Competition Constrains Adaptation to Climate Shocks

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Abstract

How does market structure affect climate adaptation decisions? To answer this question, we combine detailed weather data, financial records from small vendors working for Ghana's largest mobile money provider, and exogenous variation in market competition. Unexpected increases in temperature decrease sales revenue, seller labor supply, and the number of customers. Accurate forecasts reduce adverse effects on revenue by 50%, highlighting the value of forecast information for adaptation. However, adaptation is lower in more competitive markets due to coordination failures. Our results point to an unintended negative effect of policies designed to increase competition in retail markets.

Keywords: Climate Adaptation, Mobile Money Retailing, Household Finance, Market Competition, Coordination Failures.

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1 Introduction

Climate change is well underway, affecting natural and economic systems worldwide. Actions to adapt to climate change will determine how damaging the changes will be. It is crucial, then, to understand constraints to adaptation. These constraints might be especially severe in low-income, tropical countries already at the most significant risk of climate shocks. Typical discussions on adaptation limitations predominantly emphasize financial or technological challenges and associated costs.[2] Yet, the crucial influence of market structure, a foundation upon which these constraints rest, has not been well explored. Here, we look at how market structure affects adaptation to climate shocks.

In theory, the effect of market structure on adaptation is ambiguous. On one hand, heightened competition can increase firm productivity if a more competitive environment compels companies to evolve, streamline their processes, and innovate to maintain an edge (Porter, 1990; Geroski, 1990; Blundell et al., 1999, Syverson, 2011). On the other hand, intense competition might limit a firm's ability to absorb significant shocks, reducing its resilience. Firms in highly competitive sectors typically operate with narrow financial margins, leaving a limited buffer for shocks and potentially reducing innovation (Dasgupta & Stiglitz, 1980a; Dasgupta & Stiglitz, 1980b; Aghion et al., 2005).

To understand how market structure affects firms' adaptation responses to climate shocks, we combine three datasets: nationally representative records of mobile money transactions from Ghana's largest mobile money provider, new seller and buyer registrations, and spatially granular weather forecasts issued by the European Centre for Medium-Range Weather Forecasts (ECMWF)—the highest-quality global numerical weather forecaster. We complement these data with endline surveys to further explore mechanisms.

Markets for mobile money have been shown to improve welfare (Suri & Jack, 2016; Bill & Melinda Gates Foundation, 2021) and provide a relevant setting to investigate how competition might affect adaptation to climate shocks. First, it is an open-air marketplace, making it susceptible to interruptions from inclement weather, such as too much heat and too much rainfall. Second, it is characterized by meaningful seller absenteeism, raising the question of whether fluctuations in

[2] The literature identifies several constraints to adaptation including income/liquidity constraints and access to credit (Fankhauser & McDermott, 2014; Di Falco et al., 2011; Kahn, 2005), insurance (Annan & Schlenker, 2015), as well as institutional quality and bureaucracy (Kahn, 2005; Sobel & Leeson, 2006).

weather are a cause of such behavior. Third, there is substantial variation in the density of sellers and new entries induced by the retail network infrastructure. This allows us to examine changes in competition and how that affects adaptation decisions.

Our empirical strategy builds on methods for identifying adaptation presented in Shrader (2023). The strategy we use estimates the effect of weather shocks on market behavior and quantifies adaptation by regressing market activity on realizations of weather and weather forecasts. First, the forecasts serve to control for ex ante expectations by market participants, meaning that the weather realizations can be interpreted as shocks or surprises. This provides strong identification of weather effects purged of forward-looking adaptation actions. Second, we use the effects of forecasts on market activity to identify adaptation. Extending the identification argument of Borusyak and Hull (2023), we control for longer-horizon forecasts so that conditional variation in short-horizon forecasts identifies "news shocks" that occur at a specific point in time. By regressing market behavior on these news shocks, we can quantify the effect of forward-looking adaptation. Finally, to assess the effect that market competition has on both adaptation and weather effects, we interact weather and forecast effects with exogenous variation in market competition, following the approach of Feyrer et al. (2017).

We have three main results. First, we find evidence of adaptation. Realizations of hot weather strongly and negatively affect that day's sales revenue (similar to Addoum et al., 2020). Hot weather also has a negative impact on mobile money seller presence, and it leads to a reduction in the number of customers who visit a mobile money provider conditional on the provider being present. However, news the day before an adverse weather event substantially reduces the negative revenue effect of heat. In our primary specification, the effect is reduced by approximately 50%. Intuitively, this adaptation effect comes from two margins: (1) sellers supply more labor (show up to their kiosks) when they receive advance news compared to receiving no news, or (2) the number of customers increases. The increase in customers occurs either because sellers are now more present (indirectly) or buyers plan to conduct their transactions using the advance news (directly).

Second, we report evidence that market competition stifles adaptation and exacerbates the effects of weather shocks. In markets with more competition, realized weather shocks have a stronger negative effect on revenue. Moreover, the news shocks are no longer as helpful for reducing the effect of those shocks. Thus, sales revenue falls much more during adverse weather in highly competitive locations, indicating that competition reduces the value of adaptation responses.

Third, we explore why competition might constrain adaptation. A leading hypothesis is coordination failures. Mobile money is a two-sided market, and such markets involve interdependent decisions made by retailers and customers, resulting in positive network effects. However, coordination costs—such as buyer switching and communication barriers—hinder these benefits. Coordination costs tend to be more pronounced in competitive markets. Buyers switching which mobile money vender they visit is a necessary condition for coordination failure, and we find evidence of this behavior.[3] Buyers of mobile money might have a preferred seller, but when weather conditions are poor, they are more likely to go to the nearest seller even if that seller is usually less preferable. In areas with more robust competition, there is more scope for buyers to deviate from their preferred seller, which exacerbates coordination costs between buyers and sellers. A sufficient condition for the counter-adaptation effect is the existence of communication barriers. When a seller communicates effectively with their customer base, the benefits increase as more customers engage in similar interaction, leading to a loyal customer base. However, coordinating these decisions can often take time and effort, leading to failures in adaptation. More competitive markets might have higher communication barriers due to high coordination costs because multiple agents compete for the same customer base, leading to potential coordination failures. In less competitive areas, where a seller has a monopoly, they might have established lines of communication with customers due to a stable customer base. These sellers can have more consistent interactions with buyers, ensuring that, even in adverse weather conditions, they can maintain a consistent service quality.

Empirically, we find that in both more and less competitive markets, sellers are less likely to supply labor during unexpectedly hot conditions, but that forecasts offset this effect. Conditional on sellers being present, participants on the demand side of the market (buyers) in both more and less competitive areas are less likely to visit a given seller during hot conditions. When conditions are forecasted to be hot, demand at a given seller's kiosk falls much more in high-competition locations. This pattern of demand responses is consistent with customers switching which kiosk they visit in the face of worse weather (for example, by visiting a closer but otherwise less preferred

[3] Buyer switching is inconsistent with high search costs, because frequent customer switching indicates lower search costs.

seller). But we cannot observe what happens to demand in the case where sellers do not supply labor. Therefore, we using surveys of buyers and sellers to corroborate that buyer switching and coordination is a concern that motivates seller behavior.

We make two distinct contributions to the literature. First, we highlight and document the distinct role of market structure or competition in limiting adaptation decisions by firms. While there is a lot of interest in climate adaption and its limits (Annan & Schlenker, 2015; Di Falco et al., 2014; Tack et al., 2018), to the best of our knowledge, we are not aware of any publications that empirically examine how the competition constrains adaptation decisions of firms in a market.[4] In particular, we document the role of competition and the channels through which it might operate—coordination failures.

Secondly, we contribute to the household finance literature on how individuals and small businesses manage shocks (Karlan et al., 2014; Giglio et al., 2021; Giné et al., 2008). Our findings have implications for this body of work, as the underlying market conditions could limit firms' ability to adapt to climate shocks. We further advance the household finance literature in two ways. First, we document that unfavorable weather negatively affects the quality of financial services, as measured by retail vendor absence. This finding builds upon previous research that examined the causes of absenteeism, with prior research focusing on differences between firms and/or individuals (Bennedsen et al., 2019; Barmby & Stephen, 2000). Second, we study weather effects and competition issues in an extremely important financial services (i.e., mobile money) sector largely overlooked by previous work. The mobile money market, which has the potential to reduce poverty and improve welfare, is valued at 1.26 trillion, facilitated by digital transactions (Groupe Speciale Mobile Association [GSMA], 2023).

2 Study Setting and Data

2.1 Mobile Money Market

Mobile money is the largest digital financial service in many developing regions in sub-Saharan Africa. Over the past decade, it has evolved from a niche service in Kenya to a prevalent financial industry worth more than a trillion dollars worldwide. Mobile money transactions

[4] Kochhar and Song (2024) study how intermediate input supply affects adaptation by firms. They find that the market structure of intermediate input suppliers can affect adaptation by firms downstream in the supply chain. Their result is a complement to the own-market effects we study here.

increased from one trillion to 1.3 trillion dollars from 2021 to 2022 (GSMA, 2023). The mobile money ecosystem comprises mobile money providers (MMPs), buyers, and sellers. While MMPs facilitate the integration of all the players, sellers play a crucial role in converting physical cash into digital currency (cash-in) and, in the opposite direction, converting digital cash back to physical money (cash-out). In 2022, sellers digitized $294 million, a 17% increase from the previous year. Registered mobile money accounts increased from 1.4 billion in 2021 to 1.6 billion in 2022, representing a 13% increase (GSMA, 2023).

Ghana has recently emerged as one of the fastest-growing mobile money markets (CGAP, 2018; International Trade Administration, 2022). The first mobile money in Ghana was introduced by MTN in 2009 allowing citizens to send and receive money quickly. In the following years, three other mobile money services were launched: AirtelTigo Money, Vodafone Cash, and GMoney, resulting in four nationwide mobile money services. Currently, MTN Ghana holds a 94% market share.

2.2 Three Motivating Features of Mobile Money

Mobile money offers a good environment to study how individuals and businesses adapt to climate shocks and competition. We discuss three features that make it so.

2.2.1 Feature 1: Open-Air Transactions

Mobile money has brought about a significant change in financial transactions in areas where there is limited banking infrastructure. However, one significant difference between mobile money and traditional banking infrastructure is that mobile money transactions are typically conducted in the open air at kiosks (an example is shown in Figure A1). This makes buyers and sellers vulnerable to adverse weather conditions such as heavy rains or extreme heat. These disruptions could cause agents to suspend their services or even shut down for the day if the weather conditions persist, resulting in reduced transaction volumes, revenue losses, and decreased customer visits. To reduce losses, buyers and sellers may use adaptation techniques, such as weather forecasts, to prepare for climate shocks. Due to the open-air nature of mobile money, we can study how agents adapt to climate shocks in this market.

2.2.2 Feature 2: Agent Absenteeism at Retail Outlets

The success of mobile money services depends on the availability of sellers facilitating transactions. When sellers are absent, buyers cannot conduct transactions, reducing operational hours, transaction volumes, and, ultimately, revenues (Figure A2). Annan et al. (2023) report that absenteeism among agents leads to numerous failed transactions in Bangladesh, Tanzania, and Uganda. These failures result in opportunity costs significantly greater than the direct financial costs of conducting transactions, potentially causing considerable negative impacts on welfare. In Ghana, Annan (*JPE* forthcoming) estimates the rate of agent absence to be 22%. While various factors can impede sellers' presence at their mobile money outlets, severe weather conditions (such as extreme temperature) might play a significant role, especially since many agents operate in open and semi-open air. The fact that agent absence is prevalent, and to the extent that this might be linked to unfavorable conditions, motivates our analysis of the effects of weather shocks on labor supply and revenue.

2.2.3 Feature 3: Significant Variation in Agent Density Across Space and Time

A high concentration of sellers in a particular area can lead to intense competition, which may positively and negatively affect climate adaptation (Figure A3). In areas with a dense seller network, consumers have multiple transaction points, which could result in reduced profit margins and limit the ability of agents to invest in adaptation measures, such as infrastructure improvement. On the other hand, intense competition can also drive firms to be more efficient, promoting adaptation. Due to the different views on competition's effect on adaptation, this setting provides a unique opportunity to empirically examine the moderating role of competition on adaptation. We leverage the baseline levels of competition (and weather) to obtain exogenous variation, which assists us in estimating the impacts of competition on adaptation.

2.3 Mobile Money Data

We analyze mobile money transaction data from January 2017 to March 2019. The data consists of interactions between 11,252,921 unique buyers and 15,031 sellers identified by their unique ID numbers, the date of their interaction, and a unique financial transaction ID. In addition, we have the geolocation of mobile money sellers and the names of the respective areas, districts, and regions where they reside. The data also contain detailed information on seller and customer registrations over the study period. That dataset shows when the sellers and customers registered for mobile money and their specific locations.

2.4 Weather and Forecast Data

We obtain weather realizations and forecast data from the ECMWF. For realizations, we use the ERA5 reanalysis data (Hersbach et al. 2020). These data are available globally at a 30 km resolution over the entire sample period. We select the grid cells that overlap a polygon for Ghana and match each seller to all grid cells within 500km of their kiosk's location. Inverse distance weighting (with power parameter of 2) is used to generate measures of the daily average 2m temperature and cumulative precipitation.

For forecasts, we use real-time weather predictions issued by the ECMWF over the sample period at horizons between 1 and 2 days in advance. For the baseline results, we investigate the effect of 1-day-ahead forecasts, using the 2-day-ahead forecasts as controls. The forecasts are at a 0.25-degree resolution, and the same process used for the weather realizations is used to match forecasts for precipitation and temperature with each seller.

2.5 Estimation Sample

The mobile money data are matched to weather forecasts and realizations using a registry of the exact seller and customer locations over the sample period. This yields a final estimation dataset that contains variables for the log of total daily sales, the number of daily customers, an indicator for the supply of labor by mobile money vendors (sellers), daily average temperature realizations, daily cumulative rainfall, and forecasts of both weather variables up to 1 week ahead. We present the summary statistics in Table 1.

[Table 1 here]

The unit of analysis is the seller by day. Our final dataset comprises 15,031 sellers (see Figure A4), and the dataset covers the period from January 1, 2017, until March 31, 2019. In total, there are 12,325,420 observations of seller labor supply, and 8,770,895 observations of buyer visits and transaction amounts. The buyer visits and transaction amounts are only observed if a seller is present.

3 Empirical Strategy

3.1 Measuring Climate Effects and Adaptation

The first goal of the paper is to investigate the effect of weather and weather forecasts on demand for mobile money services. The regression to understand this effect is:

$$\begin{aligned} y_{it} &= \beta_1 temp_{0,it} + \beta_2 temp_{1,it} + \beta_3 temp_{2,it} \\ &\quad + \alpha_1 ppt_{0,it} + \alpha_2 ppt_{1,it} + \alpha_3 ppt_{2,it} + x'_{it}\theta + \epsilon_{it} \end{aligned} \tag{1}$$

where the outcome variables are the log of sales revenue for seller i on day t, an indicator for whether the seller provides labor on that day (i.e., seller presence), or the number of customers that visit the seller. For the right-hand side variables, $temp_0$ is the realized temperature, $temp_1$ is the 1-day-ahead temperature forecast, $temp_2$ is the 2-day-ahead forecast, ppt_0 is the realized precipitation, ppt_1 is the 1-day-ahead precipitation forecast, ppt_2, is the 2-day-ahead forecast. The two-day-ahead forecasts act as controls to isolate news shocks. The remaining controls are in the vector x (in baseline analysis: fixed effects for date, fixed effects for seller by month-of-year, and seller by month-of-year interacted with a linear time trend to adjust for differences over time, location, and season).

Temperature enters the specification linearly because of the high average temperature in Ghana. The average temperature is likely already hotter than levels typically associated with thermal comfort, so increases in temperature relative to this high average are expected to reduce labor supply and demand for outdoor services. We confirm that this result holds even if we model temperature non-linearly in the Appendix, Table A1.

Equation (1) identifies the effect of weather and news shocks. The temperature shocks are identified by β_1 using the logic presented by Borusyak and Hull (2023). By conditioning on expectations in the form of forecasts, the temperature effect is identified only by deviations from expectations at time t, where the ECMWF forecasts are acting as a proxy for the possible expectations of the market participants. The ECMWF forecasts are the highest quality numerical weather predictions available for the region during the study period, increasing the likelihood that the forecasts are a high-quality proxy.[5] The expectations act as a sufficient statistic for all linear confounders. Similar logic holds for the effect of 1-day-ahead forecasts, conditional on 2-day-ahead forecasts. The longer-horizon forecasts condition out linear confounders, leaving only news that arrives between day $t-2$ and $t-1$ to identify the forecast effect. Therefore, the news shock precisely identifies the effect of actions that could occur in response to information newly available on day $t-1$.

3.2 Measuring Market Competition Effects on Adaptation

Next, we explore the impact of competition on climate adaptation based on new seller entry into the retail market for mobile money. We test the effects of competition by estimating the following equation:

$$\begin{aligned} y_{it} = {} & \beta_1 temp_{0,it} + \beta_2 temp_{1,it} + \beta_3 temp_{2,it} \\ & + \beta_4 temp_{0,it} \times \widehat{SellerEntry}_{it} + \beta_5 temp_{1,it} \times \widehat{SellerEntry}_{it} \\ & + \beta_6 temp_{2,it} \times \widehat{SellerEntry}_{it} \\ & + \alpha_1 ppt_{0,it} + \alpha_2 ppt_{1,it} + \alpha_3 ppt_{2,it} + x_{it}'\theta + \nu_{it} \end{aligned} \tag{2}$$

The variables remain the same as in the baseline estimating equation, except x_{it}' which also includes $\widehat{SellerEntry}_{it}$, and the interaction between $\widehat{SellerEntry}_{it}$ and precipitation variables.

Seller entry is the count of new seller registrations in area i on day t and measures competition in each location. Estimating equation (2) works only if the joint distribution of competition and sales revenue is not correlated with weather forecasts (see for example Angrist & Krueger, 1999, Section 2.3.4 for similar identification arguments, and Annan & Schlenker, 2015, for an empirical implementation). Using the raw measure of seller entry might violate this assumption if seller entry depends on factors including weather forecasts, demand and supply dynamics, and the behavior of other market participants. We address the correlation by using the two-step approach of Feyrer et al. (2017).

First, we derive a modified competition measure based on new seller entry into the retail market for mobile money while adjusting for contemporaneous changes in new subscribers. New

[5] Shrader (2023) shows that even if the forecasts are "too good"—in the sense that they are more accurate than the expectations held by individuals—weather shocks are still identified. The forecasts are taking away some "good" variation from the weather variable, but they are also purging the weather variable of all "bad" variation that is subject to confounding expectations.

seller entry decisions depend on the pre-existing competition and sellers deciding to create a new business by entry. We instrument for new seller entry in each market area using innovations that are linked to both the feasibility and reliability of the retail network infrastructure that is necessary to conduct mobile money transactions. We model new seller entry as a function of aggregate market area-level entry and district-level temporal shocks, estimating:

$$In(SellerEntry_{it} + 1) = \alpha_{v(i)} + \gamma_{d(i)y(t)} + \varepsilon_{it} \tag{3}$$

where $\alpha_{v(i)}$ is a dummy for each market area, and $\gamma_{d(i)y(t)}$ represents a set of dummy variables for each district-year combination (sellers are located in market areas which are in turn nested in districts).

Second, based on equation (3), we generate predictions for a seller's entry:

$$\widehat{SellerEntry}_{it} = (e^{\widehat{\propto_{v(i)}} + \gamma_{\widehat{d(i)y(t)}}})/Subscriber_{v(i)t} \tag{4}$$

where $Subscriber_{it}$ represents the cumulative number of subscribers registered in an area. This adjusts for new subscriber registrations at the area level and generates a prediction for new seller entry per capita for each pair of day and market area. $\widehat{SellerEntry}_{it}$ is the area-level exogenous competition index.

This two-step approach utilizes the time series of aggregate entry decisions at the district level to predict local area seller entry. The predicted values for local new seller entry per capita are based on the timing of new entries for all the areas within a particular district. Each individual area represents a small part of the district's aggregate entry, so the instrument is exogenous with respect to within-area entry decisions. Intuitively, a given district *d(i)* houses several areas *v(i)* such that an individual area's endogenous seller entry decision will not significantly matter (Duflo and Pande, 2007). In our estimation, we explore alternative measures of competition including a policy change from Interoperability.

4 Main Results

4.1 Weather Effects and Adaptation

Table 2, Column 1 shows the results for the first estimating equation, where the dependent variable is the log of the daily sales revenue. This result captures the equilibrium response of both the demand and supply side of the market.

[Table 2 here]

The results can be interpreted as saying that when there is unexpected bad weather, people engage in fewer transactions ($\beta_1 < 0$). However, when the bad weather is anticipated, the effect on transactions is dampened ($|\beta_1 + \beta_2| < |\beta_1|$). The estimates can be thought of as a distributed lag model, but one where the effects are happening before and during the time of the weather shock, rather than during and after the shock. So, if there is a surprise negative weather event, the relevant coefficient is β_1. If there is a forecast of the event available at time $t - 1$, and the forecast turns out to be correct, then the combined effect of this forecast and the subsequent realization is $\beta_1 + \beta_2$.

Viewed through the lens of adaptation, people are taking costly action to protect themselves from the damaging effects of weather. One can infer that the actions are costly because the negative effects of bad weather are only partially offset. If adaptation was costless, then one would expect to find $\beta_1 + \beta_2 = 0$. These costs could be monetary or non-monetary. An example of monetary cost is when people might walk if the weather is nice but need to pay for transportation if the weather is unpleasant. An example of non-monetary cost could be the constraint created by plans that they already made to meet others near the mobile money provider on a given day. Our survey shows that both sellers and customers make adjustments in response to unfavorable weather conditions (Figure A5).

Throughout the paper, we focus on temperature effects. We do not find strong effects of precipitation when using the cumulative precipitation per day (the one exception is that seller labor supply is significantly lower on days when precipitation is forecasted to be higher). Using a specification that includes an indicator for whether precipitation occurs on a given day, we do find stronger effects. We refer the interested reader to the discussion in Appendix Section A.1.3.

The second column in Table 2 displays the effect of weather and news shocks on an indicator for whether the mobile money seller shows up to work at the kiosk. As in the previous result, the table indicates that adverse weather shocks reduce labor supply, and that accurate forecasts effectively offset that effect. If anything, the results suggest that adaptation is even more than complete for suppliers, although we are not able to reject the hypothesis that the sum of the coefficients is equal to 0 at high levels of confidence.

Table 2, Column 3 looks at the number of customers visiting mobile money sellers. The results are qualitatively similar to the effects on transaction amount because this measure also captures equilibrium responses—buyers can only visit a seller if that seller is present and supplying labor. The results do indicate that the transaction amount effects are not solely driven by changes in a small number of large transactions. Interpreting the realized temperature coefficient, a 1°C temperature increase reduces the number of customers by 0.25 (relative to an average of 65 customers per day; see Table 1). A day that is 32°C, versus the national average temperature of 27°C, would see a 1.5% drop in the number of customers and, as seen in Table 2, a 7% drop in the transaction amount. Adaptation again appears to be important in this case, with a forecast effect roughly equivalent in magnitude to the effect of realizations. These similar magnitudes suggest that customers can adapt to offset the effect of upcoming negative shocks (by changing transport modes, shifting the time of their visit, or other actions). Our results are robust to the use of nonlinear specifications (Table A1 and A2), controlling for longer lags in weather (Table A3), Winsorizing revenue (table A7), adding quadratic time trends (Table A8), and alternative clustering (Table A9).

4.2 The Role of Competition

Next, we estimate the effect of market competition. We first show the findings from estimating Equation 3. Table 3, Column 1 shows these results for the log of transaction amount (i.e., revenue). Across locations with high or low market competition, the effect of negative weather shocks is roughly the same. In contrast, the effect of news shocks is strongly affected by competition. In locations with average market competition (a value of 0), the news shocks do not have a significant effect on transactions, but the sign of the effect is positive, as in the baseline results. For locations with higher levels of competition, however, the effect of news shocks becomes progressively smaller, indicating less and less ex ante response by the market.

[Table 3 here]

The second column of Table 3 shows the effects on labor supply. Here, we find notable differences from the previous sales revenue result. Importantly, negative weather shocks reduce labor supply relatively more in locations with higher levels of competition. This suggests that vendors or sellers in high-competition locations are less willing to supply labor in the face of negative shocks, potentially because their lower margins make it less worthwhile to suffer the immiseration associated with working in high heat. Forecasts partly offset this effect in low-competition locations, but, as in the other results, higher competition erodes adaptation.

Table 3, Column 3 shows that this same pattern holds for the number of customers. The effects of weather shocks are the same across market structures, but news shocks serve to ameliorate the effect of realizations only in locations with lower competition.

4.3 Supplementary Evidence on Competition Effects

To complement the competition analysis in the previous section, we also implement an event study approach based on an unexpected competition policy. This approach has different identification requirements from the IV estimation.

Before May 10, 2018, mobile money customers could not transact across their network. If a customer of Network A wanted to send money to a customer on Network B, they had to first withdraw cash from a seller of Network A, and then deposit it with a seller of Network B. This process was cumbersome and gave sellers of Network B a potential monopoly. The government of Ghana and its stakeholders launched interoperability on May 10, 2018, enabling cross-network transactions. Since the launch of interoperability, both in-network and out-network transactions have surged in Ghana. In the first month following the introduction, the total value of transactions increased 85 fold, from 96.9 thousand to 8.3 million Ghanaian Cedis (GHS) (Bank of Ghana, 2018). With interoperability, the monopoly advantage of sellers diminishes, because a customer from one network can send directly to a customer on another network, without the need for multiple agents.

We exploit random variation in interoperability to estimate the impact of competition on adaptation. Our findings are displayed through event study (coefficient) plots in Figures A6 to A8. Figures A6 and A8 indicate a general decline in adaptation after the policy, consistent with our market entry results.

5 Discussion

Thus far, we have established that there are possibilities for market adaptation to climate shocks—on average, if the shock is correctly anticipated, the effect is reduced by about 50%—but that competition erodes adaptation. Our baseline findings raise four questions, which we discuss below.

First, given that competition limits firms' adaptation capacity, a natural question arises: *How long does it take for competitive firms' sales to recover following a climate shock?* This question is of particular importance because it matters for welfare. The consequences for welfare could diverge based on whether the effect is short-lived or persistent. A persistent effect of climate shocks might lead to seller exit, reducing overall supply of financial services. On the flip side, if the effects are short-lived, it could reflect poor quality of service, with sellers intermittently absent due to market unpredictability. This has implications for both seller behavior and on the adoption of retail financial services. We estimate distributed lag models in (reported in Table A3) to understand effect persistence. In less competitive locations, unanticipated temperature shocks lead to a persistent decline in revenue, and accurate forecasts fully offset this effect. In more competitive locations, revenue losses on the day of the shock are, on average, made up the next day. More accurate forecasts, however, more than fully offset this effect. Comparing the static and dynamic results, competition constrains adaptation on the day of the shock and potentially causes persistent customer switching over subsequent days.

Second, *how might competition constrain adaptation?* The most likely explanation for why competition erodes adaptation in two-sided markets (like we study) is coordination failures (Annan et al., 2024), manifested by customer switching and communication. Buyers of mobile money might have a preferred seller, but when weather conditions are poor, they are more likely to go to the nearest seller, even if that seller is usually less preferable. We test this objectively using our dataset, and subjectively through endline surveys. Table 4 indicates that a temperature increase of 1°C reduces the likelihood of a customer repeating their purchase with a particular seller. To support our findings, endline survey results, shown in Figure 1, Panels A-D, indicate that highly competitive areas tend to attract new customers, while losing existing ones. This is demonstrated by the frequency of visits and the percentage of sales obtained from existing and new customers. The bar chart indicates that, on average, existing customers generate less sales revenue compared to their counterparts in less competitive areas, while new customers bring in more sales revenue in more competitive areas.

We also examine communication through the surveys, which investigate the channels of communication used, the significance of maintaining communication, and the challenges faced by both sellers and buyers while communicating. Results are displayed in Figure 1, Panels E-H. Both sellers and buyers give high importance to staying in touch with each other. In addition, barriers to effective communication are more pronounced in areas of high competition. This is illustrated by the frequency of failed communication attempts between sellers and customers, with rates of 29% for sellers in less competitive areas, versus 36% and highly competitive areas (Figure 1, Panels E-F). This gap widens significantly between low and high competition areas, with 38% and 12% rates, respectively, according to the customer survey (Figure 1, Panel G-H). Additionally, sellers responded to questions about the competitive landscape of their locations, revealing fierce competition among sellers in competitive areas leading to diminished sales on a per seller basis (Figure A9). Our analysis indicates that markets with higher levels of competition experience more significant communication challenges. This is attributed to increased coordination costs, as multiple agents compete for the same customer base. The opposite holds in less competitive areas, where a seller has a monopoly; due to a stable customer base sellers might have established lines of communication with their clients.

6 Conclusion

This paper shows that there is scope for adaptation to climate shocks in the Ghanaian household financial services sector, but market structure plays an important role in mediating that effect. To explore the relationship between weather and market outcomes, we combined data on realizations and forecasts of precipitation and temperature with unique transaction data from Ghana's leading mobile money provider. The mobile money data record both demand for financial transactions, as well as supply of labor by mobile money sellers at the daily level for more than 8.7 million seller-buyer pairs. Estimating the impacts of weather shocks and forecasts on market outcomes using an empirical strategy that isolates weather and news shocks, we found that market participants in Ghana face severe, negative consequences from unexpected hot temperatures. If the shock is correctly anticipated, however, the effect is reduced by 50%, indicating that individuals can engage in substantial adaptation if armed with relevant and accurate information. These results hold across market outcomes measured by total revenues, number of customers, and labor supply.

Adaptation is lower, however, in areas with stronger market competition. The supply of labor falls substantially in response to negative weather shocks in areas with stronger competition. Anticipation of the shocks does not serve to reduce the effect in these areas. The supply response can be rationalized by the fact that demand also falls when weather is poor, and, in areas with higher competition, ex ante adaptation does not serve to offset this reduction. Therefore, low-margin sellers in highly competitive areas adapt less to adverse shocks.

The results expand our understanding of adaptation opportunities and constraints, particularly in developing countries settings. The reduced adaptation in competitive areas indicates that firms need a surplus to adapt. Adaptation involves fixed or variable costs, meaning that lower-margin, more competitive firms will be less able to absorb the cost of adaptation. Given the projected increases in the prevalence of negative weather shocks under climate change, the results point to the importance of relaxing constraints on adaptation.

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Tables and Figure

Table 1: Summary statistics

Variables	**N**	**Mean**	**SD**	**Min**	**Max**	**Data Source**
Total sales (daily)	8,771,540	12857.51	24713.29	0.01	1.02E+07	Provider: Admin. data
Log of sales (daily)	8,771,540	8.77	1.53	-4.61	16.14	Provider: Admin. data
Labor supply	12,325,420	0.71	0.45	0.00	1.00	Provider: Admin. data
Customers	8,771,540	65.70	49.96	1.00	7897.00	Provider: Admin. data
$temp_{0,it}$ (°C)	12,325,420	27.51	1.56	23.09	36.16	ECMWF
$temp_{1,it}$ (°C)	12,325,420	27.10	1.55	22.22	34.97	ERA5 reanalysis
$temp_{2,it}$ (°C)	12,325,420	27.16	1.50	22.47	34.65	ERA5 reanalysis
$ppt_{0,it}$ (mm)	12,325,420	3.30	5.12	0.00	173.82	ECMWF
$ppt_{1,it}$ (mm)	12,325,420	3.10	4.56	0.00	173.08	ERA5 reanalysis
$ppt_{2,it}$ (mm)	12,325,420	2.76	3.53	-0.01	209.22	ERA5 reanalysis
Competition Index	11,110,285	0.00	0.00	-0.23	0.27	Provider: Admin. data
Competition Index (standardized)	11,110,285	0.00	1.00	-92.80	112.36	Provider: Admin. data
New sellers per district	33,303	153.47	116.75	1	561	Provider: Admin. data
New sellers per area	64,397	28.31	41.24	1	407	Provider: Admin. data
Cumulative buyers per area	1,331,316	555.18	219.54	1	817	Provider: Admin. data

Notes: This table presents the summary statistics. The data sources include administrative data from the mobile money provider (Provider: Admin. data), European Centre for Medium-Range Weather Forecasts (ECMWF), and the ERA5 reanalysis data, which is the fifth generation of ECMWF reanalysis data.

Table 2: Effect of temperature and 1-day-ahead news shocks on market outcomes.

	(1) Log of sales revenue	(2) Labor supply	(3) Number of customers
$temp_{0,it}$	-0.0139***	-0.0012*	-0.2462***
	(0.0019)	(0.0006)	(0.0512)
$temp_{1,it}$	0.0061**	0.0029***	0.2124***
	(0.0026)	(0.0008)	(0.0685)
$ppt_{0,it}$	0.0001	0.00002	-0.0032
	(0.0001)	(0.00003)	(0.0035)
$ppt_{1,it}$	-0.0003*	-0.0001***	-0.0003
	(0.0002)	(0.00004)	(0.0041)
2-day-ahead forecasts	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Seller x Month FE	Yes	Yes	Yes
Seller x Month x Trend	Yes	Yes	Yes
Observations	8,770,895	12,325,420	8,770,895

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales revenue (1), labor supply (2), and number of customers or buyers (3). Labor supply is 1 if the seller records a transaction in a given day, or 0 otherwise. The specifications include additional controls for longer-horizon temperature and precipitation forecasts (2 days ahead), date fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of temperature shocks and 1-day-ahead news shocks on market outcomes interacted with the degree of competition.

	(1) Log of sales revenue	(2) Labor supply	(3) Number of customers
$temp_{0,it}$	-0.0128***	-0.0012*	-0.2453***
	(0.0020)	(0.0006)	(0.0532)
$temp_{1,it}$	0.0034	0.0033***	0.1885**
	(0.0027)	(0.0009)	(0.0719)
$temp_{0,it}$ x $\widehat{SellerEntry}_{it}$	-0.0032	-0.0022***	-0.0025
	(0.0035)	(0.0005)	(0.0636)
$temp_{1,it}$ x $\widehat{SellerEntry}_{it}$	-0.0167**	-0.0013*	-0.3539***
	(0.0059)	(0.0007)	(0.0904)
$ppt_{0,it}$	-0.00003	0.00002	-0.0090**
	(0.0002)	(0.00003)	(0.0036)
$ppt_{1,it}$	-0.0003	-0.0001**	0.00007
	(0.0002)	(0.00004)	(0.0044)
$ppt_{0,it}$ x $\widehat{SellerEntry}_{it}$	-0.0017	-0.0006	0.0522
	(0.0019)	(0.0006)	(0.0405)
$ppt_{1,it}$ x $\widehat{SellerEntry}_{it}$	-0.0030	-0.0011	0.0031
	(0.0026)	(0.0007)	(0.0575)
2-day-ahead forecasts	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Seller x Month FE	Yes	Yes	Yes
Seller x Month x Trend	Yes	Yes	Yes
Observations	7,963,147	11,110,282	7,963,147

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales revenue (1), labor supply (2), and number of customers or buyers (3) interacted with the degree of competition. Labor supply is 1 if the seller records a transaction in a given day, or 0 otherwise. The specifications include additional controls for predicted seller entry, longer-horizon temperature and precipitation forecasts (2 days ahead), date fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. ** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

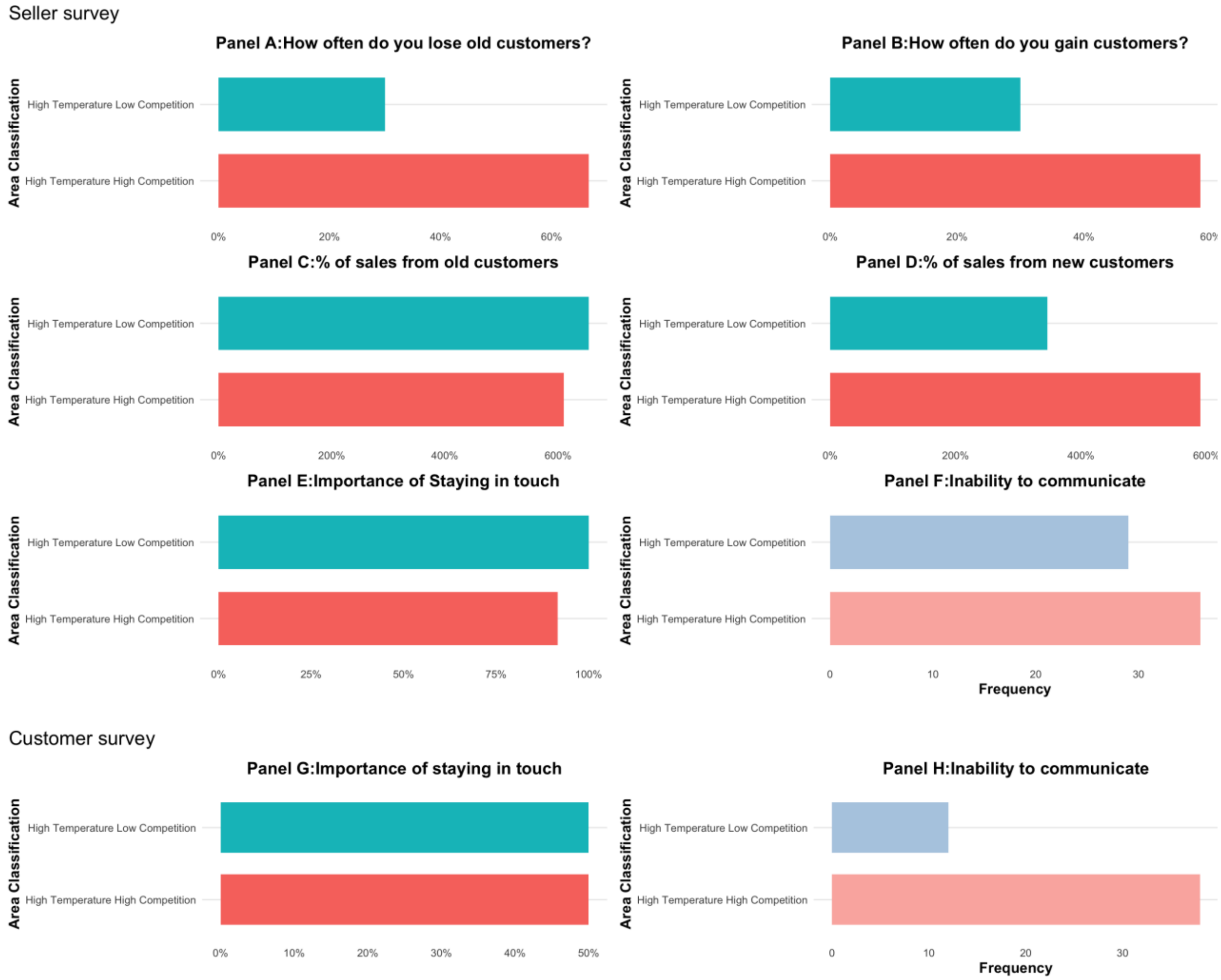
Table 4: Effect of temperature and 1-day-ahead news shocks on repeat customers

DV: A dummy variable which is 1 if the customer had a repeated transaction with a seller

	(1)
	Repeat
$temp_{0,it}$	-0.0002*
	(0.0001)
$temp_{1,it}$	0.0001
	(0.0001)
$ppt_{0,it}$	0.00003***
	(8.30e-06)
$ppt_{1,it}$	7.45e-06
	(0.00001)
2-day-ahead forecasts	Yes
Date FE	Yes
Seller x Month FE	Yes
Seller x Month x Trend	Yes
Observations	521,183,479

Notes: This table reports results from a fixed effects regression that examine the effects of weather shocks and forecasts on repeat transactions. In specification (1), repeat transaction is a dummy variable that takes one if the customer has interacted with an agent at least once in our data, otherwise 0. The specification controls for longer-horizon temperature and precipitation forecasts (2 days ahead), date-fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Descriptive evidence on coordination failures in the marketplace



Notes: The survey questions measure coordination failures among sellers and customers in high-temperature areas with low competition and high competition. Panels A-D measure customer switching among sellers while Panels E-G measure importance of and barriers to communication among sellers and customers in high-temperature areas with low competition and high competition.

Online Appendix
for
Competition Constrains Adaptation to Climate Shocks

A.1. Data details and additional results

A.1.1. Baseline competition measure

A way to understand how competition affects adaptation is to conduct an experiment involving exogenous variations in weather and market conditions. We approximate this experiment by assuming that weather conditions are random conditional on expectations as measured by forecasts and that forecast news is exogeneous conditional on longer-horizon news. This leaves us with endogenous competition, because it is influenced by various factors, such as market demand, supply dynamics, and the behavior of other players. In the results reported in Table 2, we use area and district-year variation to estimate the contemporaneous effect of exposure to more competition broadly while excluding potentially endogenous local variation in competition. Here, we use an alternative measure of competition—baseline competition. This measure reflects the existing density of agents in a market or the market structure before a weather shock occurs. We calculate baseline competition by observing competition at time $t-7$, one week before the shock, since it typically takes about a week for a mobile money business to register and start operating. In this setup, the interaction between weather variables and competition (i.e., $\widehat{SellerEntry}_{it-7}$) functions similarly to a Bartik-type instrument: baseline competition represents the "share," while the weather variables act as the "shift" or shocks.

We report estimates using baseline competition in Appendix Table A4. The results in Table A4, column 1 are similar to those in Table 4 and demonstrate that temperature shocks adversely impact sales. In these estimates, increasing competition has a small mitigating effect ($-0.0151 + 0.0015 \times \widehat{SellerEntry}_{it}$). Exactly as in Table 4, forecasts offset some of these sales reductions but a continued increase in baseline competition undoes this effect ($0.0075 - 0.0028 \times$

$\widehat{SellerEntry}_{it}$). The findings reaffirm the qualitative understanding from previous results: competition disrupts the adaptation gains of forecasts. Employing additional outcomes (i.e., labor supply and number of customers) leads to similar qualitative conclusions.

Results from the naive model that does not instrument for seller entry are shown in Appendix Table A5. These results use the raw number of agents present in a location on a given day as a measure of competition. The results broadly agree with the competition results shown in Tables 3 and A4.

A.1.2. Radio station concentration analysis

We believe that neighboring sellers serve as crucial information sources for focal sellers, and their influence is comparable to that of public data like weather forecasts (refer to Foster and Rosenzweig, 1995). This stance is buttressed by Udry's (1994) findings that individual investment returns are public within villages, impacting the functioning of local credit markets. In addition, our survey reveals that sellers and their customers predominantly obtain weather information by observing the skies, talking with friends and family, and using weather apps, above other sources (Figure A10).

To bolster the reliability of our results, we sourced supplemental data on radio station concentrations between 2017 and 2019 from the official website of the National Communication Authority of Ghana[6]. This database provides comprehensive lists of radio stations across the nation, along with their specific locations. Thus, we could track the number of radio stations in each district per year, which helped us to determine the accessibility of forecast data to sellers. Our analysis suggests that, with higher concentration of radio stations, a forecast of a 1°C temperature increase made a day in advance can boost sales by 0.03% relative to its average level, underlining the critical role of forecast information in adaptation decisions (see Table A6).

A.1.3. Robustness results and additional figures and tables

To ensure the robustness of our results, we performed a series of analyses to reinforce our primary findings. In Appendix Table A2, we replace the level of precipitation with an indicator for whether the day had non-zero precipitation (technically, precipitation greater than a trace amount of 2.54 millimeters). The temperature effects remain largely unchanged. The precipitation

[6] https://nca.org.gh/authorised-radio/, accessed April 27, 2023.

effects are stronger using this specification. A day with precipitation has significantly lower revenue, and forecasts of positive precipitation further reduce revenue. Unlike temperature forecasts, which are used by market participants to engage in more market transaction on hot days, the precipitation forecasts cause even more market participants to not engage in transactions. These differing results point to potentially different adaptation behaviors in response to temperature and precipitation. In response to anticipated hot temperatures, market participants might be able to adapt by changing the time of day they visit the seller, changing their clothing, or taking other action that protects them from heat but otherwise allows them to still transact. The precipitation results suggest that market participants find it easier to adapt to precipitation by simply staying away from the kiosks, potentially in anticipation of challenging travel conditions or less pleasant travel conditions.

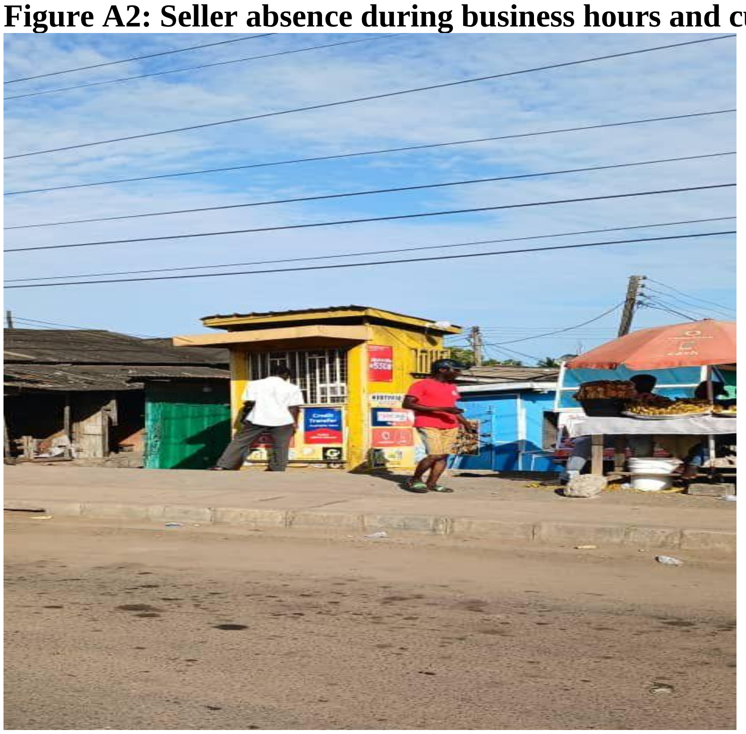
In additional robustness checks, to minimize the impact of outliers, we conducted our analysis by Winsorizing daily transaction amounts at the bottom 1% (and 5%) and the top 1% (and 5%) of the data. Similar to the results in Table 2, our findings in Table A7 demonstrate that, on average, there is adaptation if the shock is anticipated accurately. Also, when we control for quadratic trends and cluster the standard errors at the area level (to address spatial correlation), we arrive at the same conclusion (see Table A8 and A9, respectively)

A.2. Figures

Figure A1: The open-air nature of mobile money

Source: https://citinewsroom.com/2021/07/well-comply-with-10-tax-directive-but-give-us-two-months-momo-agents/, accessed October 23, 2023.

Figure A2: Seller absence during business hours and customer visits



Description: A potential customer looking into a kiosk to do a transaction when the seller is absent. Credit: photo taken by Bismark Adobaw, at Teshie-Nungua Main Street.

Figure A3: High concentration of mobile money sellers

Source: https://asetena.com/how-to-get-free-mobile-money-in-ghana/, accessed October 23, 2023.

Figure A4: Geographic distribution of sellers

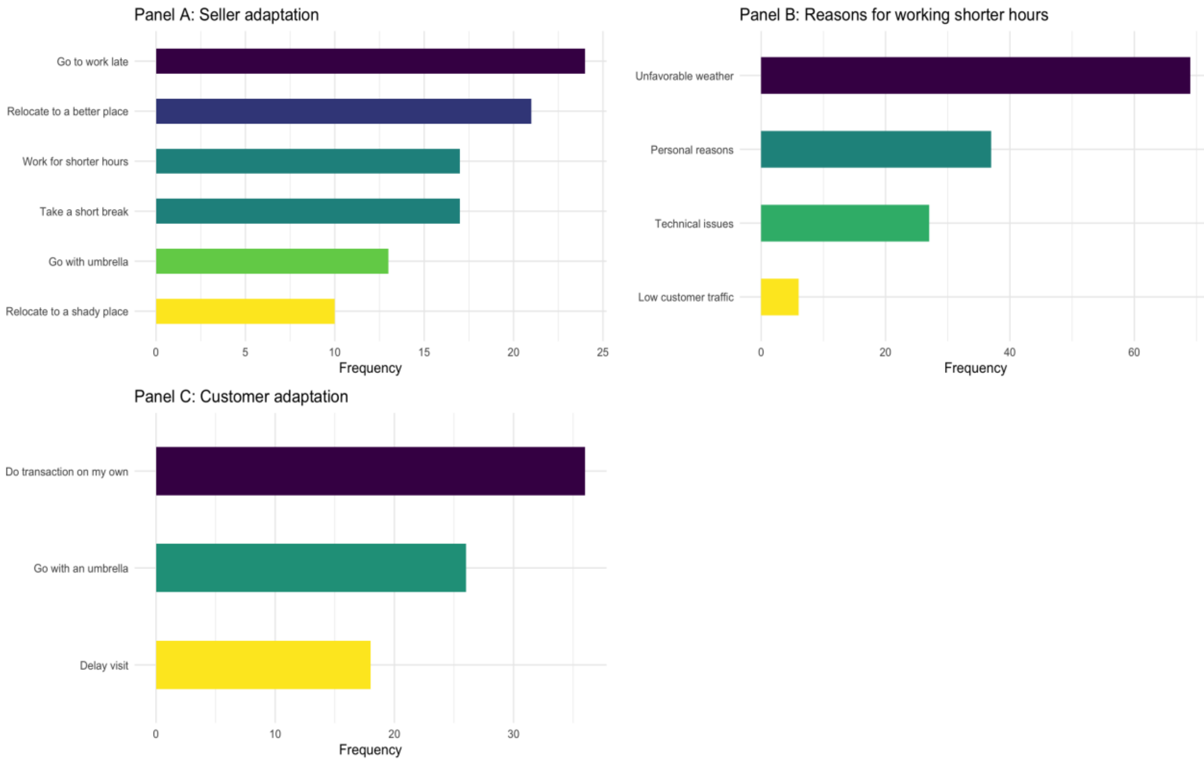
Panel A: Ghana map

Notes: Panel A, which shows the Ghana map, displays a distribution of 15,031 randomly sampled sellers, represented by dots. The grey shaded area represents the Ashanti region that contains one of our study districts, Kwabre East.

Panel B: Kwabre East District

Notes: Panel B, displays the Kwabre East District, which is located within the Ashanti Region, with sellers or markets represented by dots.

Figure A5: How sellers and customers are adapting to unfavorable weather



Notes: Adjustments to unfavorable weather conditions are depicted, with sellers (N=40) altering work routines, by for instance, going to work late, relocating, or reducing hours (Panel A). Sellers have reported that unfavourable weather conditions, which include extreme heat, heavy rainfall, and drought, are the main reason for their decision to work shorter hours (Panel B). Customers (N=40) adapted by independently completing transactions, using umbrellas, or postponing visits (Panel C).

Figure A6: Effect of the interaction between forecast and month on daily sales revenue

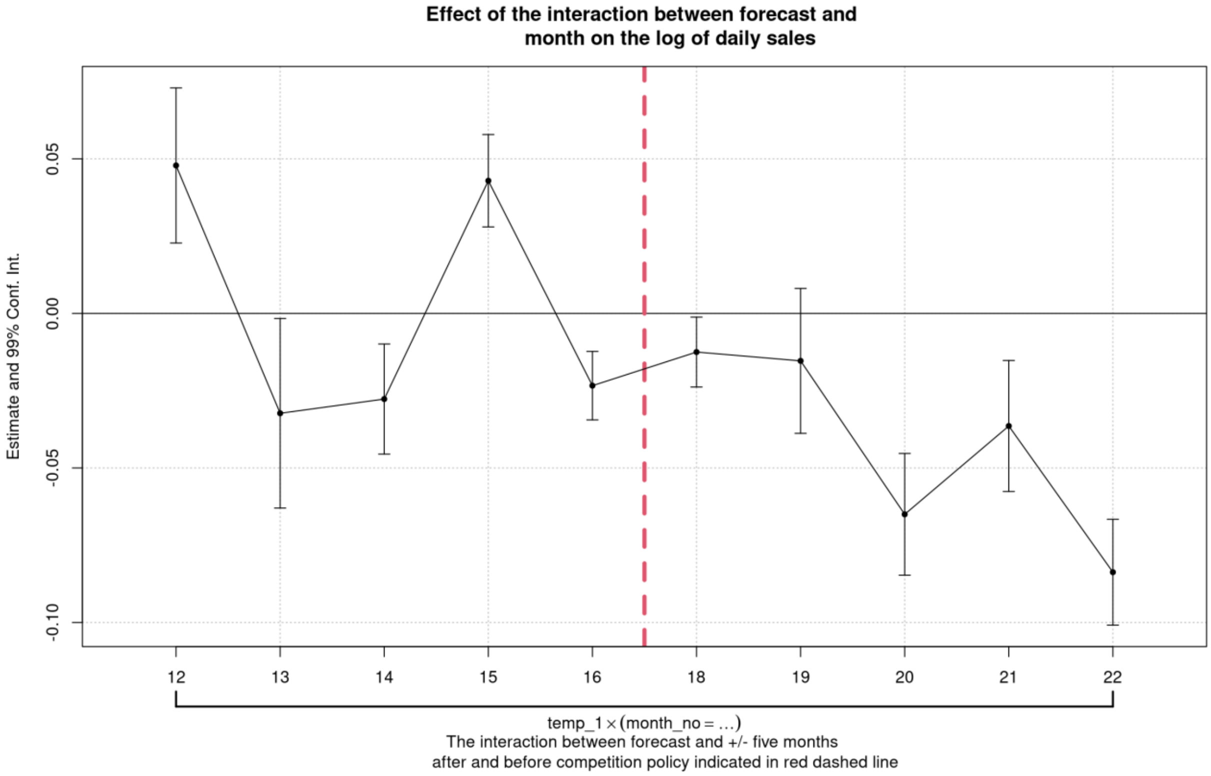


Figure A7: Effect of the interaction between forecast and month on labor supply

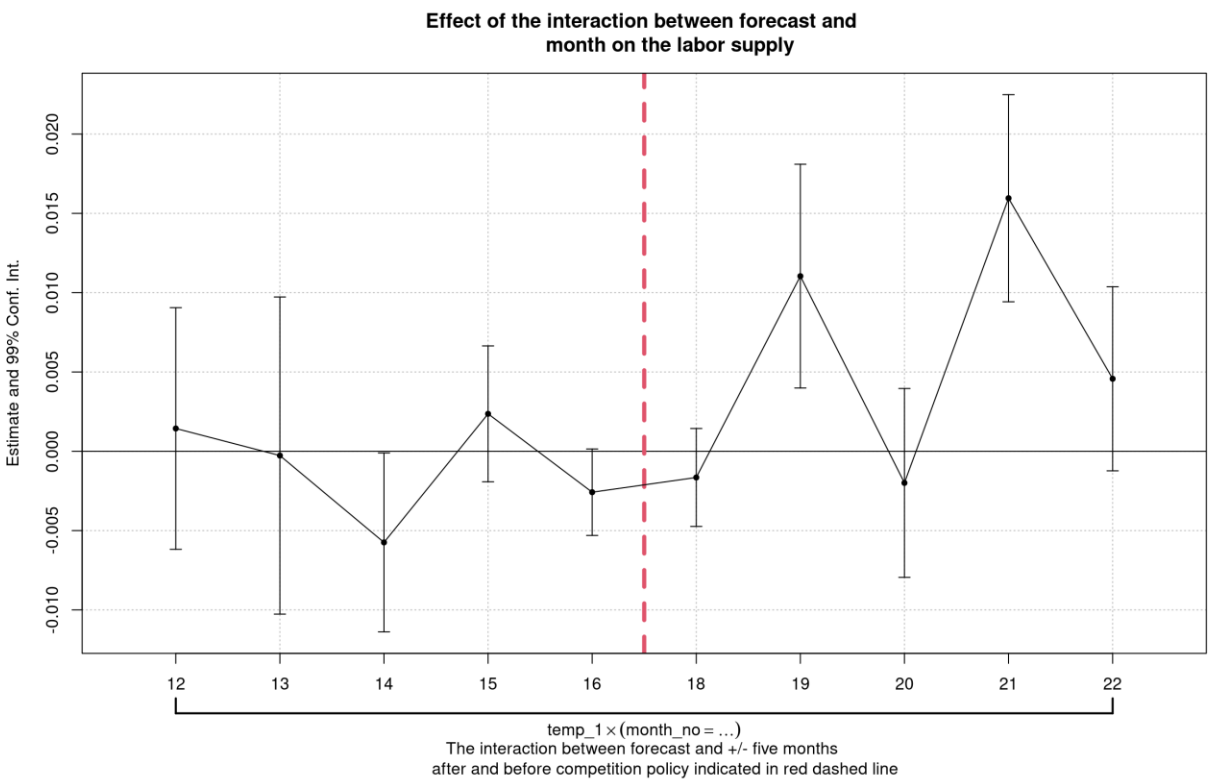


Figure A8: Effect of the interaction between forecast and month on the number of customers/buyers

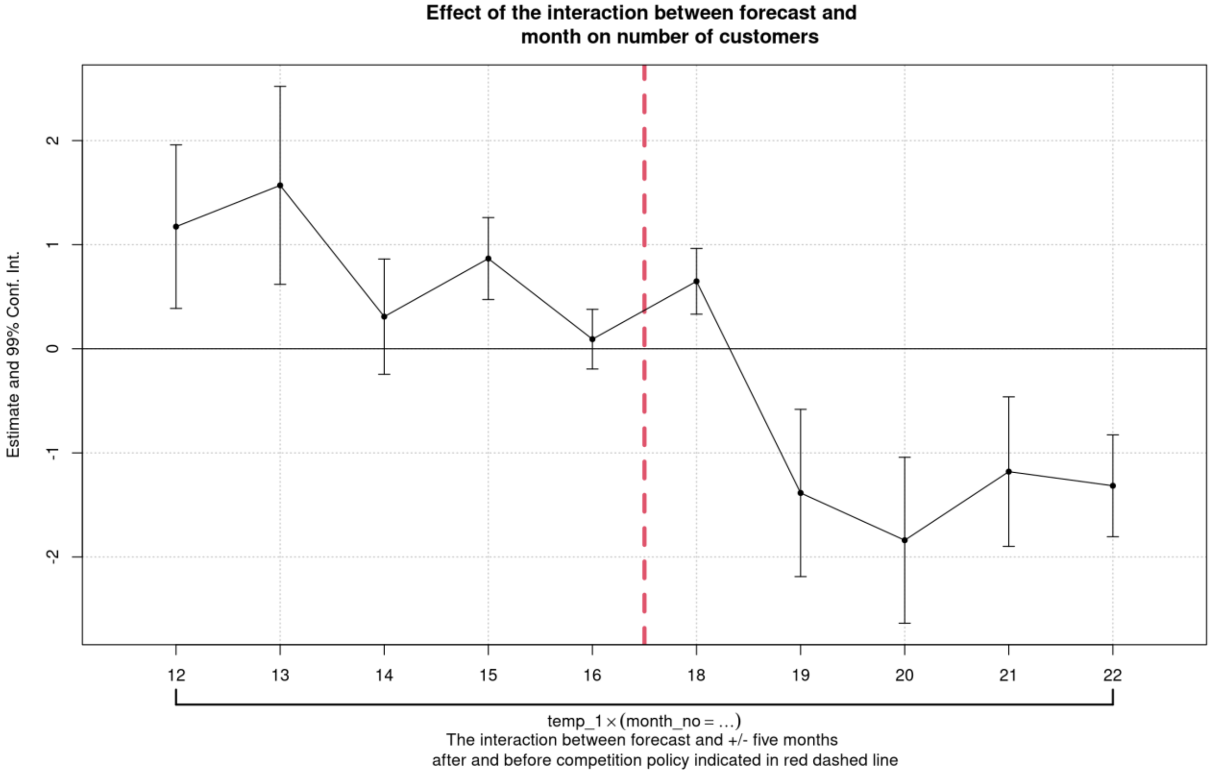
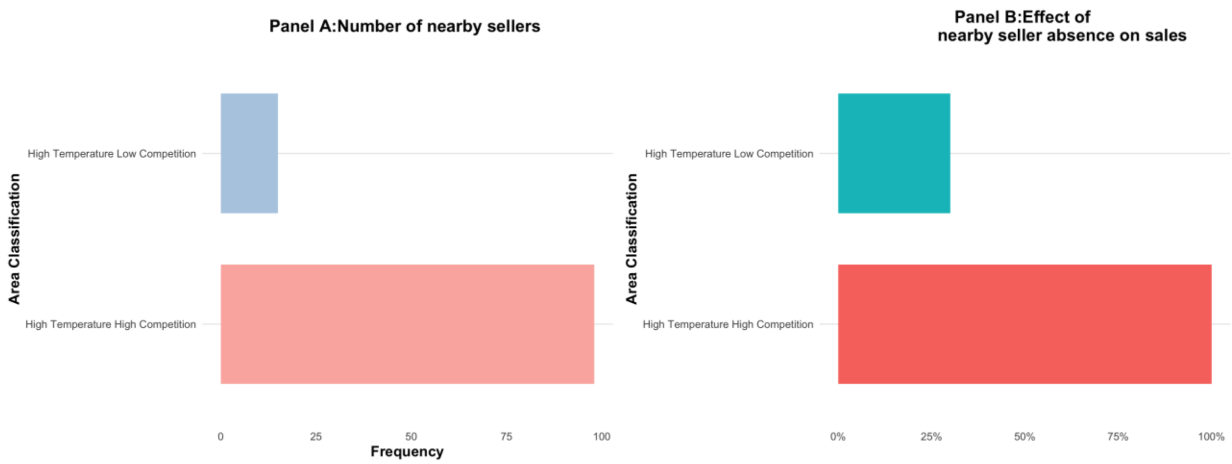
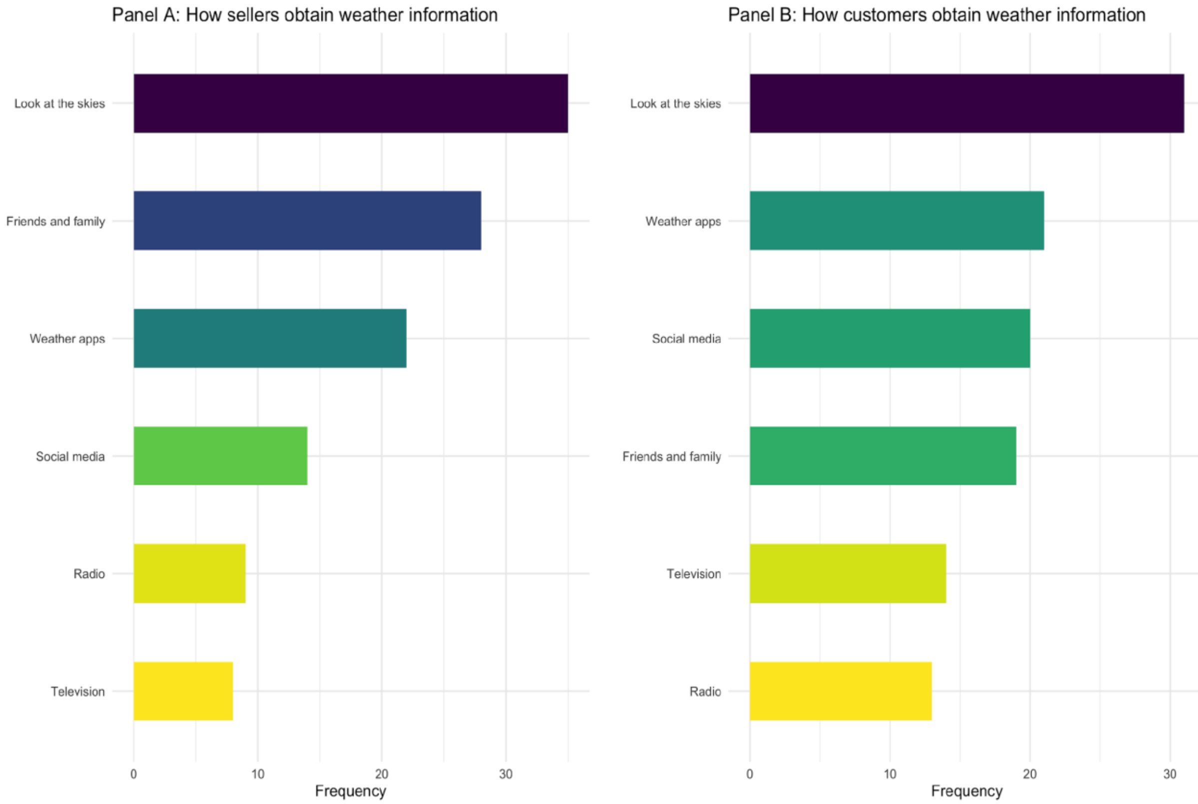


Figure A9: Seller competition



Notes: The survey questions aimed to measure competition among nearby sellers in high-temperature areas with low competition (N=10) and high competition (N=10).

Figure A10: How sellers and customers obtain weather information



Notes: Survey results indicate both sellers (N=40) and customers (N=40) primarily rely on sky observations, discussions with friends and family, weather apps, and various other sources for weather information.

A.3. Tables

Table A1: Effect of extreme temperature on market outcomes

	(1) Log of sales revenue	(2) Labor supply	(3) Number of customers
$temp_{0,it}$ bin 0	0.0088***	0.0019***	0.3236***
	(0.0025)	(0.0006)	(0.0608)
$temp_{0,it}$ bin 2	-0.0244***	-0.0013**	-0.4833**
	(0.0022)	(0.0006)	(0.0660)
$temp_{1,it}$ bin 0	0.0040	0.0048***	0.1724**
	(0.0032)	(0.0008)	(0.0869)
$temp_{1,it}$ bin 2	-0.0065**	0.0021**	0.1483
	(0.0028)	(0.0009)	(0.0992)
$ppt_{0,it}$ bin 0	0.0436***	0.0072**	1.5973***
	(0.0143)	(0.0034)	(0.3538)
$ppt_{0,it}$ bin 2	-0.0020	-0.0003	-0.0896*
	(0.0021)	(0.0004)	(0.0514)
$ppt_{1,it}$ bin 0	0.0451***	0.0008	0.6026**
	(0.0101)	(0.0023)	(0.2497)
$ppt_{1,it}$ bin 2	-0.0080***	-0.0021***	-0.3559***
	(0.0021)	(0.0005)	(0.0523)
2-day-ahead forecasts	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Seller x Month FE	Yes	Yes	Yes
Seller x Month FE x Trend	Yes	Yes	Yes
Observations	8,770,895	12,325,420	8,770,895

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales revenue (1), labor supply (2), and number of customers or buyers (3). Labor supply is 1 if the seller records a transaction in a given day, or 0 otherwise. Temperature is categorized into three bins: bin 1 represents the temperature below the 25th percentile, bin 2 represents temperature between the 25th (inclusive) and the 75th percentile, and bin 3 represents temperature at the 75th percentile and above. Similarly, precipitation is broken into three bins: bin 1 represents 0 rainfall, bin 2 represents rainfall between 0 and the 90th percentile, and bin 3 means rainfall at or above the 90th percentile. The specification controls for longer-horizon temperature and precipitation forecasts (2 days ahead), date-fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Here, a 1°C increase in extreme heat—defined as temperatures at or above the 75th percentile—results in a 2.4% decrease in total daily sales in comparison to baseline temperature ranging between the 25th and 75th percentiles. Standard errors clustered by seller. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Effect of temperature and 1-day-ahead news shocks on sales revenue amount controlling for non-linear precipitation

	(1) Log of sales revenue
$temp_{0,it}$	-0.0141***
	(0.0019)
$temp_{1,it}$	0.0057**
	(0.0026)
$ppt_{0,it} > 0$	-0.0046***
	(0.0015)
$ppt_{1,it} > 0$	-0.0042***
	(0.0015)
2-day-ahead forecasts	Yes
Date FE	Yes
Seller x Month FE	Yes
Seller x Month FE xTrend	Yes
Observations	8,770,895

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales revenue. In this regression, the level of precipitation is replaced with an indicator for positive precipitation (technically liquid water equivalent > 2.54 mm, or above trace moisture levels). In addition, the specification controls for longer-horizon temperature and precipitation forecasts (2 days ahead), date-fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Distributed lag model interacted with competition

	(1) Log of sales revenue	(2) Labor supply	(3) Number of customers
$temp_{0,it}$	-0.0131***	-0.0141***	-0.0134***
	(0.0017)	(0.0017)	(0.0017)
$temp_{1,it}$	0.0029	0.0022	0.0009
	(0.0025)	(0.0026)	(0.0025)
$temp_{0,it}$ x $\widehat{SellerEntry}_{it}$	0.0019	-0.0073	-0.0100
	(0.0058)	(0.0071)	(0.0073)
$temp_{1,it}$ x $\widehat{SellerEntry}_{it}$	-0.0312***	-0.0473***	-0.0597***
	(0.0119)	(0.0150)	(0.0163)
$temp_{0,it-1}$	0.0011	0.0002	0.0005
	(0.0016)	(0.0016)	(0.0016)
$temp_{1,it-1}$	0.0088***	0.0088***	0.0073***
	(0.0026)	(0.0025)	(0.0025)
$temp_{0,it-2}$	0.0021	0.0012	0.0018
	(0.0016)	(0.0016)	(0.0016)
$temp_{1,it-2}$	0.0262***	0.0262***	0.0262***
	(0.0026)	(0.0026)	(0.0026)
$temp_{0,it-3}$	-0.0009	-0.0027	-0.0025
	(0.0018)	(0.0017)	(0.0017)
$temp_{1,it-3}$	0.0009	0.0020	0.0029
	(0.0024)	(0.0025)	(0.0025)
$temp_{0,it-4}$		0.0047***	0.0045***
		(0.0017)	(0.0016)
$temp_{1,it-4}$		0.0035	0.0047*
		(0.0026)	(0.0026)
$temp_{0,it-5}$		0.0126***	0.0140***
		(0.0019)	(0.0017)
$temp_{1,it-5}$		0.0012	0.0080***
		(0.0026)	(0.0026)
$temp_{0,it-6}$			-0.0083***
			(0.0018)
$temp_{1,it-6}$			0.0016
			(0.0026)
$temp_{0,it-7}$			-0.0121***
			(0.0018)
$temp_{1,it-7}$			0.0082***
			(0.0025)
$temp_{0,it-1}$ x $\widehat{SellerEntry}_{it}$	0.0152**	0.0324***	0.0294***

	(0.0066)	(0.0085)	(0.0085)
$temp_{1,it-1}$ x $\widehat{SellerEntry}_{it}$	-0.0328***	-0.0452***	-0.0462***
	(0.0128)	(0.0148)	(0.0177)
$temp_{0,it-2}$ x $\widehat{SellerEntry}_{it}$	0.0044	-0.0152**	-0.0060
	(0.0068)	(0.0072)	(0.0088)
$temp_{1,it-2}$ x $\widehat{SellerEntry}_{it}$	-0.0006	0.0057	-0.0180
	(0.0119)	(0.0134)	(0.0156)
$temp_{0,it-3}$ x $\widehat{SellerEntry}_{it}$	0.0013	-0.0023	-0.0063
	(0.0057)	(0.0094)	(0.0106)
$temp_{1,it-3}$ x $\widehat{SellerEntry}_{it}$	0.0056	0.0144	0.0234
	(0.0103)	(0.0145)	(0.0161)
$temp_{0,it-4}$ x $\widehat{SellerEntry}_{it}$		0.0109	0.0026
		(0.0095)	(0.0094)
$temp_{1,it-4}$ x $\widehat{SellerEntry}_{it}$		-0.0153	-0.0116
		(0.0155)	(0.0155)
$temp_{0,it-5}$ x $\widehat{SellerEntry}_{it}$		0.0224**	0.0266***
		(0.0088)	(0.0101)
$temp_{1,it-5}$ x $\widehat{SellerEntry}_{it}$		-0.0380***	-0.0339**
		(0.0140)	(0.0160)
$temp_{0,it-6}$ x $\widehat{SellerEntry}_{it}$			0.0117
			(0.0098)
$temp_{1,it-6}$ x $\widehat{SellerEntry}_{it}$			-0.0221
			(0.0170)
$temp_{0,it-7}$ x $\widehat{SellerEntry}_{it}$			-0.0069
			(0.0098)
$temp_{1,it-7}$ x $\widehat{SellerEntry}_{it}$			-0.0040
			(0.0163)
$ppt_{0,it}$	-0.0003*	-0.0003	-0.0003
	(0.0002)	(0.0002)	(0.0002)
$ppt_{1,it}$	-0.0002	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)
$ppt_{0,it}$ x $\widehat{SellerEntry}_{it}$	-0.0012	-0.0016	-0.0022*
	(0.0013)	(0.0013)	(0.0013)
$ppt_{1,it}$ x $\widehat{SellerEntry}_{it}$	-0.0039**	-0.0036**	-0.0046**
	(0.0017)	(0.0017)	(0.0018)
$ppt_{0,it-1}$	0.0003**	0.0003**	0.0003**
	(0.0002)	(0.0002)	(0.0002)
$ppt_{1,it-1}$	0.0011***	0.0012***	0.0012***
	(0.0002)	(0.0002)	(0.0002)
$ppt_{0,it-2}$	8.63e-06	-0.00002	-0.00006

	(0.0002)	(0.0002)	(0.0002)
$ppt_{1,it-2}$	0.0004**	0.0004**	0.0004**
	(0.0002)	(0.0002)	(0.0002)
$ppt_{0,it-3}$	-0.0005***	-0.0008***	-0.0008***
	(0.0002)	(0.0002)	(0.0002)
$ppt_{1,it-3}$	-0.0006***	-0.0005***	-0.0006***
	(0.0002)	(0.0002)	(0.0002)
$ppt_{0,it-4}$		0.0006***	0.0006***
		(0.0002)	(0.0002)
$ppt_{1,it-4}$		0.0006***	0.0006***
		(0.0002)	(0.0002)
$ppt_{0,it-5}$		-0.0003**	-0.0001
		(0.0002)	(0.0001)
$ppt_{1,it-5}$		-0.0006**	-0.0004*
		(0.0002)	(0.0002)
$ppt_{0,it-6}$			-0.0006***
			(0.0001)
$ppt_{1,it-6}$			0.0007***
			(0.0002)
$ppt_{0,it-7}$			-0.00006
			(0.0002)
$ppt_{1,it-7}$			-0.0001
			(0.0002)
$ppt_{0,it-1}\ x\ \widehat{SellerEntry}_{\iota t}$	-0.0008	-0.0005	-0.0006
	(0.0015)	(0.0014)	(0.0015)
$ppt_{1,it-1}\ x\ \widehat{SellerEntry}_{\iota t}$	-0.0035**	-0.0035**	-0.0033*
	(0.0018)	(0.0018)	(0.0018)
$ppt_{0,it-2}\ x\ \widehat{SellerEntry}_{\iota t}$	-0.0005	-0.0005	-0.0003
	(0.0017)	(0.0017)	(0.0017)
$ppt_{1,it-2}\ x\ \widehat{SellerEntry}_{\iota t}$	-0.0017	-0.0022	-0.0023
	(0.0017)	(0.0017)	(0.0017)
$ppt_{0,it-3}\ x\ \widehat{SellerEntry}_{\iota t}$	-0.0008	-0.0018	-0.0021
	(0.0016)	(0.0018)	(0.0017)
$ppt_{1,it-3}\ x\ \widehat{SellerEntry}_{\iota t}$	-0.0013	-0.0006	-0.0004
	(0.0018)	(0.0018)	(0.0019)
$ppt_{0,it-4}\ x\ \widehat{SellerEntry}_{\iota t}$		-0.0018	-0.0019
		(0.0015)	(0.0015)
$ppt_{1,it-4}\ x\ \widehat{SellerEntry}_{\iota t}$		0.0023	0.0029
		(0.0020)	(0.0020)
$ppt_{0,it-5}\ x\ \widehat{SellerEntry}_{\iota t}$		0.0012	0.0010

		(0.0017)	(0.0018)
$ppt_{1,it-5}$ x $Seller\widehat{Entry}_{it}$		-0.0039	-0.0037
		(0.0025)	(0.0026)
$ppt_{0,it-6}$ x $Seller\widehat{Entry}_{it}$			0.0009
			(0.0015)
$ppt_{1,it-6}$ x $Seller\widehat{Entry}_{it}$			-0.0019
			(0.0019)
$ppt_{0,it-7}$ x $Seller\widehat{Entry}_{it}$			-0.0001
			(0.0019)
$ppt_{1,it-7}$ x $Seller\widehat{Entry}_{it}$			0.0018
			(0.0019)
2-day-ahead forecasts	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Seller x Month FE	Yes	Yes	Yes
Seller x Month FE x Trend	Yes	Yes	Yes
Observations	7,947,231	7,933,838	7,920,865

Notes: This table reports results from distributed lag models that examine the dynamic effects of weather shocks and forecasts on the log of daily sales. Specifications (1), (2), and (3) are distributed lag models with lag lengths 3, 5, and 7, respectively. In addition, the specifications control for longer-horizon temperature and precipitation forecasts (2 days ahead), date-fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. * *$p < 0.10$*, ** *$p < 0.05$*, *** *$p < 0.01$*

Table A4: Effect of temperature shocks and 1-day-ahead news shocks on market outcomes interacted with baseline competition

	(1)	(2)	(3)
	Log of sales revenue	Labor supply	Number of customers
$temp_{0,it}$	-0.0151***	-0.0023***	-0.2718***
	(0.0019)	(0.0006)	(0.0495)
$temp_{1,it}$	0.0075***	0.0049***	0.2243***
	(0.0026)	(0.0008)	(0.0678)
$\widehat{SellerEntry}_{it}$	0.2175***	0.2092***	4.4559***
	(0.0312)	(0.0101)	(1.0860)
$temp_{0,it}$ x $\widehat{SellerEntry}_{it-7}$	0.0015**	0.0013***	0.0477**
	(0.0007)	(0.0002)	(0.0217)
$temp_{1,it}$ x $\widehat{SellerEntry}_{it-7}$	-0.0028**	-0.0014***	-0.0881**
	(0.0013)	(0.0005)	(0.0401)
$ppt_{0,it}$	0.0001	-6.50e-06	-0.0032
	(0.0001)	(0.00003)	(0.0035)
$ppt_{1,it}$	-0.0003*	-0.0001***	-0.0005
	(0.0002)	(0.00004)	(0.0041)
$ppt_{0,it}$ x $\widehat{SellerEntry}_{it-7}$	-0.0006***	-0.0003***	-0.0153**
	(0.0002)	(0.00004)	(0.0063)
$ppt_{1,it}$ x $\widehat{SellerEntry}_{it-7}$	0.0014***	0.0013***	0.0220**
	(0.0003)	(0.00008)	(0.0104)
2-day-ahead forecasts	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Seller x Month FE	Yes	Yes	Yes
Seller x Month FE x Trend	Yes	Yes	Yes
Observations	8,724,818	12,220,203	8,724,818

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales (1), labor supply (2), and number of customers or buyers (3) interacted with baseline competition. Labor supply is 1 if the seller records a transaction in a given day, or 0 otherwise. The specifications control longer-horizon temperature and precipitation forecasts (2 days ahead), date fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. * *$p < 0.10$*, ** *$p < 0.05$*, *** *$p < 0.01$*

Table A5: Effect of temperature shocks and 1-day-ahead news shocks on market outcomes interacted with number of agents at the district level

	(1) Log of sales revenue	(2) Labor supply	(3) Number of customers
$temp_{0,it}$	-0.0146***	-0.0026***	-0.2557***
	(0.0019)	(0.0006)	(0.0508)
$temp_{1,it}$	0.0071***	0.0050***	0.2267***
	(0.0026)	(0.0008)	(0.0683)
$number\ of\ agents$	0.1496***	0.2404***	2.8417***
	(0.0306)	(0.0095)	(0.9384)
$temp_{0,it}\ \times number\_of\_agents$	-0.0001	0.0003	0.0138
	(0.0010)	(0.0002)	(0.0285)
$temp_{1,it}\ \times number\_of\_agents$	-0.0018	-0.0062***	-0.0511
	(0.0016)	(0.0004)	(0.0459)
$ppt_{0,it}$	0.0001	-0.00001	-0.0032
	(0.0001)	(0.00003)	(0.0035)
$ppt_{1,it}$	-0.0003*	-0.0001***	-0.0003
	(0.0002)	(0.00004)	(0.0041)
$ppt_{0,it}\ \times number\_of\_agents$	-0.0006*	0.0008***	-0.0121
	(0.0003)	(0.0001)	(0.0095)
$ppt_{1,it}\ \times number\_of\_agents$	-0.0003	-0.0004***	-0.0070
	(0.0002)	(0.00005)	(0.0064)
2-day-ahead forecasts	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Seller x Month FE	Yes	Yes	Yes
Seller x Month FE x Trend	Yes	Yes	Yes
Observations	8,770,895	12,325,420	8,770,895

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales (1), labor supply (2), and number of customers or buyers (3) interacted with number of agents at the district level. Labor supply is 1 if the seller records a transaction in a given day, or 0 otherwise. The specifications control longer-horizon temperature and precipitation forecasts (2 days ahead), date fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. * *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Table A6: Effect of temperature shocks and 1-day-ahead news shocks on log of daily sales revenue interacted with radio concentration.

	(1) Log of sales revenue	(2) Log of sales revenue
$temp_{0,it}$	-0.0136***	-0.0141***
	(0.0022)	(0.0024)
$temp_{1,it}$	0.0045	0.0010
	(0.0030)	(0.0033)
$radio_{dT}$	-0.0075**	0.0005
	(0.0035)	(0.0048)
$temp_{0,it} \times radio_{dT}$		0.00005
		(0.0001)
$temp_{1,it} \times radio_{dT}$		0.0003**
		(0.0001)
$ppt_{0,it}$	0.0001	0.0009***
	(0.0002)	(0.0002)
$ppt_{1,it}$	-0.0001	-0.0006***
	(0.0002)	(0.0002)
$ppt_{0,it} \times radio_{dT}$		-0.00005***
		(6.72e-06)
$ppt_{1,it} \times radio_{dT}$		0.00003***
		(7.93e-06)
2-day-ahead forecasts	Yes	Yes
Date FE	Yes	Yes
Seller x Month FE	Yes	Yes
Seller x Month FE x Trend	Yes	Yes
Observations	6,543,296	6,543,296

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales revenue interacted with radio concentration. Radio concentration is the number of radio stations at the district level. Model 1 has the main effect of radio concentration, while model 2 has the interaction of the number of radio stations with weather shocks and forecasts. The specifications control for longer-horizon temperature and precipitation forecasts (2 days ahead), date fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. ** p < 0.10, ** p < 0.05, *** p < 0.01*

Table A7: Effect of temperature and 1-day-ahead news shocks on Winsorized sales revenue

	(1) Winsorized sales revenue	(2) Winsorized sales revenue
$temp_{0,it}$	-104.6646***	-86.0335***
	(13.9848)	(10.8435)
$temp_{1,it}$	71.1637***	54.8147***
	(18.0473)	(14.4331)
$ppt_{0,it}$	0.89691	0.56031
	(0.9375)	(0.76315)
$ppt_{1,it}$	0.2346	-0.5613
	(1.0871)	(0.9006)
2-day-ahead forecasts	Yes	Yes
Date FE	Yes	Yes
Seller x Month FE	Yes	Yes
Seller x Month FE x Trend	Yes	Yes
Observations	8,770,895	8,770,895

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on daily sales revenue in Ghanaian Cedis, Winsorized symmetrically at the top and bottom 1% (1) and 5% (2) to minimize the impact of outliers. The specifications control for longer-horizon temperature and precipitation forecasts (2 days ahead), date-fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by seller. ** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Table A8: Effect of temperature and 1-day-ahead news shocks on market outcomes controlling for quadratic trends

	(1) Log of sales revenue	(2) Labor supply	(3) Number of customers
$temp_{0,it}$	-0.0139***	-0.0012*	-0.2491***
	(0.0019)	(0.0006)	(0.0512)
$temp_{1,it}$	0.0061**	0.0029***	0.2109***
	(0.0026)	(0.0008)	(0.0687)
$ppt_{0,it}$	0.0001	0.00002	-0.0034
	(0.0001)	(0.00003)	(0.0035)
$ppt_{1,it}$	-0.0003*	-0.0001***	-0.0006
	(0.0002)	(0.00004)	(0.0041)
2-day-ahead forecasts	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Seller x Month FE	Yes	Yes	Yes
Seller x Month FE x Trend x Trend	Yes	Yes	Yes
Observations	8,770,895	12,325,420	8,770,895

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales revenue (1), labor supply (2), and number of customers or buyers (3). Labor supply is 1 if the seller records a transaction in a given day, or 0 otherwise. The specifications control for longer-horizon temperature and precipitation forecasts (2 days ahead), date fixed effects, seller-by-month fixed effects, and seller-by-month-specific quadratic time trends. Standard errors clustered by seller. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Effect of temperature and 1-day-ahead news shocks on market outcomes, area clustering

	(1) Log of sales revenue	(2) Labor supply	(3) Number of customers
$temp_{0,it}$	-0.0139***	-0.0012*	-0.2462***
	(0.0020)	(0.0007)	(0.0553)
$temp_{1,it}$	0.0061**	0.0029***	0.2124***
	(0.0027)	(0.0009)	(0.0747)
$ppt_{0,it}$	0.0001	0.00002	-0.0032
	(0.0002)	(0.00003)	(0.0040)
$ppt_{1,it}$	-0.0003*	-0.0001***	-0.0003
	(0.0002)	(0.00005)	(0.0047)
2-day-ahead forecasts	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Seller x Month FE	Yes	Yes	Yes
Seller x Month FE x Trend	Yes	Yes	Yes
Observations	8,770,895	12,325,420	8,770,895

Notes: This table reports results from fixed effects regressions that examine the effects of weather shocks and forecasts on the log of daily sales revenue (1), labor supply (2) and number of customers or buyers (3). Labor supply is 1 if the seller records a transaction in a given day, or 0 otherwise. The specifications control for longer-horizon temperature and precipitation forecasts (2 days ahead), date fixed effects, seller-by-month fixed effects, and seller-by-month-specific linear time trends. Standard errors clustered by the area. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$