risk and Differential Firm Investment: Evidence from Dakar, Senegal*

Molly J. Doruska†

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Abstract

In many urban communities, insufficient drainage, and minimal urban planning means that seasonal rainfall brings with it the risk of regular flooding of homes and businesses. Persistent flooding poses a multitude of challenges for businesses in these areas as it can destroy inventory, limit movement of workers and customers, and overall decrease firm performance. Changing rainfall patterns due to anthropogenic climate change heightens the need to better understand the currently underexplored impacts of seasonal flooding, particularly on small firms. My work seeks to understand the impact of seasonal flooding on small firm performance and investment in urban Dakar, Senegal by collecting detailed firm-level data on investment, inventory, worker behavior, consumer behavior and flood risk perception, community data on infrastructure and drainage characteristics. I will then run a randomized experiment to understand the impacts of flood adaptation strategies and to identify local spillover effects of flood adaptation. With parameters estimated from the data and the experiment, I will develop a model of investment by firms to explore barriers to adaptation and defensive investment. I will use this model to highlight risks of anthropogenic climate change and potential policy interventions to decrease the impact of seasonal flooding.

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†Charles H. Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY, USA. mjd438@cornell.edu

1 Introduction

In many newly developed urban communities in low- and middle-income countries, the start of the rainy season is not a welcome relief, but instead a source of persistent problems. Heavy rainfall, coupled with insufficient drainage and minimal urban planning results in regular, seasonal flooding of homes and businesses (Rentschler et al. (2023)). In urban and suburban Dakar, rising floodwaters pose a multitude of challenges for people living in these areas by trapping people in their homes, increasing the risk of many diseases, and even causing death (C40 CFF (2021)). Yet, hundreds of millions of individuals live and work in these flood-prone areas. For many, the thought of living with a constant risk of floods for three months out of the year would be daunting, but economic forces drive people to continue to live in and move to these areas. This study will explore the impacts of flooding, flood risk, and potential adaptation mechanisms to flooding to better understand the yearly economic puzzle of life in these flood-prone areas.

I propose detailed data collection of firms across neighborhoods with varying levels of flood risk in the Dakar region. Existing data sources on households and enterprises in Senegal only contain a small number of firms that are relatively spread out within the urban Dakar region. However, flood risk can change firm-by-firm and block-by-block, so to best understand the impact of urban flooding and unpack how firms adapt to the every-day disaster risk of rainy season flooding, the spatial resolution of the data must be much smaller than existing data products. My data collection methods will allow me to compare flood risk and adaptation to flooding using methods that fit with the spatial nature of the problem.

I will supplement my data collection effort with a randomized experiment designed to reduce barriers to adaptation and understand the local spillover effects of firm adaptation strategies. I will randomly assign groups of nearby firms to the control or one of two treatment arms. In the first treatment arm, firms will individually choose to receive vouchers for two bags of cement or two wooden pallets. In the other treatment arm, I will gather a group of five nearby firm owners together and they will collectively decide on vouchers from the same set of possible adaptation strategies. The combined value of the vouchers will be the same across both treatment arms. By randomly varying individual versus collective adaptation strategies, I will be able to identify local spillover effects.

My data collection efforts and randomized experiment are designed to answer six research questions. I will use the data to establish stylized facts about the current equilibrium of firms and their flood risk exposure. Then, I will develop a model of investment by firms to explore barriers to investments to reduce flood damages. The randomized experiment will allow me to directly identify key parameters in the model.

The specific research questions are:

1. How does regular, seasonal flooding affect customer behavior, input supply, worker behavior and firm performance?
2. How do firms perceive their own flood risk and how does this compare to objective measures of flood risk based on elevation and land use like those from European Space Agency (2019)?
3. How do firms currently prepare for and adapt to regular, seasonal flood risk?
4. What limits adaptation and investment like raising inventory off the ground, building the floor higher up, or using pumps or barriers to reduce floodwaters in the face of regular, seasonal flooding?
5. What are the impacts of lowering the costs of flood adaptation technologies on input supply, worker behavior, and firm operations?
6. What are the spillover effects of uncoordinated flood adaptation and investment by firms on their neighbors?
7. What policies could decrease flood risk and decrease potential firm losses?

While the setting of this study is Dakar, Senegal, the challenge of urban flooding brought on by intense rains is not unique to Dakar or even low- and middle-income country settings. Large portions of the United States increasing feel the impacts of urban flooding caused by heavy rainfall or storm surges made worse by continual land development, which creates more impervious surfaces, and insufficient storm water systems (National Academies of Sciences (2019)). The impact of urban flooding, particularly on the distribution of people within a city, is particularly relevant to New Orleans and Houston after both cities suffered significant flooding damage from hurricanes (Davlasheridze and Fan (2017); Vigdor (2008); Zhang et al. (2018)). Anthropogenic climate change likely will increase extreme weather events that produce heavy rainfall that leads to urban flooding and is currently changing the water cycle leading to changes in rainfall patterns worldwide (Caretta et al. (2022)). Therefore, understanding the impacts of flooding and how we can mitigate these impacts is increasingly important for cities across the globe.

Previous research on the impacts of flooding looks at large-scale flooding events (Balboni et al. (2024); Dasgupta et al. (2011); Desmet et al. (2021); Chen et al. (2017); Gandhi et al. (2022); Jia et al. (2022); Kocornik-Mina et al. (2020); Rentschler et al. (2021); Sajid and Bevis (2021)), or extreme climate shocks that are rare (although they are becoming more common with climate change) and in the tails of the distribution of climate shocks. My research instead focuses on "everyday disasters" or the impacts of flooding that results from the average, predictable pattern of seasonal rainfall. Therefore, my research considers a fundamentally different kind of shock that has a higher likelihood of occurring but often results in more localized impacts than the previous work focused on larger, but rarer, flooding events. This project will provide evidence on how small to moderate shocks result in adaptation and influence the current distribution of firms across space, giving insight into how individuals may respond to future continual, small shifts in rainfall associated with climate change.

Because average seasonal rainfall is predictable, even if the exact timing and volume are unknown, the impact of seasonal flooding is part of the current equilibrium of firm locations and economic activity. Like other studies (Desmet et al. (2021); Brooks and Donovan (2020); Gandhi et al. (2022); Leeffers (2023); Pavel et al. (2019)), I will consider differential investment and adaptation to flooding. However, I study higher probability but more localized flooding events. I will study observed patterns of flood risk, adaptation, and investment through the lens of a structural model that yields equilibrium behaviors that vary based on the wealth of households and their perception of flooding risk in their location. With a deeper understanding of differential investment and impacts, I can better probe constraints to climate change adaptation and investment since these constraints directly impact the observed economically optimal decisions by firms.

I also build on the literature that focuses on firm adaptation to climate shocks (Balboni et al. (2024); Gandhi et al. (2022); Hsiao (2023); Jia et al. (2022); Rentschler et al. (2021); Patel (2024)) Gandhi et al. (2022) and Hsiao (2023) consider the aggregate impacts and adaptation for cities, while we look at the individual firm level like Rentschler et al. (2021),Jia et al. (2022),Balboni et al. (2024), and Patel (2024). However, unlike Jia et al. (2022), I focus on a low-income country setting with less developed flood risk assessment and insurance products. Both Rentschler et al. (2021) and Balboni et al. (2024) focus on supply chain responses to firms after flooding events. I expand ideas development by Patel (2024) within agricultural systems to urban firms. My data collection efforts focus on firm investments before flooding to reduce impacts and thus I study a different part of firm adaptation strategies. My work also builds on Brooks and Donovan (2020) who highlight the market impacts of building bridges to reduce flood damage in Nicaragua and Leeffers (2023) who demonstrates that information can induce individual action to reduce flood risk. Overall, this project will provide evidence on how small to moderate shocks result in adaptation and influence the current distribution of firms across space, giving insight into businesses may respond to future continual, small shifts in rainfall associated with climate change.

Finally, my theoretical framework and estimation strategy incorporate the equilibrium decision making and externalities of firms unlike previous studies that focus on larger, rare disasters that do not influence the current equilibrium or capture externalities in the same way. For example, when firms add pavement or barriers, they increase impervious surfaces. Adding impervious surfaces reduces water drainage in these areas and creates increased risk of flooding for others without additional investments by neighboring firms or the community in stormwater sewer systems or other drainage infrastructure. Thus, nearby firms now face higher flood risk which could potentially change their adaptation and investment strategy as they respond to increased flood risk caused by the actions of other firms around them. My research setting is uniquely suited to better investigate and understand differential investment in response to natural disasters and climate change.

2 Firm Model

I begin by describing the choices made by an individual firm playing a non-cooperative, single shot game. I will then describe how the game changes when a neighborhood of firms cooperates and determines their flood mitigation choices together. Finally, I will consider different variants of the game where there is mutual insurance against flood loss in the neighborhood or firms punish their neighbors for increasing the flood risk of others.

I consider small, price-taking firms. There are two states of the world: rain causes a flood for the firm with probability r_{in} and no rain that causes flood for the firm with probability $(1 - r_{in})$. A firm's flood risk is the composite of the neighborhood flood risk r_n and their individual flood risk r_i. The neighborhood flood risk r_n is between 0 and 1. The individual flood risk component r_i is an adjustment to the neighborhood flood risk that depends on unique characteristics of the firm, like being on a small ridge or at the bottom of a hill, and any adoption of barriers (b) in by the firm or other firms in the neighborhood. Individual flood risk $r_i(b)$ is bounded such that $r_{in}(b) \in [0, 1]$. Note that the choice of barriers b is part of a broader choice of adaptation measures M. For simplification, I assume firms earn revenue that depends on the flooding. The choice of mitigation strategy affects expected firm revenue.

Firms invest in flood mitigation technologies prior to the rainy season and then realize the results of rainy season flooding. Each firm chooses whether or not to use one, both or neither of two mitigation technologies M: shelving (s) to raise merchandise above prospective flood waters, a barrier (b) to keep flood waters out of the store, both (bs), or neither. Each mitigation technology has a direct cost but mitigates flood-related damages. Shelving costs c_s and a barrier costs c_b where $c_b > c_s$.

In the case of a flood, firm i faces damage D_i which is a function of their mitigation choice M_i and their neighbor's mitigation choices $\mathbf{M}_{-i}$. Barriers are the only choice that matters for other firm flood damage, so I simplify notation to consider the vector $\mathbf{b}_{-i}$ which is a vector of the mitigation technology choices of all firms in the neighborhood of i that are not firm i. Denote the damage of a flood to the firm with the function $D_i(M_i, \mathbf{M}_{-i})$.

Isolating the impact of the firm's choice of mitigation technology on flood damage, if a firm chooses to do nothing, they face damage $D_i(0, .)$. If a firm chooses shelving as their only mitigation choice set, they face damage $D_i(S, .)$ and the firm faces damage $D_i(B, .)$ if they choose a barrier as their only mitigation choice. If a firm chooses both shelving and a barrier, they face damage $D_i(BS, .)$. Damage is greater if the firm does nothing and decreases with the cost of the technology:

$$D_i(0, .) > D_i(S, .) > D_i(B, .) > D_i(BS, .) \tag{1}$$

The choice of mitigation technology also impacts firm revenue in both the flooded and non-flooded state with

$$\frac{dRevenue}{dM}|state = flood > \frac{dRevenue}{dM}|state = notflood \tag{2}$$

With a slight abuse of notation, denote $\frac{dRevenue}{dM}|state = flood$ as $\frac{dRevenue_f}{dM}$ and $\frac{dRevenue}{dM}|state = notflood$ as $\frac{dRevenue_{nf}}{dM}$.

A firm's flood damage also depends on the choice of their neighbors. Investing in a shelf only decreases a firm's flood damage and does not impact the flood damage of its neighbors. If a firm chooses a barrier, the flood damage to their neighbors increases because the barrier diverts water away from the firm and towards neighboring firms. Let $\mathbf{b}_{-i}$ denote the number of neighboring firms that invest in a barrier. The flood damage of firm i, $D(., \mathbf{M}_{-i})$ increases as $\mathbf{b}_{-i}$ increases and is unchanged by neighboring firms building shelving or doing nothing. Firms can observe barriers outside of other firms and thus form expectations of other firm's behaviors.

When there is not a flood, the firm's profit function is:

$$\pi_{nf} = Revenue_{nf}(M_i) - Cost(M_i) \tag{3}$$

since $D_i(M_i, \mathbf{M}_{-i})$ equals zero without a flood.

When there is a flood, the firm's profit function is:

$$\pi_f = Revenue_f(M_i) - Cost(M_i) - D_i(M_i, \mathbf{M}_{-i}) \tag{4}$$

The firm maximizes expected profits:

$$\max_{M_i} E[r_{in}(M_i, E[\mathbf{M}_{-i}])][Revenue_f(M_i) - Cost(M_i) - D_i(M_i, E[\mathbf{M}_{-i}])] \\ + E[(1 - r_{in}(M_i, E[\mathbf{M}_{-i}])][Revenue_{nf}(M_i) - Cost(M_i)] \quad (5)$$

The first order condition to the firm i's profit maximization problem that defines firm i's best response function is:

$$E[r_{in}(M_i, E[\mathbf{M}_{-i}])](\frac{dRevenue_f}{dM_i} - \frac{dCost}{dM_i} - \frac{dD_i}{dM_i}) + \frac{\partial E[r_{in}]}{\partial M_i}([Revenue_f(M_i) - Cost(M_i) - D_i(M_i, E[\mathbf{M}_{-i}])]) \\ + E[(1 - r_{in}(M_i, E[\mathbf{M}_{-i}])](\frac{dRevenue_{nf}}{dM_i} - \frac{dCost}{dM_i}) + \frac{\partial E[(1 - r_{in})]}{\partial M_i}[Revenue_{nf}(M_i) - Cost(M_i)] = 0 \quad (6)$$

where I supress arguments in the expected flood risk function for notational ease.

I can rewrite this equation to

$$E[r_{in}]\frac{dRevenue_f}{dM_i} + E[(1 - r_{in})]\frac{dRevenue_{nf}}{dM_i} + \frac{\partial E[r_{in}]}{\partial M_i}Revenue_f(M_i) + \frac{\partial E[(1 - r_{in})]}{\partial M_i}Revenue_{nf}(M_i) = \\ \frac{\partial Cost}{\partial M_i} + E[r_{in}]\frac{\partial D_i}{\partial M_i} + \frac{\partial E[r_{in}]}{\partial M_i}(Cost(M_i) - D_i(M_i, E[\mathbf{M}_{-i}])]) + \frac{\partial E[(1 - r_{in})]}{\partial M_i}Cost(M_i) \quad (7)$$

which shows that firms equate the expected marginal benefits of a mitigation strategy with the expected marginal costs where the marginal costs include the marginal costs of the strategy and the marginal damages from flooding. This equation governs the firm's decision in a non-cooperative one-shot game.

If, however, the firm is instead making a joint decision with the other firms in its neighborhood, I can specify their decision as one that maximizes the joint profits of all firms. For a neighborhood of firms $i = 1, ..., I$, the firms solve the maximization problem:

$$\max_{M_1,...,M_I} \sum_{i=1}^{I} E[r_{in}(M_i, \mathbf{M}_{-i})][Revenue_f(M_i) - Cost(M_i) - D_i(M_i, \mathbf{M}_{-i})] \\ + E[(1 - r_{in}(M_i, \mathbf{M}_{-i}))][Revenue_{nf}(M_i) - Cost(M_i)] \quad (8)$$

The first order condition for firm 1's mitigation strategy choice to describe is:

$$E[r_{in}](\frac{dRevenue_f}{dM_1} - \frac{\partial Cost}{\partial M_1} - \frac{\partial D_1}{\partial M_1})\frac{\partial E[r_{in}]}{\partial M_1}([Revenue_f(M_1) - Cost(M_1) - D_1(M_1, \mathbf{M}_{-1})])$$
$$+E[(1-r_{in})](\frac{dRevenue_{nf}}{dM_1} - \frac{\partial Cost}{\partial M_1}) + \frac{\partial E[(1-r_{in})]}{\partial M_1}[Revenue_{nf}(M_1) - Cost(M_1)] - E[r_{in}]\sum_{i=2}^{I}\frac{\partial D_i}{\partial M_1} = 0 \tag{9}$$

I can rewrite this equation as

$$E[r_{in}]\frac{dRevenue_f}{dM_1} + E[(1-r_{in})]\frac{dRevenue_{nf}}{dM_1} + \frac{\partial E[r_{in}]}{\partial M_1}Revenue_f(M_1) + \frac{\partial E[(1-r_{in})]}{\partial M_1}Revenue_{nf}(M_1) =$$
$$\frac{\partial Cost}{\partial M_1} + E[r_{in}]\frac{\partial D_1}{\partial M_1} + \frac{\partial E[r_{in}]}{\partial M_1}(Cost(M_1) - D_1(M_1, \mathbf{M}_{-1})]) + \frac{\partial E[(1-r_{in})]}{\partial M_1}Cost(M_1) + E[r_{in}]\sum_{i=2}^{I}\frac{\partial D_i}{\partial M_1} \tag{10}$$

In the cooperative framework, each firm also considers how their choice of mitigation strategy potentially increases flood damages of neighboring firms. This last term in equation (10) represents the externality, the additional effect of a barriers on other firms in the neighborhood.

Alternatively, since firms are not anonymous to other firms in their neighborhood and barriers are observable, firms could instead play a dynamic game with mutual insurance similar to the village economies in Townsend (1994). In this setting, firms maximize profits over time. Suppose there is an initial date $t = 0$ with a future end date T. Let β denote the discount rate on time. With a social planner's utility weights for firm's λ_i where $0 < \lambda_i < 1$ and $\sum_i \lambda_i = 1$, then the firm's maximization problem is:

$$\max_{M_{it}} \sum_{i=1}^{I} \lambda_i \sum_{t=0}^{T} \beta^t E[r_{int}(M_{it}, \mathbf{M}_{-it})][Revenue_f(M_{it}) - Cost(M_{it}) - D_i(M_{it}, E[\mathbf{M}_{-it}])]$$
$$+ E[(1 - r_{int}(M_{it}, \mathbf{M}_{-it}))][Revenue_{nf}(M_i) - Cost(M_{it})] \tag{11}$$

The first order condition for firm 1's mitigation strategy choice in time t is:

$$\lambda_1\beta^t E[r_{int}](\frac{dRevenue_f}{dM_1}-\frac{\partial Cost}{\partial M_1}-\frac{\partial D_1}{\partial M_1})+\lambda_1\beta^t\frac{\partial E[r_{in}]}{\partial M_1}([Revenue_f(M_1)-Cost(M_1)-D_1(M_1,\mathbf{M}_{-1})])$$
$$+\lambda_1\beta^t E[(1-r_{int})](\frac{dRevenue_{nf}}{dM_1}-\frac{\partial Cost}{\partial M_1})+\lambda_1\beta^t\frac{\partial E[(1-r_{in})]}{\partial M_1}[Revenue_{nf}(M_1)-Cost(M_1)]$$
$$-\sum_{i=2}^{I}\lambda_i\beta^t E[r_{int}]\frac{\partial D_i}{\partial M_{1t}}=0 \quad (12)$$

After dividing by $\lambda_1\beta^t$, I can rewrite this equation as

$$E[r_{int}]\frac{dRevenue_f}{dM_{1t}}+E[(1-r_{int})]\frac{dRevenue_{nf}}{dM_{1t}}+\frac{\partial E[r_{in}]}{\partial M_1}Revenue_f(M_1)+\frac{\partial E[(1-r_{in})]}{\partial M_1}Revenue_{nf}(M_1)=$$
$$\frac{\partial Cost}{\partial M_{1t}}+E[r_{int}]\frac{\partial D_1}{\partial M_{1t}}+\frac{\partial E[r_{in}]}{\partial M_1}(Cost(M_1)-D_1(M_1,\mathbf{M}_{-1})])+\frac{\partial E[(1-r_{in})]}{\partial M_1}Cost(M_1)$$
$$+\frac{\sum_{i=2}^{I}\lambda_i}{\lambda_1}E[r_{int}]\sum_{i=2}^{I}\frac{\partial D_i}{\partial M_{1t}} \quad (13)$$

Like the cooperative framework, each firm also considers how their choice of mitigation strategy potentially increases flood damages of neighboring firms. The difference comes in how these weights determine that risk is shared throughout the neighborhood over time.

Finally, firms could instead punish other firms for erecting barriers and causing harm to other neighbors in a penal code framework similar to Abreu (1988). In this case, there would be additional costs to barriers raising the likelihood that firms elect to build shelves or do nothing as opposed to building barriers. Increasing costs of barriers would be an alternative way to internalize the externality without relying on cooperation among firm owners.

3 Data and Experimental Design

3.1 Primary cross-sectional data collection

I will conduct a firm survey in June and July 2024 that collects detailed data on inventory, customer traffic, worker attendance, and investment in flood mitigation technologies like raising up shelving units or drainage systems. I will interview the business owner to best capture data on individuals making investment and business decisions. I will record detailed geolocation data of households and neighborhood to best utilize spatial data analysis techniques.

I also will collect data on flood experience and perceptions of flood risk to document how measured flood risk compares to experiences and perceptions of firms operating in these areas. I will specifically ask about the firm's experience with flooding during the past rainy season, their expectations for the upcoming rainy season, and their experience in the past rainy season and expectations for the future rainy season with flooding in the neighborhood they live in. Collecting data on both the firm and the neighborhood will allow me to identify potential differences in perceptions and impacts of varying flood experiences. To better understand how experience informs current perceptions, I will collect data on when the firm opened at its current location.

I will also collect information on any infrastructure, investment, and adaptation the firm themselves undertook to reduce their own flooding risk by both reducing the probability of suffering any loss or mitigating losses when flooding occurs. I will also document and collect data about the condition of the neighborhood and any infrastructure or public investment in the neighborhood that mitigates or worsens flooding. A comparison of the two will help me better understand flood risk, perception, and effective adaptation and mitigation measures.

3.2 Data on flood risk in Dakar

I collected data on flood risk starting with an assessment of flood risk in Dakar by European Space Agency (2019). I map the European Space Agency's data on the extent of flooding, their hazard level (measured on a 0 to 10 scale) to small areas in Dakar, and their classification of neighborhoods into low, medium, or high flood risk. These maps can be found in Figures 1, 2 and 3.

3.3 Experimental Design

Following the baseline cross-sectional data collection described above, I will conduct a clustered randomized experiment designed to reduce barriers to adaptation and understand the local spillover effects of firm adaptation strategies. I will randomly assign groups of firms to the control or one of two treatment arms where firms are offered their choice of vouchers for different flood adaptation strategies. I will use this experimental design to understand the impacts of these flood adaptation strategies, to explore the cost barrier to flood adaptation measures, and to identify the local spillover effects of different flood adaptation strategies.

3.3.1 Treatment arms

Neighborhoods of firms will be allocated to one of two treatment arms or the control. In the first treatment arm, the individual strategy treatment arm, firm owners will be given a choice of vouchers for two bags of cement or two wooden pallets. I give firms the choice of strategy because I anticipate sufficient heterogeneity across firms. Some firms may not have

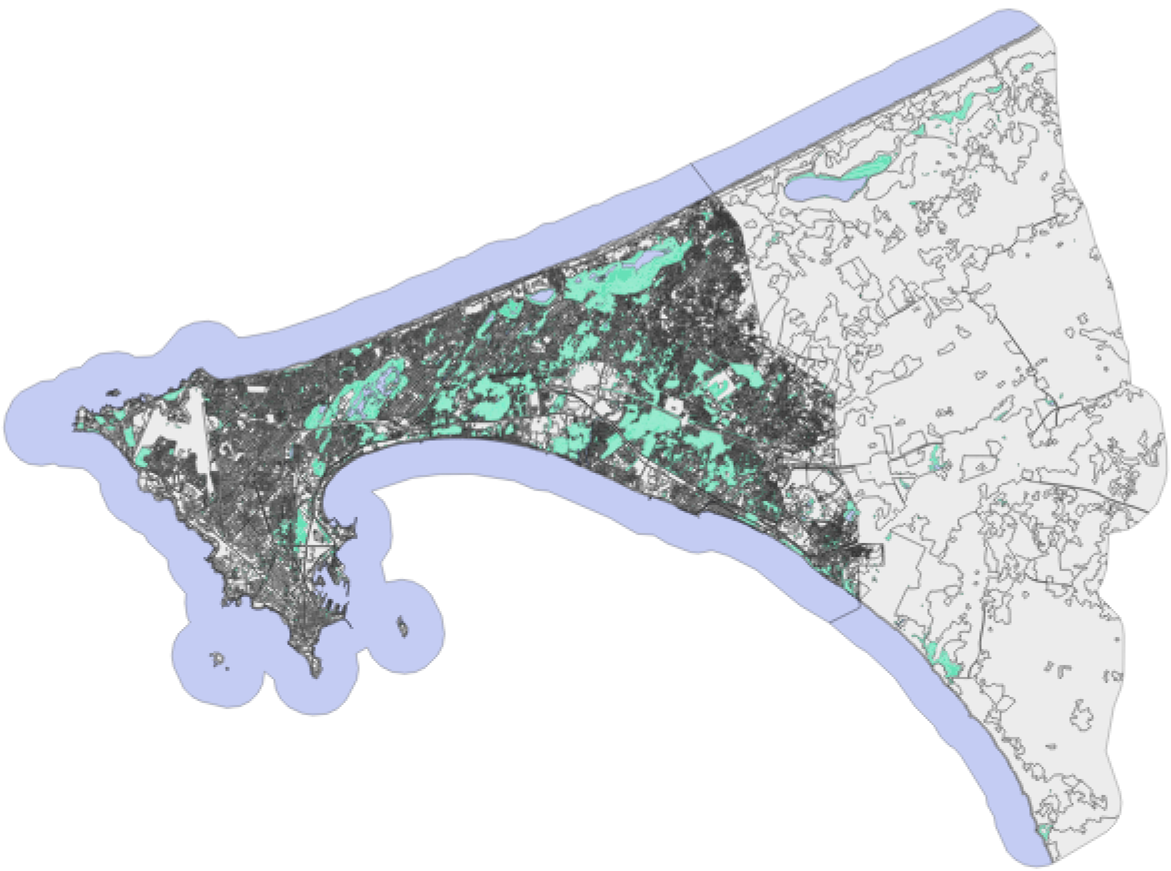

Figure 1. Map of Flooded Areas in Dakar. The bright blue color represents areas that flooded. The blue-gray areas are those that are always water. All other areas are gray. Data from European Space Agency (2019).

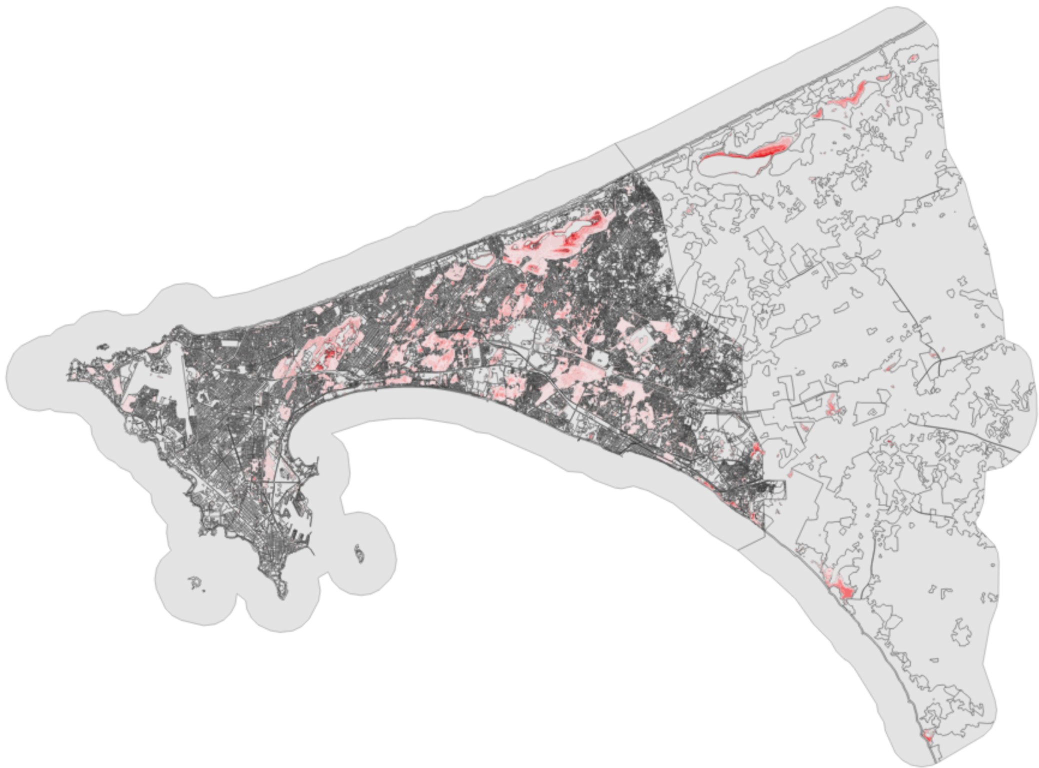

Figure 2. Map of the Hazard Codes in Dakar. Gray areas are those with no hazard codes. Hazard codes represented by shades of red and pink. The darker red colors represent higher hazard levels. Data from European Space Agency (2019).

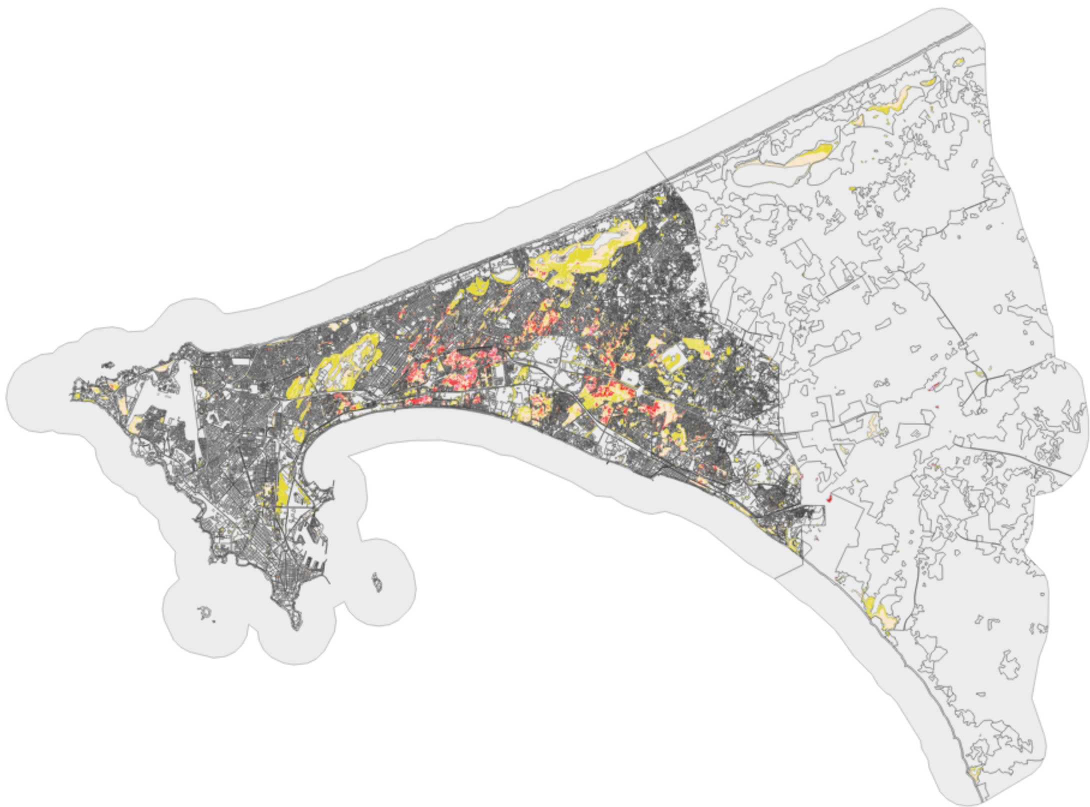

Figure 3. Map of the Hazard Codes in Dakar. Gray areas are those with no hazard codes. Low flood risk areas are yellow. Orange and red represent medium and high flood risk areas. Data from European Space Agency (2019).

space for additional shelving units while other firms may not need or want any sort of barrier outside their store. The menu of options allows firms to choose the strategy that best fits their location and needs.

In the other treatment arms, I will gather all firms in the neighborhood cluster, and they will decide as a group which vouchers they would like to receive. Each firm will still receive the same number of vouchers; however, the choice is at the neighborhood level. While some strategies benefit the firm individually (pallets) other strategies (cement for barriers) may benefit firms across the group differently. The variation in choice at the individual or neighborhood level will allow me to identify the impact of local spillovers.

Firms will make their choices right at the beginning of the rainy season in late July or early August. I will then conduct a short, phone follow-up survey with all firms across all treatment arms in November at the end of the rainy season. This phone survey will collect data on the firm's flood experience during the rainy season including if they had to close, any damages or dips in customers from flooding, and any time employees missed work due to flooding.

3.3.2 Sample selection and power

I will recruit 750 firms to my study. I will allocate 250 firms in local neighborhoods of five to one of the three treatment arms. Included firms must:

1. Have a permanent location where one of the adaption choices menu options could be used;
2. Have between a single owner operator and 10 employees;
3. Be in the retail sector selling food, clothes, and other small consumer goods.
4. Be open at least five days a week in the dry season.

I will stratify the neighborhoods in my sample on flood risk using data from European Space Agency (2019). I will then randomly select the five firms that meet my inclusion criteria in each neighborhood using the right-hand rule. I will sample the owner of the firm and the owner will make the choice in either treatment arm. All firm owners must be at least 18 years old, be in good health, and speak Wolof.

We will recruit 750 firms for the study, 250 firms for each treatment arm. Assuming a standard deviation of 0.3, 0.05 significance level, and 85% power, I estimate a detectable difference of 15% in flood investment strategies based on flood risk with a sample of 44 neighborhoods of five firms or 220 firms in each treatment arm. I base my sample size calculations on data collected by Leeffers (2023) who found an 8-15% increase in cleaning of drainage canals, a flood mitigation strategy.

4 Empirical Strategy

The empirical analysis will contain three main avenues of inquiry. First, I will explore the relationship and impact of flooding on firm performance and investment to establish key stylized facts about the current equilibrium decisions of firms. Then, I will use my experiment to identify key parameters and limits to firm investment. I will calibrate the analytical model of firm investment described in the previous sections to better understand the distributional impacts of seasonal flooding and to probe potential mechanisms that limit a firm's ability to adapt to seasonal flooding using simulations.

4.1 Outcomes

In this section, I describe my outcomes of interest and, where relevant, the key hypotheses for the cross-sectional data analysis and the experiment.

For the experiment, my primary outcomes of interest are:

1. **Choice of Treatment Technology:** I will collect data on what technologies firms choose in each of the two treatment arms. I will also track voucher redemption across treatment arms.

2. **Investment:** I will collect data on firm investment in flood control technologies, including items like shelving and barriers. The experiment directly lowers the cost to firm investment, and thus I hypothesize both treatment arms will increase firm investment in flood mitigation or adaptation technologies as they decrease the costs of these strategies. The treatment arms could also increase information about flood risks and ways to adapt to floods.

My secondary outcomes of interest in the experiment are:

1. **Flood Experience:** I will collect data on firm flood experience over the course of the rainy season. I hypothesize that firms in my treatment arms will experience fewer floods. I predict there will be a strong effect for firms who invest in technologies that protect the entire firm, like barriers. I also predict that treatment firms will experience less monetary flood damage.

2. **Firm Inventory:** I will collect data on how frequently the firm runs out of goods and reasons why the firm cannot stock more of these goods. I will also collect data

on frequently sold items and the number of these frequently sold items the firm has in stock. I hypothesize that the treatment arms, designed to induce flood adaptation strategies, will increase the storage capability of firms and reduce their flood risk, thus increasing their inventory and reducing the frequency at which firms run out of inventory.

3. **Firm operating hours:** I will collect data on firm operating hours and forced closures due to floods. I hypothesize that adaptation technology that protects the outside of the firm and not just the inside of the firm (like a barrier) will decrease the likelihood a firm will have to close and will increase their operating hours.

4. **Customer Traffic:** I will collect data on how many potential customers enter a store and how many sales are made in a typical day. I predict that adaptation technologies that protect the outside of the firm will increase the number of potential customers that enter the store. For adaptation technologies that help the firm maintain inventory (like shelving), I hypothesize that firms will see increased sales as they are better able to stock goods that customers would like to purchase.

5. **Worker attendance:** I will collect data on frequently workers do not attend work. I predict that adaptation technologies that protect the outside of the firm will decrease the number of days employees do not show up.

6. **Firm Revenue and Profits:** I will collect data on monthly firm revenue and profits. If investment decreases flooding, I hypothesize that my treatments will increase monthly firm revenue and profits.

In the cross-sectional data analysis, my outcomes of interest are:

1. **Risk perception:** I will collect data on firm beliefs about flooding. I hypothesize that firms may perceive their flood risk differently than assessed flood risk from remotely sensed products. I hypothesize that firms who report more frequent flooding will also perceive that they are in higher flood-risk areas.

2. **Investment:** Firms in more flood-prone areas are more likely to need these technologies, which increases the likelihood they invest in flood mitigation or adaptation technologies. However, firms in these areas may have less cash on had to invest in these technologies as they repeatedly face loses from flooding. Thus, it is unclear how existing flood risk affects firm investment choices in flood mitigation technologies.

3. **Flood Experience:** Firms in flood-prone areas likely experience more flooding. However, they may also be better adaptive to deal with floods. Thus, I hypothesize that firms in higher risk areas experience more floods but face less monetary damage from flooding.

4. **Firm Inventory:** I hypothesize that firms in more flood-prone areas will have less inventory because flooding could destroy their stock and thus smaller inventories reduces the risk of flood damage. I predict firms in flooded areas run out of items more frequently.

5. **Firm operating hours:** Floods can force firms to close and thus I predict firms in more flood-prone areas will have shorter operating hours.

6. **Customer Traffic:** Flooded areas can be harder to get to, so I hypothesize firms in more flood-prone areas will have fewer potential customers that enter the store and make fewer sales.

7. **Worker attendance:** Flooded areas can be harder to get to, so I hypothesize firms in more flood-prone areas will have more workers not show up to work.

8. **Firm Revenue and Profits:** Firms in more flood prone areas are likley to face fewer customers and more frequent damage. Thus, I hypothesize that these firms will have lower monthly revenue and profits.

4.2 Cross-sectional analysis to establish stylized facts

A firm's location choice, and thus their flood risk, is endogenously determined along with our key outcome measures of interest. Thus, I will expand upon my empirical estimation use spatial first differences and boundary discontinuity design to better identify the impact of flooding on our outcomes of interest. Employing these empirical strategies that have distinct identifying assumptions allows me to use the features of my data collection efforts to best understand the relationship between seasonal flooding and household welfare and investment.

The spatial first differences estimator, developed by Druckenmiller and Hsiang (2019), is similar to other first difference approaches across time using time-series or panel data, but spatial first differences is for cross-sectional data analysis because the difference is between points across space. This approach is uniquely suited to identify geographic factors, like flood risk, because the spatial first difference approach compares directly adjacent observations and then simultaneously compares all observations to an adjacent observation. Spatial first differences eliminates omitted variables that are common to all adjacent observations since those are differenced out in the estimation (Druckenmiller and Hsiang (2019)). The spatial first difference estimating equation for adjacent observations i and $i-1$ is

$$y_i = y_{i-1} = (FloodRisk_i - FloodRisk_{i-1})\beta + (x_i - x_{i-1})\alpha + (\varepsilon_i - \varepsilon_{i-1} \tag{14}$$

where y_i is the outcome of interest for firm i, $FloodRisk_i$ is the measured flood risk of firm i, x_i are the unobserved characteristics of firm i,and ε_i is the error term. Outcomes of interest include investment, worker productivity and absenteeism, stock levels, or perception of flood risk in the case of firms. Using the notation Δ to denote the differences, the estimating equation is:

$$\Delta y_i = \Delta FloodRisk_i \beta_{SFD} + \Delta\varepsilon_i \tag{15}$$

and this equation can be estimated using OLS (Druckenmiller and Hsiang (2019)). Under the spatial first differences approach, β_{SFD} identifies the causal impact of measured flood risk on my outcomes of interest as long as unobserved variables are not systematically correlated between immediately adjacent observations. Because I plan to sample firms that are close to one another and flood risk can vary greatly across small areas, it is unlikely that there will be systematic correlation between unobservable and we can use the spatial first differences approach to estimate the causal impact of flooding.

I will supplement this approach with an empirical analysis using a regression discontinuity design which will identify the causal impact of flooding under a similar, but not identical identifying assumption. The boundary discontinuity design in space will compare observations that are just on either side of the flood zone boundary. Let B_i denote the distance between household or firm i and the flood zone boundary, f_0 denote the flood zone boundary and let $(B_i \geq f_0)$ denote households or firms that are inside the flood zone boundary. Then, the estimating equation for the regression discontinuity design is

$$y_i = \alpha + B_i\delta + [I(B_i \geq f_0)]\beta_{RD} + [B_i \times I(B_i \geq f_0)]\gamma + \varepsilon_i \tag{16}$$

Under this approach, β_{RD} will identify the causal impact of flood risk so long as the allocation of one household or firm to either side of the flood risk boundary is as good as randomly assigned. In this approach, I will use standard econometric methods and restrict our sample to only households that are close to a flood risk boundary (Calonico et al. (2014)). I will use objective flood risk boundaries, like those developed by European Space Agency (2019), to define the borders in this setting which may be less likely to be used by households in urban Dakar when they are deciding where to live. Even so, flood risk is at least somewhat known within the area and there is the potential for non-random sorting along the flood risk boundary. I will statistically test for this using standard econometric techniques. If there is evidence of non-random sorting, I will rely on the spatial first difference approach to identify the impacts of flooding.

Finally, I can use historical flood experience in an event-study like framework. Seasonal flooding in urban Dakar is primarily due to poor drainage after hard rainfall. Unlike sea-level rise or river flooding, urban flash flooding is more random and is determined on which areas have blocked drainage during heavy rainfall. While some areas are generally more prone to flooding, whether a firm experienced a flood can plausibly be random as firms cannot fully control whether drainage systems adequately prevent flooding in their area during a specific storm. Thus, I can treat past experience of flood as plausibly random and use historical flood experience and the time since a firms flood to explore how flooding affects firm performance.

4.3 Empirical strategy for analyzing the experiment

Following collection of the phone survey data, I will estimate the impact of firm adaptation strategies using the following estimating equation:

$$y_{in} = \alpha + Individual_n \beta_E + Community_n \gamma_E + \delta X_{in} + \varepsilon_i n \tag{17}$$

where y_{in} is the outcome of interest for firm i in neighborhood n, $Individual_n$ is an indicator variable for a neighborhood of firms assigned to the individual choices of adaptation strategy treatment arm, $Community_n$ is an indicator variable for a neighborhood of firms assigned to the community choice treatment arm, and X_{in} is a vector of firm level controls. In the vector of firm-level controls, I will include a term for the distance to the nearest firm in each of the other treatment arms. This term will allow me to control for spillover effects not captured within the experimental design. I will estimate an intent-to-treat (ITT) based on treatment assignment. Since I am tracking voucher redemption, I can also use treatment assignment as an instrument for redeeming the voucher and thus using the technology to estimate the local average treatment effect (LATE). I will cluster my standard errors at the level of treatment assignment, the neighborhood level. I will also report Conley (1999) standard errors to account for spatial correlation in outcomes.

In this framework, β_E will give the causal impact of being in the firm's individual choice adaptation strategy arm on firm flood experience and γ_E will identify the causal impact of being in the community's choice adaptation strategy arm relative to the control. I will test the difference between β_E and γ_E to see how the individual and community choices differentially impact firm performance. I will estimate the intent to treat impacts for both treatment arms. I will collect data on voucher redemption as data on use of these strategies, but use of any adaptation strategy is a firm choice and endogenous. I will also use treatment assignment as an IV for flood adaptation and test to ensure treatment assignment is a valid instrument for flood adaptation. Finally, to increase power I will pool the individual and community treatment arms to identify the intent to treat impacts of any adaptation strategy.

For the outcome measures of some investment technologies, flood experience, inventory, operating hours, customer traffic, worker attendance, and firm revenue and profits, I will collect baseline measures of these outcomes. I will then use an ANCOVA specification to measure the treatment effects if the autocorrelation between the baseline and endline outcome measure is at least 0.5 (McKenzie (2012)).

4.4 Baseline balance

I will conduct balance analyses across all primary outcomes and key firm characteristics measured in the cross-sectional survey. I will include both t-test of differences between control and treatment arms and F-tests of the joint null that the vector of outcome and firm characteristics are statistically equivalent between the control and treatment arms. If I find baseline imbalance for more than five percent of variables, I will include the unbalance covariates as controls in my analysis of the experiment.

4.5 Missing data

I will asses the rate of missingness for outcomes of interest at baseline. If the missingness rate is less than or equal to 20 percent, I will continue with the described analysis. If the missingness is greater than 20 percent, I will not report analyses for those outcome variables.

For missing data in the covariates, I will follow the procedure describe in Lin et al. (2016). I will include observations with missing covariates so long as the outcome and treatment assignment are non-missing. For covariates with no more than 10 percent of missing values, I will code missing values as the sample mean or sample median if the covariate is not symmetrically distributed. For covariates with more than 10 percent of missing values, I will include an indicator variable for missing values and code the missing value to the sample mean or median using the same procedure as before.

4.6 Extreme values

I will winsorize all relevant outcome variables to the 99th, 95th, and 90th percentile to mitigate the impact of extreme values on the analysis.

4.7 Multiple outcome and multiple hypothesis testing

I organized my outcomes of interest into different areas. To account for multiple hypothesis testing, I will control for the area-wise error rate. I will estimate adjusted p-values using the methodology developed by Westfall et al. (1993). I will report adjusted p-values as robustness checks.

4.8 Treatment Choice

The neighborhood choice treatment arm is specifically designed to push firm owners towards a more cooperative equilibrium. I will look at how the choice of treatment technology differs between my two treatment arms to understand if the treatment mode influenced technology choices and firm decision making.

4.9 Heterogeneity Analysis

In my experiment, I give firms the choice of bags of cement of wooden pallets. Firms could combine their bags of cement, especially in the community choice treatment arm, to construct larger barriers or structure to protect firms or areas from flooding. Thus, I will conduct a heterogeneity analysis based on the concentration on treated firms within an area. I will specifically consider the concentration of cement in these small neighborhoods to look at potential agglomeration effects.

Furthermore, these flood adaptation technologies likely matter more in more flood-prone areas. I will consider how the impact of the technologies differs across more or less flood-prone areas. Additionally, flood risk within these small neighborhoods can also differ slightly, so I will conduct a heterogeneity analysis to see if the treatment differentially impacted the most flood-prone firms within these communities.

During the baseline data collection, the rains began. I will collect rainfall data from CHIRPS (Funk et al. (2015)) to empirically measure rainfall and corroborate my notes from the field. I will consider heterogeneity in the cross sectional data collection based on whether or not it rain the day you were surveyed or the day before you were surveyed. I will also consider heterogeneity in treatment outcomes in the experiment based on rainfall during data collection. Specifically, I will test if baseline data collection or treatment choice occurring on a day when it rained or the day after it rained influences any of my listed outcomes. Perhaps rain occurring around data collection makes the risk of flooding more salient for individuals and thus they are more likely to act.

Finally, I will conduct a heterogeneity analysis based on baseline firm productivity. Perhaps, more productive firms are better able to make, and profit from, investments in defensive technologies like barriers and wooden pallets. I will test for difference in outcomes based on an index of productivity measures collected in the baseline survey.

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