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Jun Rentschler
Ella Kim
Stephan Thies
Sophie De Vries Robbe
Alvina Erman
Stéphane Hallegatte

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Abstract

This study explores how businesses in Tanzania are impacted by floods, and which strategies they use to cope and adapt. These insights are based on firm survey data collected in 2018 using a tailored questionnaire, covering a sample of more than 800 firms. To assess the impact of disasters on businesses, the study considers direct damages and indirect effects through infrastructure systems, supply chains, and workers. While direct on-site damages from flooding can be substantial, they tend to affect a relatively small share of firms. Indirect impacts of floods are more prevalent and sizable. Flood-induced infrastructure disruptions—especially electricity and transport—obstruct the operations of firms even when they are not directly located in flood zones. The effects of such disruptions are further propagated and multiplied along supply chains. The study estimates that supply chain multipliers are responsible for 30 to 50 percent of all flood-related delivery delays. To cope with these impacts, firms apply a variety of strategies. Firms mitigate supply disruptions by adjusting the size and geographical reach of their supply networks, and by adjusting inventory holdings. By investing in costly backup capacity (such as water tanks and electricity generators), firms mitigate the impact of infrastructure disruptions. The study estimates that only 13 percent of firms receive government support in the aftermath of floods.

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Floods and Their Impacts on Firms: Evidence from Tanzania

Jun Rentschler[1], Ella Kim[1], Stephan Thies[1,2], Sophie De Vries Robbe[1], Alvina Erman[1], Stéphane Hallegatte[1]

[1]*The World Bank, Washington DC, USA*
[2]*School of International and Public Affairs, Columbia University, New York, USA*

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1. Introduction

In April 2018, large parts of Tanzania were affected by severe flooding. Especially in the country's commercial capital of Dar es Salaam, flooding caused the loss of lives and widespread damages and disruption. By one estimate, the flooding in Dar es Salaam affected between 900,000 and 1.7 million people, either directly or indirectly (Erman et al. 2019). These resulting economic losses to the population were equivalent to 4 percent of the city's GDP. On average, affected households lost 23 percent of their annual income. And these economic figures do not reflect some of the hidden consequences of disasters, including impacts on people's health and children's educational attainment.

Yet, the 2018 floods were by no means an isolated incident. Changing precipitation patterns, urban expansion into high-risk flood zones, and a lack of effective drainage infrastructure are all contributing to frequent and intense flood events. Recurring floods also mean that firms and households are constantly recovering from and bracing for flooding, which in turn affects their livelihoods and socio-economic prospects. Impacts on public services and infrastructure systems can also have substantial repercussions on those that rely on these services. For instance, this study shows that Tanzania's power outages increase from an average of 18 hours per month in the dry season to 57 hours in the rainy season – with substantial knock-on effects on household well-being and firm productivity.

Much progress has been made in developing our understanding of the impacts of natural shocks on households—not least through rich and dedicated household surveys that shed light on the drivers of exposure, vulnerability, and resilience (Erman et al 2019). However, firm surveys that explore the business costs of natural hazards and infrastructure disruptions are rare in most developing countries, and virtually nonexistent for Tanzania. As a result, there is only limited understanding of how firms are affected by and cope with natural shocks and the associated infrastructure disruptions. This makes it difficult for governments to fully assess economic losses after a disaster, and to identify and prioritize resilient infrastructure investments to ensure business continuity and enhance firms' resilience to natural shocks.

To address this gap, we conducted a specialized firm survey in Tanzania to explore the impacts of natural shocks—particularly floods—on firms and the infrastructure services they rely on. Analyzing the results of the survey, this study addresses several interrelated questions:

1. What are the impacts of natural shocks on firms? For example, destroyed assets, disrupted water, electricity, transportation, and telecommunications services; impacts on workers.
2. What is the role of supply chains in propagating and multiplying disruptions? In other words, from suppliers to clients and end-users.
3. What adaptation strategies are used by firms? For example, additional inventories, own generators, and own water sources or tanks.

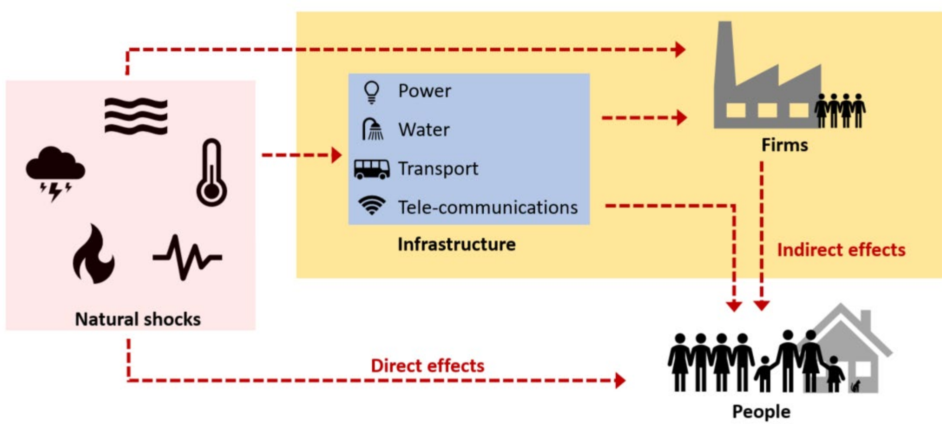
The results from this study confirm that natural shocks have substantial impacts on firms. A single flood in 2018 directly damaged and destroyed an estimated $7.8 million worth of Tanzanian firms' buildings, machineries, and inventories. The study also finds that, in the aftermath of a disaster, indirect effects—particularly those resulting from disrupted transport infrastructure—prevent employees in up to 40 percent of firms from coming to work and hinder firms' ability to receive supplies on time or to maintain sales. It also finds that 30–50 percent of all supply and delivery delays of firms in the study region can be attributed to the propagation of shocks through supply networks. The study presents evidence that firms perform operational adjustments to adapt to disaster risk and that these adjustments can depend on the type of disaster risk experienced. In particular, direct risks of on-site flooding tend to be associated with asset loss avoidance strategies (smaller inventories, lower generator ownership) while indirect risks are correlated with strategies to bridge disruptions (larger inventories, bigger supply networks).

Section 2 of this study provides an overview of relevant evidence from the literature. Section 3 describes the firm survey, including the sampling strategy, sample characteristics, and questionnaire design. Section 4 summarizes the findings on the type and magnitude of disaster losses incurred by firms. Section 5 presents the main results on different coping strategies adopted by affected firms, and Section 6 concludes with key messages.

2. Evidence from the literature: business impacts of disasters and factors of recovery

Disasters impact firms and households through various channels (figure 1). Most visibly, firms incur direct losses as natural shocks destroy or damage facilities, machinery, or inventories. But the disruption of essential infrastructure services, such as power grids or road networks, causes additional indirect costs for enterprises. These effects, which can already have severe macroeconomic consequences, are further multiplied through supply chain linkages as firms incur the additional costs of risk reduction and disaster coping strategies. This section offers a brief overview of the literature in this field. Detailed reviews exist that explore how disasters can cause impacts at the firm, household and macro levels (Botzen et al. 2019; Kousky 2014; Rentschler 2013).

Figure 1: Natural shocks affect people directly and through infrastructure disruptions and impacts on firms



Source: Rentschler et al. 2019a.

Direct asset losses are the most tangible impact of disasters on firms. In high-income countries, a range of institutions, such as insurance companies or governmental organizations, collect data on direct losses (for the United States, see, for example, Smith and Katz 2013). In developing countries, where insurance markets and data collection are limited, less is known about the direct losses that firms incur. While databases such as EM-DAT provide some data on aggregate direct disaster losses, few quantitative firm-level studies have been conducted. One exception is De Mel et al. (2012), who analyze the impact of the

2004 Indian Ocean tsunami on Sri Lanka's micro, small and medium enterprises. They estimate that three months after the disaster, directly impacted firms had lost about 50 percent of their revenues, more than 80 percent of their capital stock, and about 15 percent of their profits. They also show that profits in firms supported through a randomly allocated grant recovered to pre-disaster levels about two years faster than in non-supported firms. Another study (Asgary et al. 2012) evaluates the firm-level effects of the 2010 floods in Pakistan. With a sample of 500 small firms, the authors show that firms with no preparatory measures were severely impacted by the floods. More than 50 percent of firm owners lost access to their business facilities and reported some damage to facility buildings; one-third completely lost their inventories, resulting in 1–3 months of median business disruptions; and 10 percent never reopened.

Firms also experience significant indirect effects of disasters. These cause electricity blackouts and disrupt water supply and transportation networks, which in turn cause output loss in firms, hindering their recovery (Hallegatte et al. 2019). Various modeling studies have estimated the macroeconomic impact of disaster-related infrastructure disruptions (see, for example, Cho et al. 2002; Gordon et al. 1998; Kroll et al. 1991; Tsuchiya et al. 2007). Rose and Liao (2005) demonstrate how a major earthquake disrupting the Portland water supply system could reduce total outputs by up to 41 percent, with indirect effects responsible for 7 percent of reductions. Other studies also indicate the indirect disaster effects of infrastructure disruptions. Rose et al. (2007) estimate that a two-week blackout in Los Angeles could cost the city $2.8 billion, or 13 percent of its total economic activity over that period. Investigating the impact of a 90-day disruption at the twin Texas seaports of Beaumont and Port Arthur, Rose and Wei (2013) find that indirect losses alone could reduce regional gross output by as much as $13 billion.

Frequent disruptions of electricity, water or transport infrastructure also mean that firms cannot produce at full capacity. Rentschler et al. (2019a) build a microdata set of about 143,000 firms to estimate the monetary costs of infrastructure disruptions in 137 low- and middle-income countries. Their estimates suggest utilization losses of $151 billion a year: $107 billion due to transport disruptions, $38 billion due to blackouts, and $6 billion due to water supply disruptions. Natural shocks play a significant role in such infrastructure disruption. Reviewing thousands of power outages from 28 countries in the European Union and North America, Rentschler et al. (2019b) suggest that 20–80 percent of all power outages are caused by natural shocks. Data constraints mean that such estimates do not usually exist in developing countries, making it difficult to estimate the productivity losses associated with natural shocks.

Supply chain linkages amplify the impacts of disasters. Much of the literature on this topic focuses on aggregate-level outcomes and uses sectoral input-output models to assess the supply chain propagation of shocks (Acemoglu et al. 2012; Henriet et al. 2012; Okuyama et al. 2004). However, as Hallegatte (2019) points out, this approach limits the modeling of highly heterogeneous disaster impacts and complex interactions among firms.

A more recent literature uses firm-level data to overcome this shortcoming, with several studies focusing on the effects of the 2011 Great East Japan Earthquake (Boehm et al. 2019; Carvalho et al. 2017; Inoue and Todo 2019; Kashiwagi et al. 2018; Kashiwagi and Todo 2019; Todo et al. 2015). Boehm et al. (2019) find most firms do not look for new suppliers when their regular supply lines are interrupted in case of a disaster. As suppliers cannot be exchanged promptly, earthquake losses are propagated and multiplied through the supply network. In a simulation model, Inoue and Todo (2019) show that, in the context of Japan, these indirect propagation effects can exceed direct losses by factor 20. Analyzing the impact of disasters on US firms between 1978 and 2013, Barrot and Sauvagnat (2016) find that, when a supplier is hit by a major disaster, dependent firms experience an average drop by 2–3 percentage points in sales growth after the event. Given that suppliers represent a small share of firms' total intermediate inputs, they conclude that these estimates are strikingly large.

The vulnerability of firms depends on their sector and their position in the supply chain. Colon et al. (2019) show that, after the 2016 Morogoro flood in Tanzania, the supply chain amplification of disasters is higher for nonprimary products. Agriculture products, which as primary products are less dependent on other supply chains, are less affected by disruptions than secondary products (such as processed food), which rely on the supply of primary agricultural products. Mainly due to a lack of data, most research on supply chain propagation of disaster effects has focused on industrialized countries.

Firms have a range of coping measures to mitigate losses, speed up recovery, and smoothen expenses to ensure business continuity. This study uses survey data to estimate whether Tanzanian firms implement similar coping measures to those identified by Dormady et al. (2017) in a case study of firms affected by Hurricane Sandy in the United States. The most common coping mechanisms relate to a firm's decisions about its capital, assets, labor, inputs, and production technology (figure 2). But a lack of access to credit, inadequate governmental support, or limited cash can make certain coping measures unaffordable or inaccessible, particularly for informal and small firms (Rentschler et al. 2019a).

Figure 2: Coping measures firms can use to mitigate the adverse effects of infrastructure disruptions

Capital	**Labor**	**Inputs**	**Technology**
- relocate - replace production assets - backup machinery	- hire/fire employees - work overtime	- switch suppliers - hold excess inventories - substitute - use more/less	- adjust - increase efficiency
Financed through…			
- reduced profit margin	- borrowing	- insurance	- governmental support

Source: Rentschler et al (2019a), Dormady et al. (2017)

Disasters not only cause damages in their aftermath, as background risk can suppress positive risk taking and investments. The mere possibility of a disaster can also prevent firms from hiring staff or investing in productive assets, such as machinery. Tanner et al. (2015) argue that the possibility of a disaster and its associated assets losses can reduce planning horizons and make business investments less attractive, causing firms to stay below their production possibilities and underperform. These inefficiencies should be accounted for as disaster losses that are incurred before the occurrence of a disaster. However, in the absence of dedicated surveys, the lack of data has made the quantification of this effect difficult.

3. Data and methodology

3.1. A dedicated firm survey

This study presents evidence from a dedicated Tanzanian firm survey conducted with 837 businesses in Dar es Salaam and the provinces of Tanga and Dodoma. The survey explores the real costs of disasters on firms—both through direct damage to assets and operations, and the indirect costs of perpetuated economic inefficiencies and coping measures. The survey's target population was all 58,959 firms in Dar es Salaam, Tanga, and Dodoma that were registered with the National Bureau of Statistics' (NBS) in 2015. This excluded informal firms, which contribute significantly to the Tanzanian economy (Adams et al. 2013). Firms listed in the NBS registry without a contact telephone number were also excluded from the sampling frame. Hence, all survey results should be interpreted as representative of more formal business activities.

To ensure that robust estimation results can be obtained for different subpopulations, the survey used a dedicated sampling strategy. Based on information from the NBS, all registered firms were divided into five distinct strata, depending on their reliance on transport systems. Ordered from low to high transport reliance, these strata contain firms from the following sectors:

1. Accommodation and food service activities, Construction
2. Communication and other services
3. Manufacturing, Mining, Water, Energy, Agriculture
4. Transportation and storage
5. Wholesale and retail trade, Repair of motor vehicles and motorcycles

The sample selection was completed in one stage, with firms selected through a systematic random sampling method from each stratum. In terms of regional distribution, the sample contains 623 firms from Dar es Salaam, 101 from Dodoma, and 113 from Tanga. For a full overview of the total and sampled number of firms by region and strata, see Table A.1 (appendix A). The survey was implemented over 50 days between Tuesday 25th September and 13th November 2018. About 10 percent of listed firms were interviewed, with the main reasons for the low response rate being incorrect addresses, expectation of payment for survey participation, and concerns about disclosure of tax-relevant information.

The survey contained about 390 questions divided into nine modules focusing on various aspects, including reliance on different infrastructure types, disaster experience, information on suppliers and clients, and firm characteristics such as size, investment volumes, and operational costs. All results in this study are based on data collected through this survey, unless otherwise stated. Tables 1–4 present an overview of the average characteristics, infrastructures and dependencies, expenditures and investments of firms in Dar es Salaam, Dodoma and Tanga computed from the survey.

Table 1: Descriptive statistics on firms' characteristics

Variable	Available observations	Mean	Median	Standard deviation	Min	Max
Age of firm (years)	837	12.44	9	12.08	1	85
Number of employees, including owner	837	14.73	4	179.77	1	8,501
Share of female workers	757	36.6%	30%	36.0%	0%	100%
Number of suppliers	805	8.11	7	8.91	1	165
Share of firms selling to general public	837	89.3%	1	1.09%		

Table 2: Sample characteristics on infrastructures and dependencies

Variable	Available observations	Share of firms
Firms dependent on electricity as critical input	837	91%
Firms dependent on communication services as critical input	837	56%
Firms dependent on water as critical input	837	33%
Firms dependent on gas as critical input	837	13%
Share of water tank ownership (conditional on "firm requires water")	279	64%
Share of generator ownership (conditional on "firm requires electricity")	761	30%

Note: Shares of dependency on electricity, water, gas and communication services as main input source do not add up to 100 percent because a firm can depend on several input sources simultaneously.

Table 3: Descriptive statistics on firms' expenditures

Variable	Available observations	Mean	Median	Standard deviation	Min	Max
Water usage (liter/month)	243	240,716	6,087	2,435,105	3	40,000,000
Water expenditure ($/month)	198	279	16.57	3,430	4E-05	132,522
Implied water price ($/liter)	186	0.08	0.003	0.21	1E-09	1.08
Electricity usage (kWh/month)	742	18,115	140	435,949	0.01	13,300,000
Electricity expenditure ($/month)	744	6,909	22.09	205,612	4E-06	6,292,263
Implied electricity price ($/kWh)	740	3.4	0.16	4.8	3E-08	795
Operational cost ($/month)	691	7,146	369	63,343	0	2,208,695
Wage costs ($/month)	636	12,019	530	125,944	0	3,533,912
Transport costs ($/month)	707	2,066	79.51	44,383	0	1,766,956
Firms' premises replacement costs ($)	227	44,222	442	87,828	0	397,565
Machinery replacement costs ($)	723	45,609	4,417	224,012	0	4,417,391

Table 4: Descriptive statistics on firms' investments

Variable	Available observation	Mean	Median	Standard deviation	Min	Max
Total investment ($)	837	5,186	0	36,025	0	750,956
Investment in machinery ($)	793	1,637	0	12,076	0	176,696
Investment in product design and development ($)	797	326	0	2,596	0	79,513
Investment in upgrading/repairing buildings ($)	790	1,408	0	13,703	0	220,870
Other investment in business expansion ($)	793	1,952	0	20,323	0	397,565
Investment in disaster protection measures ($)	792	67.66	0	561	0	22,087

3.2. Methodology

To analyze which coping strategies are implemented by firms that are at risk of experiencing a disaster, this study uses generalized linear regression models (GLM). We use reported direct and indirect disaster risks as well as actual flood experience as explanatory variables (X) to explain variations in the dependent variable (y) while controlling for a range of potential confounding variables (Z). The dependent variables analyzed in the following are inventory size, supply network size, generator ownership, water tank ownership, and investment volumes.

If y is continuous—for example, in the case of firms' inventory size—ordinary least square regressions are carried out, where

$$y = X'\beta + Z'\theta + \epsilon.$$

Here, X is the vector of explanatory variables; Z is a set of controls; and ϵ is the error term. All regressions take the survey design, stratification, and respective sampling weights into account.[1] Estimates are hence representative for the overall population of firms in Dar es Salaam, Dodoma, and Tanga. As the sample size is relatively small compared to the overall population size (about 1.4 percent of the NBS registry), no finite population correction is employed. Standard errors ϵ are clustered at the ward level.

If y is binary—for example, in the case of firm generator ownership—a logit model is used, where

$$P(y = 1) = E[y] = g(X'\beta + Z'\theta).$$

All variables are defined as before and g is the logit link function, taking the form

$$g(\eta) = \frac{\exp(\eta)}{\exp(\eta) + 1}.$$

As before, appropriate sampling weights and stratification are considered.[2] If data on dependent or independent variables for specific firms was missing—that is, there was no response to the survey—these firms were excluded from the respective regressions. Some parts of the questionnaire were only posed to relevant firms— for example, questions on water tank ownership were only posed to firms that require water to run their business. As a result, some regressions rely on sample sizes below the survey sample size of 837, reducing the robustness of statistical estimates. We note that the survey design in combination with the above statistical techniques do not allow us to confirm causal effects. Surveyed measures of disaster exposure are likely to suffer from measurement error. Further, estimates are prone to omitted variable bias resulting in endogeneity issues. Nevertheless, the GLM methodology allows us to analyze correlations, which can be suggestive for potential coping mechanisms at work.

[1] Here, the weights are excluded from the regression formula for simplicity.

[2] Estimates β, γ and θ from the logit model cannot be interpreted as estimates from a linear probability model: β_j does not indicate the marginal effect of changes in X_j on $P(y = 1)$, but indicates the marginal effect on the log odds ratio—that is, $\log\left(\frac{P(y=1)}{P(y=0)}\right)$. To obtain easily interpretable results, mean marginal effects are reported when logistic regressions are employed. The mean marginal effect indicates the average effect for a unit change in X_j on $P(y = 1)$ across all firms. Indexing individual firms with i and the total number of firms n, the mean marginal effect can hence be calculated as $\frac{1}{n}\sum_i \frac{\partial P(y_i=1)}{\partial X_{ij}}$ suppressing sampling weights for simplicity.

4. Summary of descriptive results on the scale and type of disaster losses

Firms incur a wide range of losses due to disasters, both in terms of direct damages and indirectly transmitted costs. Based on the data collected for this study, Appendix B offers a full discussion of the scale and type of firms' disaster losses.

The survey data reveals that flood risks are high throughout most of Tanzania and confirm that firms face substantial recurring losses. Indeed, 47.7 percent of firms state that they perceive at least moderate risk of on-site flooding, and 26.8 percent perceive the risk to be high or very high. Firms also recognize potential indirect effects on their operations—for example, due to supply chain or infrastructure disruptions. Indeed, 64.2 percent of firms perceive at least moderate risk of indirect risks; 33.6 percent perceive the risk to be high or very high. The survey also confirms that floods are the predominant natural hazard to Tanzanian firms: 16.6 percent of all firms reported having experienced flooding on their premises (21.4 percent in Dar es Salaam).

Self-reported data from this survey suggest that firms in Dar es Salaam, Dodoma, and Tanga incurred at least $7.6 million in direct losses and damages due to flooding on business premises in 2018. This estimate is a lower bound estimate for several reasons: First, losses incurred by informal firms are not included, as they were not sampled for data collection. Second, firms only reported losses for the year of their worst disaster experience. For 58.6 percent of firms the worst flood experience was in 2018 and hence data for these firms are observable and included in the estimate. For the other 41.4 percent of firms' losses in 2018 are not observable and not included in the estimate. Third, the estimate refers to a single event (e.g. the major April 2018 floods), rather than annualized losses.

For the average firm in the three study areas, direct damage due to flooding exceeded monthly operational costs by a factor of 1.32 (±0.37). However, for at least 75 percent of businesses, damages were smaller than their monthly operational costs, while for 5 percent of firms flood damage costs exceeded monthly operational costs by a factor of at least 8.13 (Table 5).

Table 5: Cost factors: damage due to flooding on business premises relative to monthly operational costs

			Quantiles				
Damage category	**Mean**	**Standard deviation**	**25%**	**50%**	**75%**	**95%**	**99%**
Buildings	0.42	0.15	0	0	0.16	1.93	6.5
Equipment, machinery, and assets	0.56	0.14	0	0	0.14	4.05	5.38
Access to site	0.31	0.25	0	0	0	0.9	10.72
Other	0.03	0.02	0	0	0	0.07	2
Total direct damages	**1.32**	**0.37**	**0.01**	**0.17**	**0.87**	**8.13**	**13.35**

Note: Factors <1 indicate that flood damages are smaller than monthly operational costs, factors >1 indicate the opposite.

Besides asset damages, firms also reported significant sales losses in the aftermath of floods. About 40 percent of firms reported that one week after flooding, their sales had "somewhat reduced," around 11 percent reported that sales had halved, while approximately 16 percent of firms reported a short-lived increase in sales. Notably, there is a significant delay in sales losses affecting firms, with more firms affected one month after a flood than in the immediate aftermath. This suggests that damages are passed on through transmission channels over time. Indeed, the main reasons why firms experienced a fall in sales relate to supply chain issues—either as transportation routes are disrupted, or as clients experience financial losses, which are partly passed on from their own clients. Overall, about 75 percent of affected firms reported reduced sales a month after a disaster.

The survey also reveals that natural shocks affect the ability of employees to commute and work (and thus earn an income), and hence obstruct firms' ability to continue operations. Disruptions to public transport are highly significant for commuters in all three study areas. In an average firm, about 69 percent of workers use the bus as their main mode of transport to work. This is followed by walking (20 percent), motorbike (5 percent), and bike (2.6 percent). About 41 percent of firms reported that damaged public transport infrastructure prevented workers from coming to work in the aftermath of floods, including low-intensity flooding during regular rainy seasons.

During floods and heavy rainfall, water and power outages are common in Tanzania; 81 percent of surveyed firms experienced a power outage during the most serious disaster, lasting on average 4.9 days. More firms in Dar es Salaam (91 percent) and Tanga (84 percent) experienced power outages than in Dodoma (28 percent). However, the outages lasted longer in Dodoma and Tanga (12 days) than Dar es Salaam (2.7 days). Three-quarters of firms do not have an alternative electricity source, but 23 percent reported switching to a generator when facing a power outage. Mean costs of the back-up electricity supply are comparable to normal electricity costs.

While Tanzanian firms already face frequent electricity and water disruptions during the dry season, the survey shows that these are amplified in the rainy season. An average firm experiences power outages on about 2.6 days per month in the dry season, with this number nearly doubling to 5.1 days in the rainy season, when outages also last longer. While the mean outage duration is about 5.4 hours in the dry season, these increase to around 11.2 hours in the rainy season. Taking both effects into account and correcting for outliers, an average firm experiences around 17.8 total hours of power outage each month in the dry season, rising to 57 hours in the rainy season.

The lack of reliable and resilient infrastructure systems causes economic efficiency losses. A global study by Rentschler et al (2019) highlights the substantial drag that unreliable infrastructure imposes on firms in developing countries. In Tanzania, firms are incurring estimated utilization losses of nearly $670 million a year (1.8 percent of national GDP) from power and water outages and transport disruptions. The firm survey collected for this study allows us to estimate the share of these utilization losses that are caused by natural shocks. Power disruptions alone are responsible for $216 million in utilization losses a year, of which 47 percent ($101 million, or 0.3 percent of GDP) are solely due to power outages caused by rain and floods. The remaining 53 percent are due to baseline power outages associated with causes other than rain and flooding (such as load shedding or equipment failure). For transport disruptions, about 46 percent of utilization losses ($150 million, or 0.4 percent of GDP) are due to disruption caused by rain and floods. The survey does not find that rain and floods have any significant impact on the incidence of water supply disruptions.

5. Measures that enable firms to cope and recover

This section explores mechanisms firms can use to mitigate and prevent losses from natural shocks, cope with impacts, and adjust to background risks, following a framework by Dormady et al. (2017) (figure 2, Section 2). In particular, this study aims to understand firm's operational decisions in the context of the Triple Dividend concept (Tanner et al., 2015). The concept suggests that disasters cause adverse impacts not only in their aftermath (e.g. through damages and losses), but also in advance. The mere presence of the risk of a disaster, could cause firms to underinvest in building upgrades or machinery, or to adjust their supply chain network. In other words, firms take operational decisions in a way to minimize losses in the case of disasters, but these decisions come at the expense of productivity and efficiency. Measures to increase firms' disaster resilience can not only yield the dividend of reduced disaster losses, but also of increased economic productivity. In this section we investigate whether firms do indeed adopt some of the following strategies in anticipation of potential disaster losses:

- Inventories: Holding higher levels of input inventories can help firms to deal with supply disruptions in the case of disasters. However, if flooding occurs on-site, more inventories may mean more losses.
- Supply network: Relying on a large number of suppliers from different regions can reduce the risk of supply disruptions. At the same time a large supply network can increase indirect disaster exposure through supply chain multiplication effects.
- Backup capacity: Water tanks and electricity generators can bridge disruptions and outages.
- Investment behavior: Reducing investments in business development or upgrades of productive assets can reduce the risk of heightened disaster losses.

5.1. Firms adjust their inventories to mitigate and respond to disruptions

This study finds evidence that Tanzanian firms are adjusting the size of their inventories to reduce potential disaster losses. While bulk procurement of inputs could help to lower costs for most firms, holding large input inventories exposes firms to the risk of floods destroying such inventories. Indeed, firms that have recently experienced flooding on their business premises tend to have input inventory sizes that are smaller by about 7 (±3) days' worth of production compared with unaffected firms (table 6).[3] This suggests that firms try to avoid future destruction of inventories by holding smaller stocks or that recovery of losses from previous floods is still ongoing.

Besides real flood occurrences, firms' *perception* of disaster risks can also explain inventory decisions. While these results are subject to higher estimation uncertainty, results suggest that firms that perceive high risks of on-site flooding also tend to hold smaller inventories, while high indirect risk perception is associated with larger inventories (Table 6). This pattern can be observed more pronouncedly for firms in Tanga and Dar es Salaam when regionally disaggregating the effects (Table D.2, appendix D). Firms with recent disaster experiences also hold smaller input inventories. This suggests that many inventories,

[3] Input inventory sizes are measured as the maximum number of days that a firm can sustain current activity with its stock of inventories. A similar analysis was conducted for the size of output inventories but yielded few informative results.

worth about 14 (±6) days of independent production, are lost during disasters and cannot be recovered within a two-month period (Table 6).[4]

Table 6: Regression results for the impact of disaster risk perception and disaster experience on input inventory sizes

	Input inventory size				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Direct disaster risk perception (no risk)					
Low risk	1.445				1.096
	(6.534)				(6.793)
Moderate risk	-4.665				-5.549
	(4.546)				(6.345)
High risk	-7.566				-8.019
	(5.583)				(8.678)
Very high risk	-6.212				-11.06
	(6.197)				(10.78)
Indirect disaster risk perception (no risk)					
Low risk		-3.167			-1.208
		(4.780)			(4.789)
Moderate risk		-3.540			1.777
		(4.310)			(5.570)
High risk		-3.917			5.493
		(4.588)			(7.775)
Very high risk		5.054			14.37
		(8.588)			(13.25)
Experienced flooding on business premises					
Yes			-7.196***		-5.817*
			(2.660)		(2.983)
Longest supply delivery delay in days				-0.00785	-0.00369
				(0.0624)	(0.0694)
Time since last serious disaster (>12 months)					
<2 month	-14.73**	-10.66	-12.99*	-14.16**	-14.86**
	(6.059)	(6.565)	(6.743)	(6.559)	(5.869)
2–12 months	-1.026	-0.131	-0.697	-2.096	-1.090
	(3.692)	(3.578)	(3.793)	(3.730)	(3.196)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	576	576	574	558	556
R-squared	0.078	0.076	0.075	0.060	0.077

Note: Fixed effects include region-and sector-specific fixed effects. Input inventory sizes are measured as the maximum number of days that a firm can sustain current firm activity with its current stock of inventories. Controls include age of the firm, number of employees and log operational costs. "Time since last serious disaster" refers to whether the most recent disaster that a firm experienced was up to 2 months, 2–12 months or more than 1 year ago. The variable flood experience indicates whether firms have experienced flooding on their business premises

Standard errors (in parentheses) are clustered on the ward level: $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$

[4] All results presented here should be interpreted with caution as variations in input inventory sizes across firms are large and regressions explain only a small fraction in the overall variance. Even after controlling for a range of fixed effects and other potentially confounding factors, the R^2 for most regressions lies between 6 and 10 percent. This indicates that other firm characteristics explain inventory size of firms or that self-reported answers are subject to large uncertainties.

5.2. Supply chains can help diversify disaster risks

Firms can mitigate the impacts of potential disasters by adjusting the size and spatial reach of their supply networks (Dormady et al. 2017). For instance, by relying on a larger number of suppliers and those in spatial proximity, firms can diversify the risk of supply chain disruptions – though potentially incurring higher costs than through a more concentrated supply network. To assess this often-overlooked risk management strategy, this section explores variation in the number of suppliers and the spatial extent of the supply network.

5.2.1. Impact on supply chains

Disasters not only affect firms directly by damaging their assets, obstructing workers to come to work or reducing sales; they also affect every link in their supply network – ranging from their immediate suppliers to those further up their supply chain by several degrees.

Across the three study areas, 37 percent of firms reported experiences of supply disruptions after a disaster. For about 6 percent of firms, these disruptions lasted longer than a week (figure C.1, appendix C). Transport disruptions are cited by about 50 percent of firms as the primary reason for supply chain disruptions (figure C.10, appendix C). Firms tend to stick to their suppliers even when they cannot supply; only 13 percent reported that they switched suppliers in response to disruptions. Of those that did, 97 percent had switched back to their original suppliers or intended to do so. There were some regional differences in this behavior, with firms in Dodoma more likely (41 percent) to switch suppliers than firms in Tanga (8 percent) and Dar es Salaam (13 percent).

The fact that only 13 percent of firms reported changing suppliers during disruptions indicates that short-term elasticities of substitution for firm inputs may be low in Tanzania. Previous literature has found that low substitution elasticities translate into costly supply chain multiplication effects, thus propagating shocks (Barrot and Sauvagnat 2016; Boehm et al. 2019). Colon et al. (2019) first presented evidence of this effect for Tanzania. The firm data presented here sheds further light on the size of the effect.

The data collected through this survey suggest that the primary reasons for general supply and delivery delays in Tanzanian firms are upstream supply chain issues. About 53 percent of firms reported that their supplies were delayed as a result of problems with the supplier's supplier (figure C.11, appendix C), and 32 percent indicated that issues with their own suppliers were the primary reason for delayed deliveries to their clients (figure C.12, appendix C). This highlights that a significant share of delays can be explained by supply chain multiplication effects.

By correcting for network multiplication effects, we show that most residual supply chain delays can eventually be attributed to disruptions of transportation and power infrastructure. For instance, if a firm reports that the delayed delivery of supplies is partly due to transport disruptions and partly due to delayed dispatch by their supplier – then the delayed dispatch can in turn be partly explained by transport disruptions further up the supply chain. Hence, ultimately, any delays from suppliers must be attributable to infrastructure disruptions or on-site flood impacts that affected up-stream suppliers. By proportionally re-attributing the reasons for supply and delivery delays, we account for the supply chain multiplier and estimate the underlying reasons for supply and delivery delays.[5] This shows that network effects are responsible for about 30–50 percent of all supply and delivery delays in Tanzanian firms. In particular, after correcting for multiplier effects, most supply delays can be attributed to up-stream disruptions transportation and power infrastructure (Figures 3 and 4).

Figure 3: Reasons for delivery delays by firms' suppliers (survey data and induced multiplicator effects)

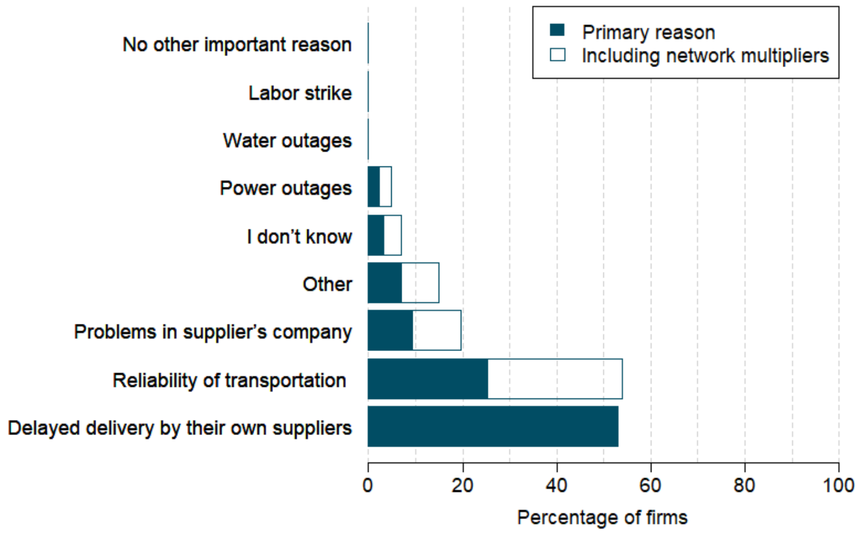
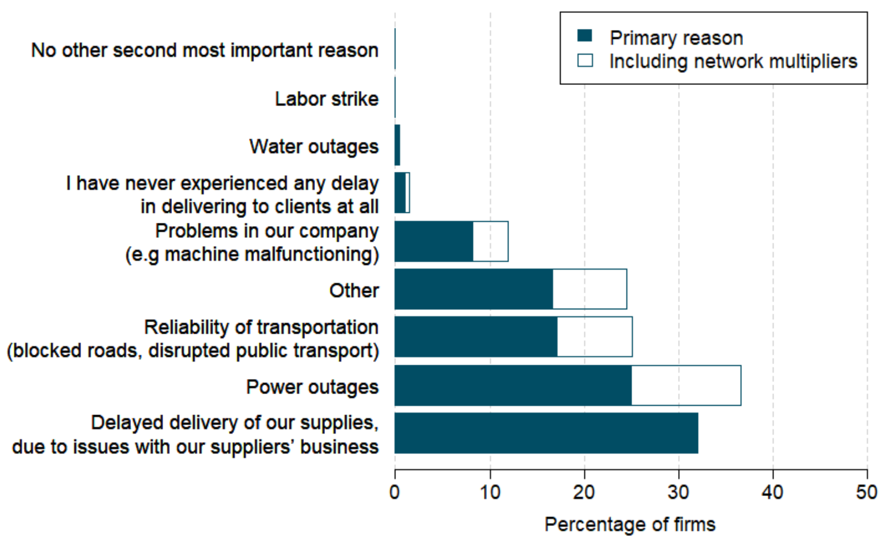


Figure 4: Reasons for delivery delays to firms' clients (survey data and multiplicator effects)



5.2.2. Diversify risk by increasing the number of suppliers

By relying on a larger number of suppliers, firms can reduce the risk of being cut off from inputs deliveries during disaster-related disruptions. Indeed, we find that firms' perceptions matter. Firms that perceive higher *indirect* disaster risks maintain a larger number of suppliers—on average, about two more than

[5] If x_s is the share of delays attributed to delays in the supply chain and x_i is the share of delays attributed to reason i, then (assuming proportionality) the overall share of delays caused by reason i is: $\tilde{x}_i = \frac{x_i}{1-x_s}$.

firms that do not report any risk (table 7, regression specifications 2 and 4). This can indicate that firms either try to hedge against disaster risks through a larger network, or that those with a larger network are more exposed to indirect risks (for example, through network multiplication effects).[6] In contrast, firms that report *direct* on-site flood risks do not have a significantly different number of suppliers compared with firms without on-site risk. These findings are consistent, as an increased number of suppliers can hedge against supply chain disruptions, but not against on-site flooding.

In addition, we find that firms that previously experienced flooding on their premises have about 1.8 fewer suppliers than comparable firms. By contrast, firms that experienced a recent disaster tend to have more suppliers across the regression specifications, though the effect is small. For every additional month passed since the last disaster, the number of suppliers decreases on average by 0.02. The small size of this effect is consistent with the observation that only 13 percent of firms switch suppliers in the aftermath of a disaster. The survey results show that larger firms (as measured by their volume of operational costs) have larger supply networks and that there is significant cross-sectoral variation in the number of suppliers—for example, firms in the transportation and storage sectors have on average about 5.6 (±1.5) suppliers fewer than firms in the accommodation and food service sectors.

Table 7: Regression results for the supply network size

	Total number of suppliers			
VARIABLES	(1)	(2)	(3)	(4)
Direct disaster risk perception (no risk)				
Low risk	0.349			-0.0177
	(0.654)			(0.660)
Moderate risk	0.743			0.963
	(1.212)			(1.257)
High risk	0.488			1.714
	(1.660)			(2.427)
Very high risk	-1.182			-0.608
	(1.051)			(1.654)
Indirect disaster risk perception (no risk)				
Low risk		2.498***		2.482***
		(0.820)		(0.770)
Moderate risk		2.341**		2.044**
		(1.130)		(1.010)
High risk		0.0575		-0.150
		(0.830)		(1.167)
Very high risk		2.649**		2.831*
		(1.229)		(1.662)
Experienced flooding on business premises				
Yes			-1.849**	-1.748
			(0.853)	(1.323)
Time since last serious disaster (months)	-0.0247***	-0.0224***	-0.0263***	-0.0201***
	(0.00597)	(0.00714)	(0.00705)	(0.00584)
Log (total operational costs in $/month)	1.195**	1.160**	1.190**	1.167**

[6] As indicated by the R-squared, regression results should be interpreted with caution since a large amount of variance in the total number of suppliers cannot be explained.

	(0.526)	(0.515)	(0.518)	(0.524)
Sector (Accommodation and food service activities, Construction):				
Communication and other services	-2.333**	-2.111**	-2.305**	-2.129**
	(1.026)	(0.975)	(0.996)	(0.960)
Manufacturing, Mining, Water, Energy, Agriculture	0.502	0.630	0.587	0.435
	(1.368)	(1.424)	(1.438)	(1.358)
Transportation and storage	-5.801***	-5.643***	-5.726***	-5.640***
	(1.438)	(1.522)	(1.413)	(1.550)
Wholesale and retail trade, Repair of motor vehicles and motorcycles	1.222	1.130	1.201	1.001
	(1.248)	(1.248)	(1.288)	(1.145)
Region (Dar es Salaam)				
Dodoma	0.945	0.0536	0.127	-0.221
	(1.796)	(1.374)	(1.778)	(1.528)
Tanga	-4.005***	-4.431***	-4.390***	-4.543***
	(0.660)	(0.733)	(0.755)	(0.813)
Controls	YES	YES	YES	YES
Observations	660	660	658	658
R-squared	0.105	0.114	0.107	0.122

Note: Controls include age of the firm and number of employees
Standard errors (in parentheses) are clustered at the ward level: *p<0.1 **p<0.05 ***p<0.01

5.2.3. The geographical extent of a supply network can determine risk

Firms can also reduce the risk of local shocks by varying the spatial extent of their supply network. However, for the surveyed firms, local suppliers play a dominant role. About 50 percent of the firms in Dodoma, Tanga and Dar es Salaam are less than 10 kilometers away from their average supplier, making them vulnerable to local disruptions. For 80 percent of firms, the average supplier is less than 50 kilometers away. Only a few firms maintain a dispersed supply network—only for about 10 percent of firms, the average supplier is over 200 kilometers away. For the case of Tanzanian firms covered by this survey there is no detectable significant relationship between disaster risk perception or actual flood experience and distance to the average supplier, when employing linear regressions (table D.3, appendix D). Instead, differences in supply network extents across firms can mainly be explained through region and sector fixed effects, with firms in Dodoma and Tanga maintaining on average more spread out supply networks than those in Dar es Salaam.

5.3. Investing in backup capacity can ensure business continuity but also results in risks

By investing in water tanks and electricity generators, firms can ensure business continuity even when infrastructure systems are disrupted by disasters (Hallegatte et al. 2019). The survey data show that about 64 percent of the firms that depend on water for their production own a water tank, and 30 percent of firms own power generators. The evidence presented in this section shows that water tank and generator ownership are strongly driven by economic factors, such as the local price of water and electricity or firms' usage levels. There is some evidence that experiencing a flood on business premises increases the probability of water tank ownership, but decreases the probability of owning a power generator.

5.3.1. Water tanks

About 33 percent of firms in Dar es Salaam, Dodoma and Tanga need water to run their firms. This dependence varies by sector (figure C.4, appendix C). Their source of water also differs: 67 percent of firms obtain their water via central distribution, but local wells are also a common source of water supply, especially in Dar es Salaam, where 30 percent of firms get their water this way (figure C.5, appendix C). Almost 64 percent of water-dependent firms in the three study areas maintain a water tank to bridge water supply disruptions.[7]

Firms that have experienced a flood on their business premises are significantly more likely (on average, by 28.3 (±10) percentage points) to own a water tank (table 8).[8] Higher direct and indirect disaster risks are associated with larger probabilities of water tank ownership. A firm from the high direct risk group is, on average, about 27.8 (±18) percentage points more likely to own a water tank than one that did not report any disaster risk. The remaining results indicate that larger firms (proxied by monthly operational costs) are more likely to own a water tank. Increasing the firm size by 1 percent increases the probability of owning a water tank on average by 8.6 (±2.6) percentage points. Furthermore, higher water usage and water costs are associated with larger probabilities of water tank ownership.[9]

Table 8: Mean marginal effects of selected variables in full water tank ownership regression ‡

VARIABLES	Mean marginal effect	Standard error (delta method)
Direct disaster risk perception (no risk)		
Low risk	0.125	(0.119)
Moderate risk	0.202	(0.125)
High risk	0.278	(0.181)
Very high risk	0.175	(0.158)
Indirect disaster risk perception (no risk)		
Low risk	0.223	(0.160)
Moderate risk	0.056	(0.163)
High risk	0.094	(0.166)
Very high risk	0.067	(0.191)
Experienced flooding on business premises (no)		
Yes	0.283***	(0.101)
Log (water usage, liters/month)	0.029*	(0.017)
Log (costs of water, $/liter)	0.026**	(0.013)
Log (total operational costs, $/month)	0.086***	(0.026)
Main source of water (central distribution)		
Water vendor	-0.206	(0.159)
Other	-0.191	(0.135)

Note: ‡ Please refer to Table D.4, appendix D for detailed regression results of the full generalized linear models. Reference levels of categorical variables in parentheses.
Standard errors are clustered on the ward level in parentheses: *** p<0.01 ** p<0.05 * p<0.1

[7] Mean water tank ownership varies by sector, but is subject to a large estimation error due to the small sample size of firms that require water (280 firms). For a graphical overview see figure C.6, appendix C.
[8] As linear estimators are hard to interpret in a logistic regression, table 8 presents mean marginal effects of selected variables for the full regression model. Full results from logistic regressions are presented in table D.4, appendix D. Discrepancies in the significance of direct estimators and marginal effect estimators can arise. Here, coefficients are interpreted if the marginal effects estimate, or the direct estimator are significant at 10 percent.
[9] Note that the results for water tank ownership rely on a relatively small sample size of about 170 firms.

5.3.2. Backup generators

In Dar es Salaam, Dodoma and Tanga, 91 percent (±1.5) of firms rely on electricity for their production; of these, about 30 percent (±2) own a generator to bridge power supply disruptions. Electricity in the surveyed regions is mainly provided through national utility TANESCO (98.5 percent), and electricity dependence is consistently high across sectors (figure C.7, appendix C). The probability of generator ownership decreases on average by 9.3 (±4.7) percentage points if a firm has experienced on-site flooding (table 9).[10] This stands in contrast to backup water tanks, where on-site flood experience is associated with higher ownership. A potential explanation is that electricity generators are more prone to be damaged by flooding than water tanks. Self-reported direct and indirect disaster risk perception have no detectable impact on the probability of electricity generator ownership.

In general, the probability of generator ownership is mostly driven by economic factors, as well as regional and sector-specific effects. Increasing electricity prices by 1 percent results on average in 4.2 (±1.9) percentage points higher probabilities of generator ownership. Similarly, higher electricity usage and bigger firm sizes, proxied by monthly operational costs, are associated with higher ownership rates. Firms that need to halt production immediately without electricity are also significantly more likely to own a generator, on average by 9.9 (±5.1) percentage points.

Table 9: Mean marginal effects of selected variables in full generator ownership regression ‡

VARIABLES	Mean marginal effect	Standard error
Region (Dar es Salaam)		
Dodoma	-0.105	(0.065)
Tanga	-0.130***	(0.045)
Direct disaster risk perception (no risk)		
Low risk	-0.037	(0.049)
Moderate risk	0.027	(0.057)
High risk	0.008	(0.065)
Very high risk	0.123	(0.086)
Indirect disaster risk perception (no risk)		
Low risk	-0.024	(0.072)
Moderate risk	-0.029	(0.074)
High risk	-0.076	(0.074)
Very high risk	-0.026	(0.087)
Experienced flooding on business premises (no)		
Yes	-0.093*	(0.047)
Log (electricity usage, in kwh/month)	0.091***	(0.014)
Log (costs of electricity, in $/kwh)	0.042**	(0.019)
Log (total operational costs, in $/month)	0.025*	(0.013)
Time until firm needs to halt production without electricity (no halt)		
Under 6 hours	-0.024	(0.050)
More than 6 hours	-0.042	(0.053)
Immediate	0.099*	(0.051)

Note: ‡ Please refer to Table D.5, appendix D for detailed regression results. Further controls include sector fixed effects, number of employees, firm age, time since last serious disaster. Reference levels of categorical variables in parentheses. Standard errors are clustered on ward level in parentheses: *** p<0.01 ** p<0.05 * p<0.1

[10] Table 9 presents mean marginal effects of the full model specification. Direct estimates from the different logistic regressions employed can be found in table D.5, appendix D.

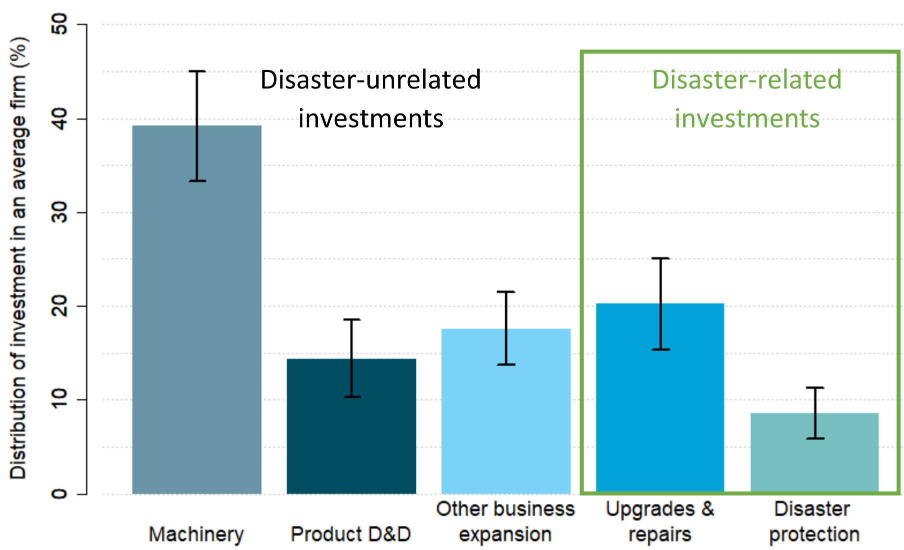
5.4. Do firms adjust investment volumes to flood risk?

This section explores how the presence of disaster risks can impact firms' investment decisions. On the one hand, firms that face (or perceive) higher disaster risks may refrain from undertaking productive investments in business development, for fear of potential asset losses. On the other hand, at-risk firms may increase their investments in disaster protection measures and repair works. The results presented in this section suggest that firms indeed adjust their investment volumes in response to disaster risks.

Investment behavior is heterogenous in all three study areas. About half the firms reported that they had made no investments in the 12 months before the survey; 30 percent invested up to $700; and 5 percent reported investing very large volumes, between $14,000 and $750,000. These investments were unequally distributed across categories, with the average firm investing mainly (40 percent) in machinery. About 20 percent of investments went towards upgrades and repairs, and less than 10 percent were related to disaster protection (Figure 5). [11]

Figure 5: Distribution of investments in an average firm

Survey question: How much did you invest in the past 12 months in (1) new machinery, (2) product design and development, (3) upgrading/repairing building and land, (4) other measures of business expansion, (5) flood protection



Note: Product D&D refers to product design and development. Whiskers indicate 95 percent confidence intervals.

Regressions on the probability of investing (table D.6 and D.7, appendix D) and on the size of investment volumes (table D.8, appendix D) indicate stark regional differences in investment behavior, even after controlling for a range of effects.[12] The estimates suggest that firms in Dodoma are 40 percent more likely to invest thank firms elsewhere, and that investment volumes are 1.8 to 3 times larger in Dodoma and

[11] See figure C.9, appendix C, for investment distribution by region.

[12] Since a large fraction of firms reported zero investments, two sets of regressions were run. The first set analyzes the probability of investment—that is, *p(investment>0)*. Results of the full logistic regression are displayed in table D.6 and mean marginal effects in table D.7 (appendix D). The second set of regressions analyzes investment amounts for all firms that actually invest; since the investment distribution is highly skewed, the analysis is run in logs. Results are displayed in table D.8.

Tanga compared to firms in Dar es Salaam. In line with intuition, the estimates suggest that bigger firms, as measured through their monthly operational costs, are more likely to invest and invest larger volumes.

Firms that perceive direct disaster risks to be high are less likely to invest; but when they do, they spend larger volumes. A firm that reports a very high risk of being directly affected by a disaster is on average 23.2 (±7.2) percentage points less likely to make any investments than a firm that does not report risk. Yet, investment volumes react in the opposite direction: firms reporting moderate to very high direct risk invest 1.9 to 2.4 times more than firms that do not report such risks (tables D.7 and D.8, appendix D).

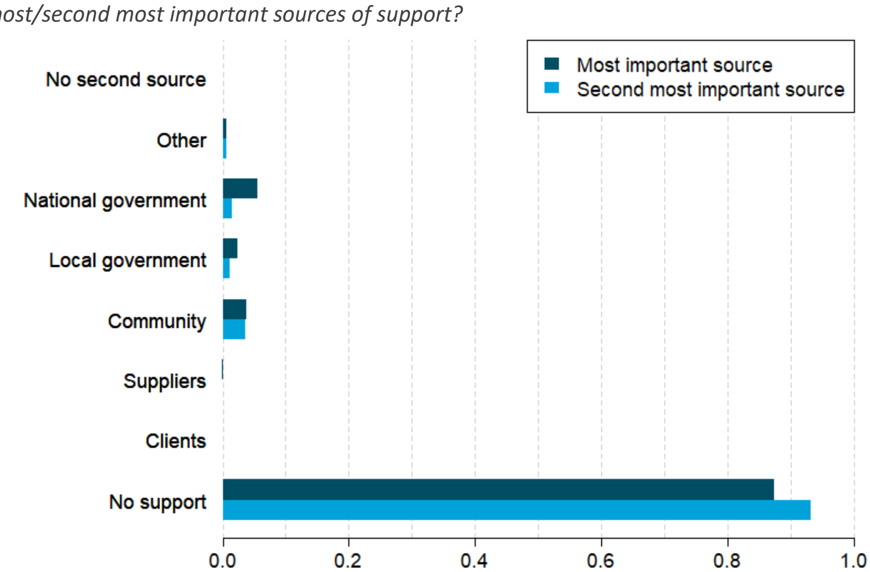
When classifying investments into disaster-unrelated investments (machinery, product design and development, and other business expansion) and disaster-related investments (upgrades, repairs, and disaster protection investments), there are few systematic patterns in the probability of investment. However, results suggest that for firms reporting indirect disaster risks, disaster-related investments are around 1.4–2.3 times larger (table D.8, appendix D). Large self-reported direct disaster risks appear to have little impact on disaster-related investments, including repairs. Instead, disaster-unrelated investment volumes are up to 2.8 times larger if direct risks are very high, compared to the no-risk group.

5.5. Few support mechanisms are in place for affected firms

Even if firms take preparatory measures to adjust to disaster risks, the occurrence of an event might force them to rely on external support. The survey found a lack of such external support for disaster-affected firms in all three study areas. About 87 percent of firms received no support in the months following a disaster (figure 6). When they did receive support, it was from national government (5.5 percent), communities (3.9 percent) or local government (2.4 percent). With respect to financial support for reconstruction, the survey indicates that 3 (±1.4) percent of firms have received support from a governmental source and 1 (±0.5) percent of firms are covered by insurance. Among firms that have received support, on average 36 (±12) percent of damages were covered for firms receiving government support, rising to 68 (±11.9) percent for those with insurance cover.

Figure 6: Most firms in Tanzania have no external source of support for coping with negative shocks

Survey question: Tell me about the most serious disaster that affected your firm. Following the disaster, what were your most/second most important sources of support?



Firms in Dar es Salaam are significantly less likely to receive any government support than those in Dodoma and Tanga.[13] On average, firms in Tanga are 17 (±5) percentage points more likely to get post-disaster governmental support than their counterparts in Dar es Salaam (table D.9, appendix D). Moreover, across all firms in the sample, every month that passes since the last disaster increases their likelihood of obtaining governmental help by 0.07 percentage points on average. This small but significant effect indicates that post-disaster government support tends to be "too little, too late".

In summary, these results suggest that firms may lack financial resilience to extreme events. Disasters, such as flooding, are often regional events affecting multiple households and firms; but both community resilience and local governmental support are of insufficient size to be effective coping mechanisms. More transregional and national support mechanisms could help reduce risks and speed up recovery in the aftermath of a disaster.

6. Key messages

Leveraging novel data from a specialized firm-level survey, this paper presents new evidence on the impacts of natural hazards on Tanzanian firms. Flooding is the predominant disaster affecting businesses in Dodoma, Tanga, and Dar es Salaam, often destroying valuable production assets of Tanzanian firms. The study also reveals that firms are keenly aware of these risks and adjust their operations accordingly. The data suggest that firms have inefficient inventory holdings due to on-site flood risks or potential supply chain disruptions.

Overall, the findings from this firm survey highlight the potential of policy interventions in multiple areas to mitigate the adverse effects of disaster risks on firms.

Investments in more resilient transport infrastructure can ensure job accessibility, protect supply chains, and reduce loss multipliers. Disrupted transport infrastructure is the key driver of the indirect losses experienced by firms, leaving employees unable to come to work, and causing supply and delivery delays, which multiplicatively propagate through the entire supply network. Investing in the resilience of transport network – starting with the most critical network segments – can help to reduce the propagation of such disruptions and costs.

Flood prevention measures can prevent firms from adopting expensive coping measures and promote business continuity. Firms adapt their operations depending on the risks they face. Firms with higher risks of on-site flooding hold fewer inventories, are less likely to own an electricity generator, and have smaller supply networks. Firms that experience more frequent disruptions of infrastructure and service delivery systems tend to have more suppliers and hold larger inventories. These results suggest that firms face a trade-off between avoiding asset losses and bridging disruptions in case of a flood event. Supporting firms to strengthen resilience – both on-site and in their operations – can reduce the need for costly coping measures.

[13] "Receiving any governmental support" in the aftermath of a disaster is defined as receiving help from local or national government as the most or second most important source of support.

Strengthening government support to help Tanzanian firms cope and recover from shocks. About 87 percent of firms report that they have not received any financial support in the aftermath of a disaster, and only 1 percent of firms report having received insurance payouts for damaged buildings, pointing to the potential of a larger role for governments in ensuring private sector resilience to disasters. With limited options for firms to absorb losses and rebuild from disasters, governments can improve access to insurance to help firms cope with disaster losses with a mix of subsidies and regulations. Governments can also support firms to develop business continuity plans to improve overall disaster preparedness.

Complementing existing household survey-based analyses, this new Tanzanian firm survey yields detailed insights on the direct and indirect firm-level costs of natural hazards, along with firms' decision-making factors to deal with increasing extreme events. More research on firm-level effects of natural hazards is called for to better target policy interventions towards the needs of firms – and the critical goods, services, and jobs which they provide.

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Appendices

A. Survey data collection and sampling

Table A.1: Total and sampled number of firms in Tanzania, by stratum and region

Region	Stratum (sector)	Number of firms	Percentage in region total	Number of firms surveyed	Percentage in region sample
Dar es Salaam	Accommodation and food service activities, Construction	5,105	12.8	84	13.5
	Communication and other services	6,385	16.1	120	19.3
	Manufacturing, Mining, Water, Energy, Agriculture	10,458	26.2	170	27.3
	Transportation and storage	1,115	2.7	48	7.7
	Wholesale and retail trade, Repair of motor vehicles and motorcycles	16,844	42.2	201	32.3
	Subtotal	***39,907***	***100***	***623***	***100***
Dodoma	Accommodation and food service activities, Construction	941	10.6	11	10.9
	Communication and other Services	3,469	39.2	40	39.6
	Manufacturing, Mining, Water, Energy, Agriculture	2,100	23.7	22	21.8
	Transportation and storage	42	0.5	4	4.0
	Wholesale and retail trade, Repair of motor vehicles and motorcycles	2,295	26	24	23.8
	Subtotal	***8,847***	***100***	***101***	***100***
Tanga	Accommodation and food service activities, Construction	1,289	12.6	15	13.3
	Communication and other Services	3,898	38.2	38	33.6
	Manufacturing, Mining, Water, Energy, Agriculture	2,517	24.7	31	27.5
	Transportation and storage	236	2.3	2	1.8
	Wholesale and retail trade, Repair of motor vehicles and motorcycles	2,265	22.2	27	23.9
	Subtotal	***10,205***	***100***	***113***	***100***
Total		**58,959**	**100**	**837**	**100**

B. Descriptive results on the scale and type of disaster losses

b.1. Firms perceive high levels of flood risk

Flood risks are high throughout most of Tanzania, and the survey data confirm that firms are aware of these risks. Indeed, 47.7 percent of firms stated that they perceive at least moderate risk of on-site flooding, and 26.8 percent perceive the risk to be high or very high. Firms are also aware of the potential indirect effects on their operations—for example, due to supply chain or infrastructure disruptions. Indeed, 64.2 percent of firms stated that they perceive at least moderate risk of indirect risks; 33.6 percent perceive the risk to be high or very high. The perception of disaster risks differs significantly across regions (figure B.1 and B.2), with firms in Dodoma exhibiting consistently higher levels of perceived risk. However, this perception of risk does not necessarily align with actual experience of flood events. In Dar es Salaam, 21.4 percent of businesses had experienced flooding on their premises, compared to 11.6 percent in Tanga, and just 1.1 percent in Dodoma. The risk perception scores are likely to be affected by two main factors: the (perceived) probable maximum loss, and the (perceived) average hazard level. So, even if the hazard level is average in Dodoma compared to other locations, if a disaster occurs, firms may perceive the consequences as being more severe, due to potential supply chain disruptions, limited access to recovery support, prolonged reconstruction periods, or other reasons.

Figure B.1: Firms' perception of direct risk, disaggregated by region

Survey question: How do you rate the risk of flooding and other natural shocks to the premises of your firm?

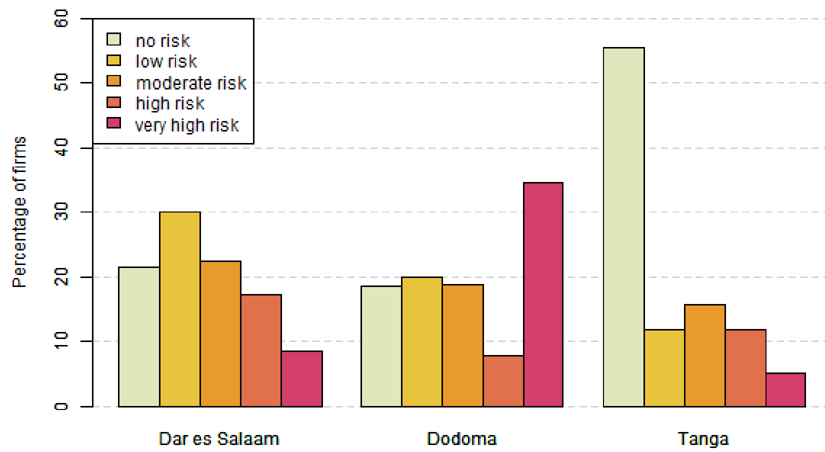
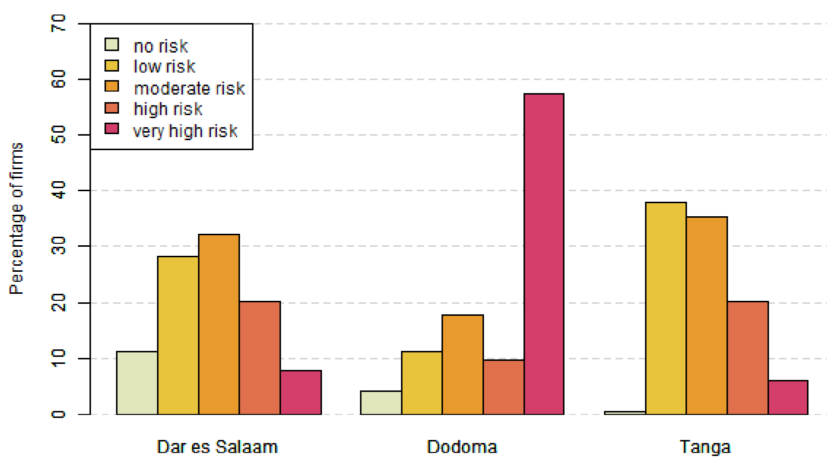


Figure B.2: Firms' perception of indirect risk, disaggregated by region

Survey question: How do you rate the risk of indirect impacts of flooding and rain to your business?



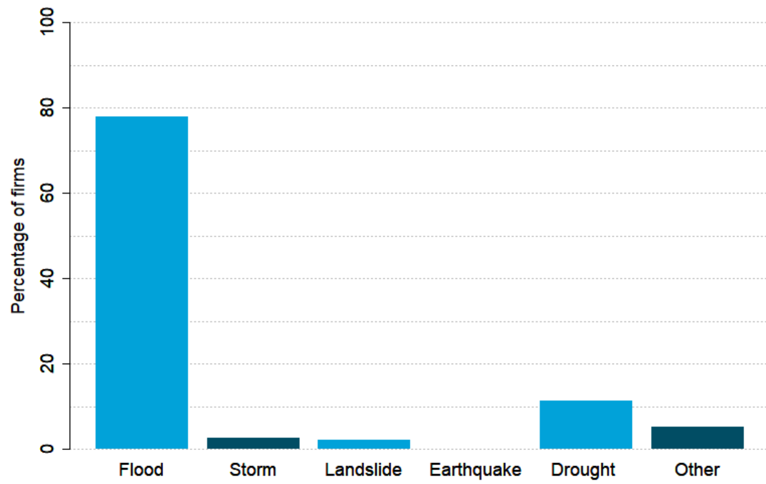
b.2. Firms' direct flood exposure and associated losses

Floods are the predominant natural threat to firms

The survey confirms that floods are the predominant natural hazard to Tanzanian firms (figure B.3). Floods are a common disaster in the country, and firms are often directly exposed: 16.6 percent of all firms reported having experienced flooding on their premises. Geographic differences exist, as 21.4 percent of firms in Dar es Salaam, 11.6 percent of firms in Tanga, and 1.1 percent of firms in Dodoma reported having been directly hit by a flood. This is not necessarily an indication of low flood hazards in Dodoma—in fact, the province has experienced severe flooding in recent years. Rather, it reflects that most of the surveyed firms are not directly located in these flood zones. But even if they are not directly affected by flooding, disrupted infrastructure and supply chains can have substantial indirect consequences.

Figure B.3: Flooding is the predominant hazard self-reported by firms

Survey question: Tell me about the most serious shock that affected your firm. Of what type was that shock?



Notably, recall periods are short. When asked about the most severe disaster they ever experienced, 63 percent of firms referred to events that occurred within 12 months of the data collection in September 2018. Three main factors are likely to drive this observation. First, the high frequency of flood events simply means that there is always a recent event firms can refer to—in Dar es Salaam, for example, urban flooding is a monthly or weekly occurrence, especially in the rainy seasons. Second, there is a recency bias—that is, when asked about the "most severe event", people are more likely to recall recent events. Third, Dar es Salaam experienced unusually severe floods in April 2018, which affected businesses and transport networks and claimed the lives of at least 20 people. This severe event is likely to be picked up in these self-reported exposure estimates, as it preceded data collection by only six months.

Floods cause direct asset losses and damages

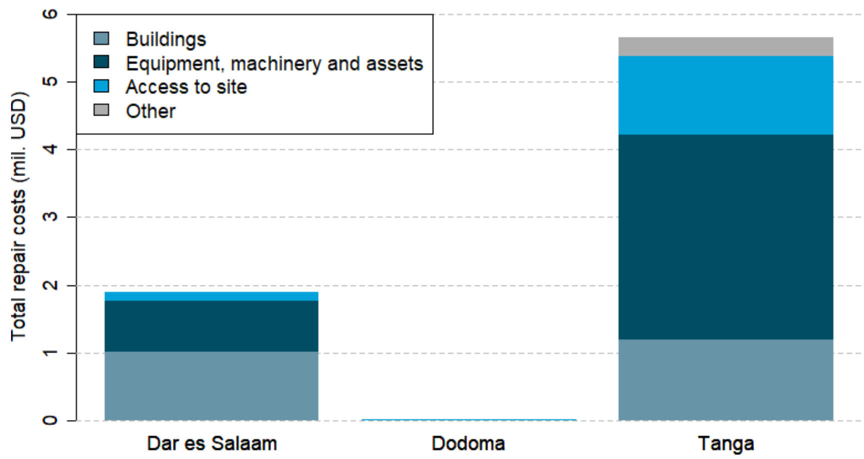
On-site asset losses

Self-reported data from this survey suggest that firms in Dar es Salaam, Dodoma, and Tanga incurred at least $7.6 million in total losses and damages due to flooding on business premises in 2018. This estimate is a lower bound estimate for several reasons: First, losses incurred by informal firms are not included, as they were not sampled for data collection. Second, firms only reported losses for the year of their worst disaster experience. For 58.6 percent of firms the worst flood experience was in 2018 and hence data for these firms are observable and included in the estimate. For the other 41.4 percent of firms' losses in 2018 are not observable and not included in the estimate. Third, the estimate refers to a single event (the major April 2018 floods), rather than annualized losses.

Direct losses due to flooding differ across regions and damage categories (figure B.4). In Dar es Salaam, flooding mainly caused costs to buildings ($ 1 million) and equipment, machinery, and assets ($700,000). In 2018, only one firm in Dodoma reported flooding on business premises, resulting in small estimated total costs for the province. In Tanga, estimated costs to buildings were similar to those in Dar es Salaam, but losses for equipment, machinery, and assets amounted to $3 million, resulting in total costs around $5.65 million. Why losses in Tanga are reported to be significantly higher than in Dar es Salaam (which experienced severe floods in 2018) remains a partly open question – but, subjective loss estimates by respondents could be one explanation.

Figure B.4: Repair costs due to flooding in 2018, by type and region

Survey question: Tell me about the most serious shock that affected your firm. What was the estimated cost to replace or repair (1) damaged buildings, (2) equipment, machinery, and assets, (3) access to site, (4) other damage?



Considering all data on the worst disasters experienced, the distribution of absolute damages and damages relative to operational costs is highly skewed (tables 5 and B.1). For the average firm that experienced flooding on its premises, repairs amounted to about $2,150 (±787), with building repairs and equipment replacements comprising the largest share of costs (Table B.1). For 50 percent of firms, total costs caused by flooding on business premises were under $100, while 5 percent experienced damages exceeding $13,000 (with 1 percent exceeding $24,000).

The distribution of flood damage relative to operational costs is also highly skewed. For the average firm in the three study areas, direct damage due to flooding exceeded monthly operational costs by a factor of 1.32 (±0.37). However, for at least 75 percent of businesses, the associated costs were smaller than their monthly operational costs. The average factor of 1.32 was driven by the 5 percent of firms where flood damage costs exceeded monthly operational costs by a factor of at least 8.13 (table 5).

Table B.1: Cost of on-site damage due to flooding, by asset type ($)

			Quantiles				
Damage category	**Mean**	**Standard deviation**	**25%**	**50%**	**75%**	**95%**	**99%**
Buildings	988	459	0	4.4	88.3	2,208	15,653
Equipment, machinery, and assets	871	355	0	0	133	3,576	15,272
Access to site	197	119	0	0	2.8	425	4,256
Other	92.4	52.6	0	0	0	88	2,110
Total direct damages	**2,150**	**787**	**8.83**	**88.4**	**282.7**	**13,418**	**24,479**

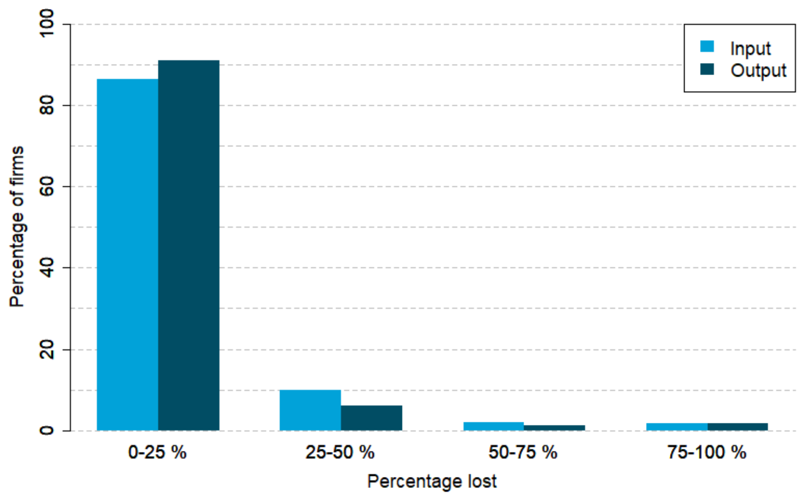
Self-reported repair expenditures do not necessarily correspond to repair needs as financial and capacity constraints may force firms to leave some damage unrepaired. Such constraints tend to be particularly stark for informal and small enterprises. As well as financial costs, firms reported significant clean-up times to repair damage from flooding, on average spending 18 days in Dar es Salaam and Tanga and 6 days in Dodoma.[14]

Inventory losses

The survey also enables an estimation of flood-related inventory losses, as flooding destroys valuable production inputs or produced outputs ready for sale. The survey data suggest that most firms in Tanzania lose 0–25 percent of their input and output stock (figure B.5). Firms also reported that only about 2 percent of total repair costs and lost stock is covered by insurance or government support. Of the 837 firms sampled, only six had insurance coverage and nine got government support (for more details, see section 5.5).

Figure B.5: Share of input and output inventories lost

Survey question: Tell me about the most serious shock that affected your firm. What percentage of your input/output stock did you lose?



Note: This figure only includes firms that reported flooding on their business premises.

b.3. Flooding causes notable reductions in sales

As well as direct damages, firms reported significant sales losses in the aftermath of floods. About 40 percent of firms reported that one week after flooding, their sales had "somewhat reduced," around 11 percent reported that sales had halved (figure B.6), and approximately 16 percent of firms reported a short-lived increase in sales. Notably, there is a significant delay in sales losses affecting firms, with more firms affected one month after a flood than in the immediate aftermath. This suggests that damages are passed on through transmission channels over time.

Indeed, the main reasons why firms experienced a fall in sales relate to supply chain issues—either as transportation routes are disrupted, or as clients experience financial losses, which are partly passed on from their own clients (figure B.7). Overall, about 75 percent of affected firms reported reduced sales a month after a disaster (figure B.6). Recovery periods tend to differ significantly across firms. Fifty percent

[14] Note the low (1.1 percent) level of direct flood exposure of firms in Dodoma.

of firms reported that they had returned to pre-flood sales in under a week, while 75 percent recovered after a month. However, 1 percent needed more than 1.5 years to return to pre-disaster sales (table B.2).

Figure B.6: Reduction in sales in the first week and first month after a disaster

Survey question: Tell me about the most serious shock that affected your firm. By how much did you have to reduce sales in the first week/first month following the disaster?

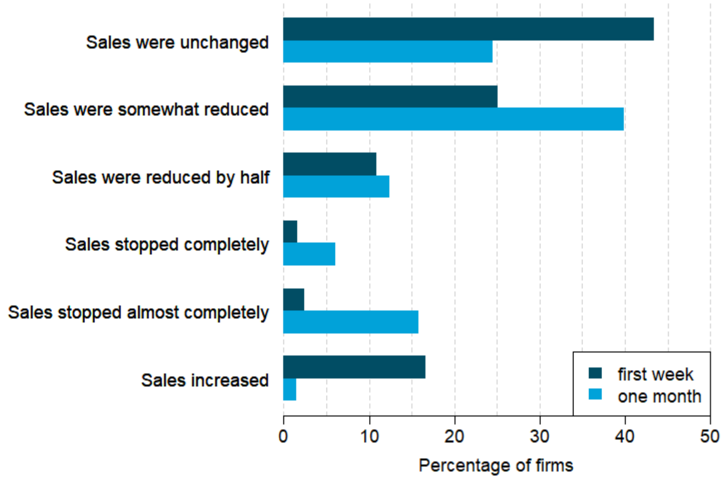


Figure B.7: Reasons for reductions in sales

Survey question: Tell me about the most serious shock that affected your firm. What is the primary/secondary reason for these sales reductions?

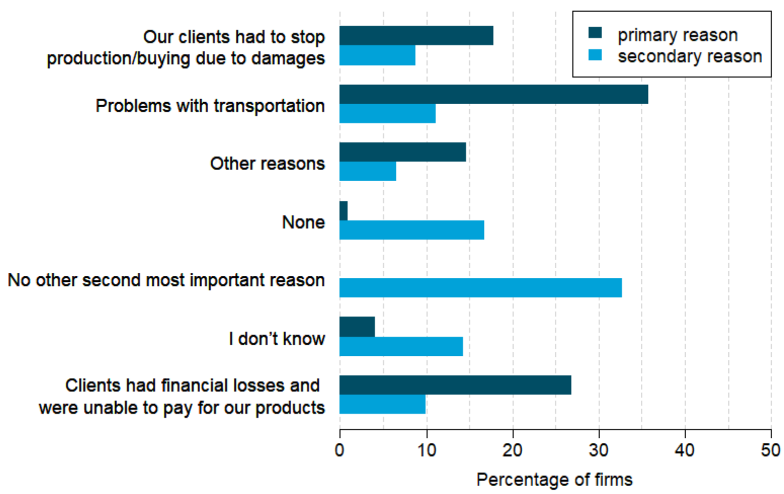


Table B.2: Time required to return to pre-disaster sales

Survey question: Tell me about the most serious shock that affected your firm. After how many days did you return to your sales before disaster?

			Quantiles				
	Mean	**Standard deviation**	**25%**	**50%**	**75%**	**95%**	**99%**
Days required	32.1	4.23	0	5	30	180	507

b.4. Impact on jobs

The survey reveals that natural shocks affect employees' ability to commute and work, and therefore earn an income, as well as firms' ability to continue operations. Disruptions to public transport are highly significant for commuters in all three study areas. In an average firm, about 69 percent of workers use the bus as their main mode of transport to work (figure B.7). This is followed by walking (20 percent), motorbike (5 percent), and bike (2.6 percent). About 41 percent of firms reported that damaged public transport infrastructure prevented workers from coming to work in the aftermath of floods.

But the ability of workers to get to work is not only affected during or after extreme flooding; it is also relevant during the regular rainy and dry seasons. In an average firm, 15 percent of employees cannot get to work during a typical rainy season month, compared to only 2 percent in the dry season; 35 percent are late for work during a typical rainy season month, compared to 8 percent during the dry season (Figure B.8). Delays and absences are more prevalent in firms whose employees mainly commute by bus. During the rainy season, absenteeism in an average firm whose employees walk to work is about 10 percentage points lower and lateness is about 13 percentage points lower than in a firm whose employees commute by bus. These effects are also present during the dry season, but smaller in magnitude (see table D.1, appendix D for regression results). These estimates suggest a similar order of magnitude as by Erman et al (2019), who find that in the 2018 flood, 68 percent of affected households and 26 percent of sampled households reported having missed days of work due to April floods.

Other reasons for missing work in the aftermath of a disaster included repairing flood damage at home or taking care of affected family members (figure B.9).

Figure B.7: Most Tanzanian workers commute to work by bus

Survey question: What is the most common mode of transport chosen by your workers to come to work?

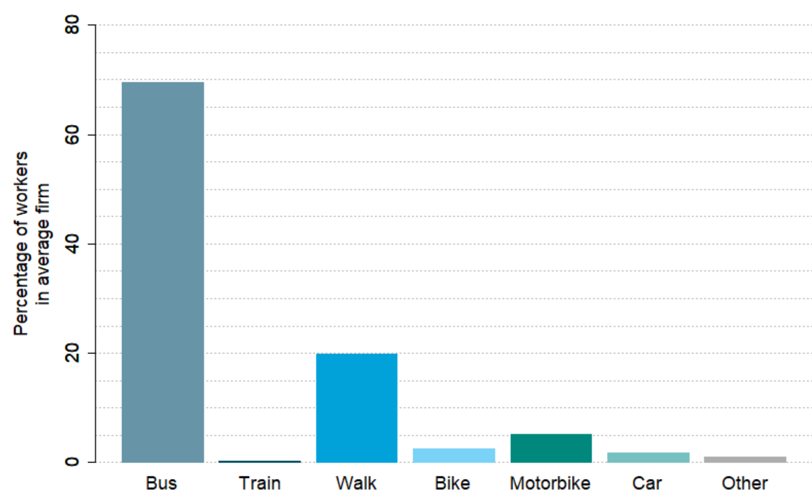


Figure B.8: Percentage of workers who are absent or late for work due to infrastructure disruptions

Survey question: In a typical month during the rainy / dry season, how many workers (including the firm's owner) are completely unable to come to work / arrive late to work due to transport disruption?

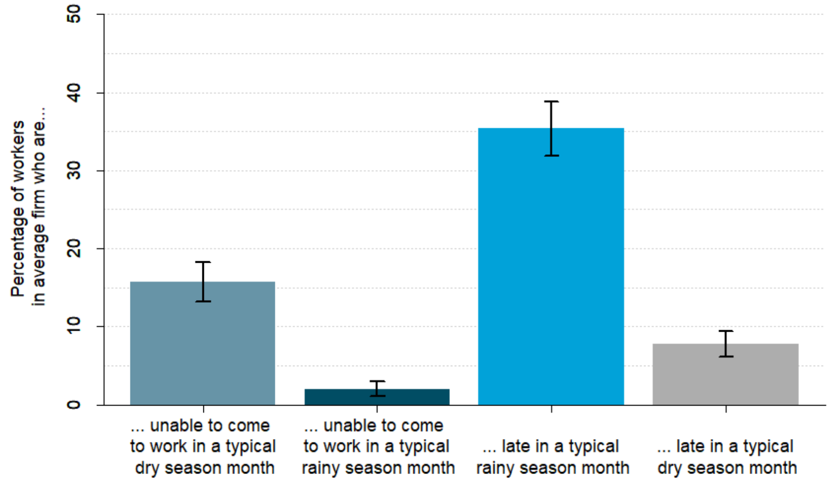
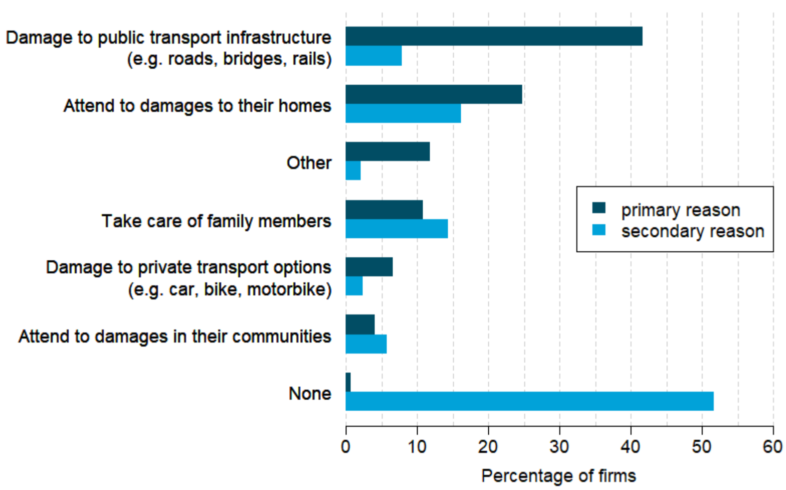


Figure B.9: Reasons for workers' absence after a disaster

Survey question: Tell me about the most serious shock that affected your firm. What was the most/second most important reasons for workers absence?



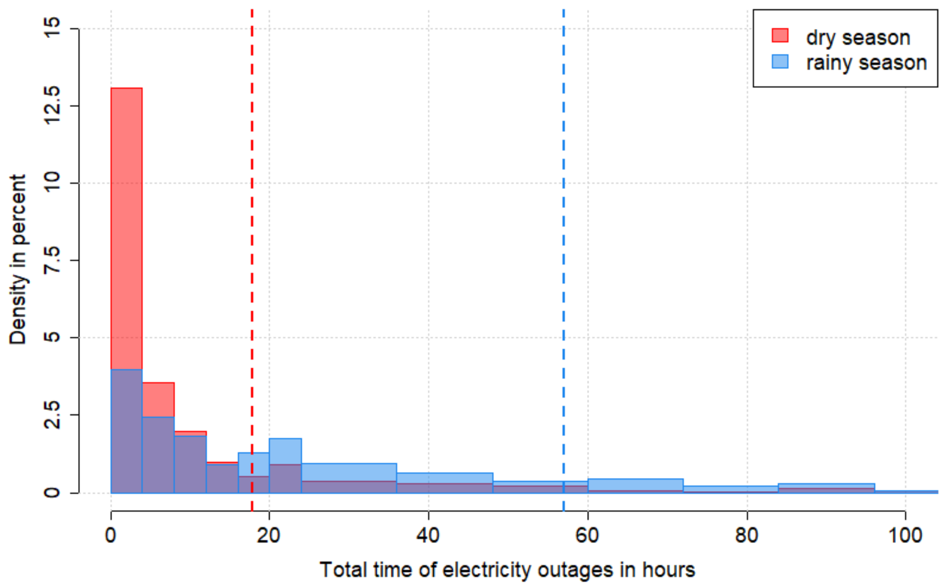
b.5. Impacts due to disrupted power and water infrastructure

During disasters, water and power outages are common in Tanzania; 81 percent of firms surveyed experienced a power outage during the most serious disaster, lasting on average 4.9 days. More firms in Dar es Salaam (91 percent) and Tanga (84 percent) experienced power outages than in Dodoma (28 percent). However, the outages lasted longer in Dodoma and Tanga (12 days) than Dar es Salaam (2.7 days). Three-quarters of firms said they do not have an alternative electricity source, but 23 percent reported switching to a generator when facing a power outage. Mean costs of the back-up electricity supply are comparable to normal electricity costs.

While Tanzanian firms already face frequent electricity and water disruptions during the dry season, the survey shows that these are amplified in the rainy season. An average firm experiences power outages on about 2.6 days per month in the dry season, with this number nearly doubling to 5.1 days in the rainy season, when outages also last longer. While the mean outage duration is about 5.4 hours in the dry season, these increase to around 11.2 hours in the rainy season. Taking both effects into account and correcting for outliers, an average firm experiences around 17.8 total hours of power outage each month in the dry season, rising to 57 hours in the rainy season (Figure B.10). Water supply disruptions, on the other hand, seem to be largely unaffected by the rainy season, with firms experiencing about 2.4 days of water supply disruptions on average in both seasons.

Figure B.10: Electricity outage time differs significantly in the dry and rainy seasons

Survey questions: On how many days per month do you usually experience power outages during/outside the rainy season? How long does a power outage usually last during/outside the rainy season?



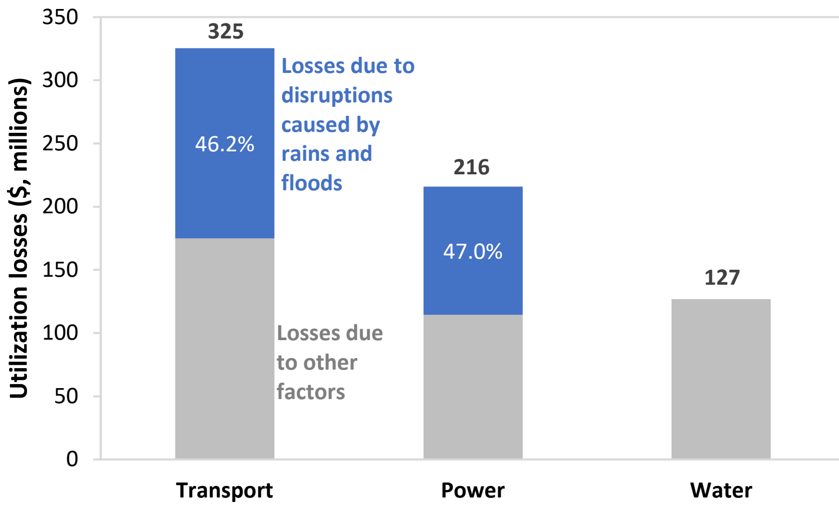
Note: Total time is calculated as number of days that firms experience outages times the average length of an outage in hours per day. Dashed lines indicate mean number of disruption hours. Note that this is a density histogram facilitating group comparisons. The area of all bins sums to 100%.

b.6. Utilization rates: disasters cause firms to underutilize their production capacity

The lack of reliable and resilient infrastructure systems causes economic efficiency losses. A global study by Rentschler et al (2019) constructed a microdata set of about 143,000 firms to estimate the monetary costs of infrastructure disruptions in 137 low- and middle-income countries. Specifically, the study assessed the impact of transport, electricity, and water disruptions on the capacity utilization rates of firms. It estimates that utilization losses amount to $151 billion a year, thus highlighting the substantial drag that unreliable infrastructure imposes on firms in developing countries. In Tanzania, firms are incurring estimated utilization losses of nearly $670 million a year (1.8 percent of national GDP) from power and water outages and transport disruptions (Figure B.11). The authors suggest that a substantial share of these losses could be due to natural shocks, which interrupt infrastructure services.

The firm survey collected for the case of Tanzania allows us to revisit the utilization loss figures and estimate the share that is indeed caused by natural shocks. Power disruptions alone are responsible for $216 million in utilization losses a year, of which 47 percent ($101 million, or 0.3 percent of GDP) are solely due to power outages caused by rain and floods. The remaining 53 percent are due to baseline power outages associated with causes other than rain and flooding (such as load shedding or equipment failure). For transport disruptions, about 46 percent of utilization losses ($150 million, or 0.4 percent of GDP) are due to disruption caused by rain and floods. The survey does not find that rain and floods have any significant impact on the incidence of water supply disruptions.

Figure B.11: Losses from infrastructure disruptions reported by Tanzanian firms



Source: based on Rentschler et al. 2019.

C. Additional figures

Figure C.1: Reported length of supply disruptions after most serious shock

Survey question: Tell me about the most serious shock that affected your firm. For how long were your suppliers unable to supply?

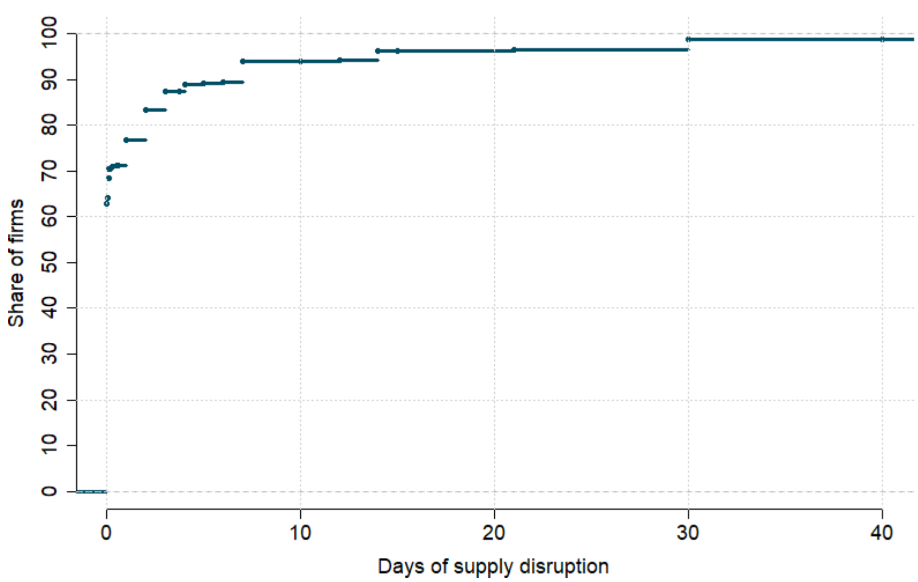
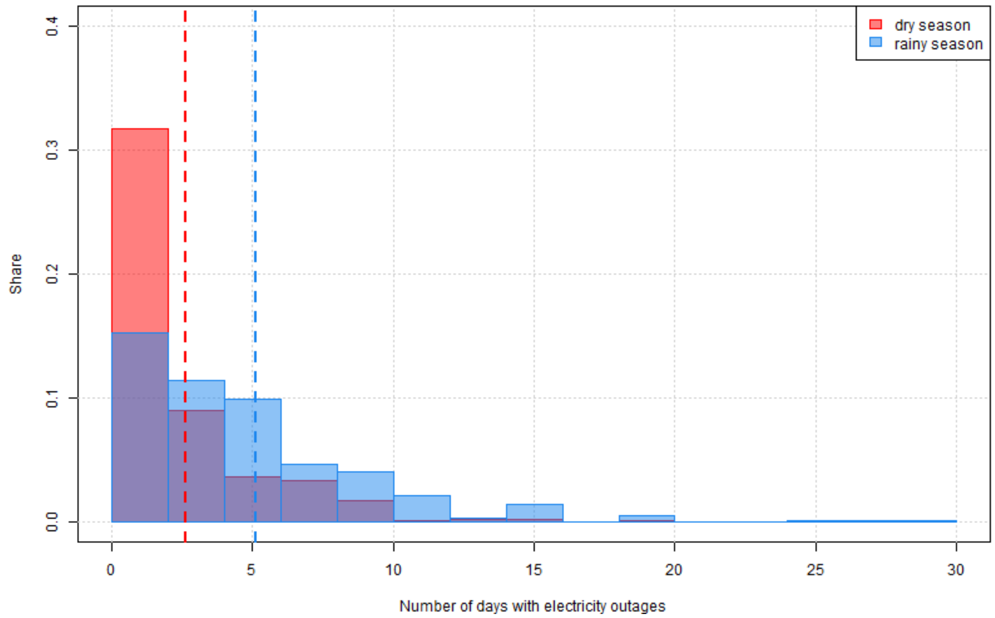


Figure C.2: Number of days with electricity outages

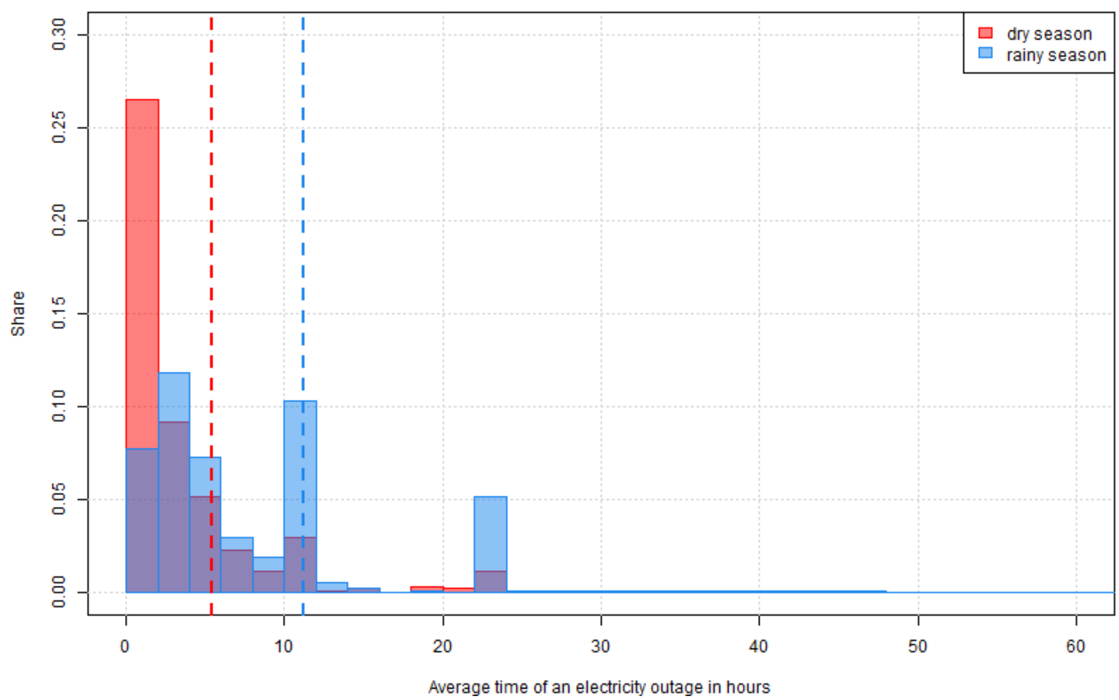
Survey question: On how many days per month do you experience power outages during/outside the rainy season?



Note: Dotted lines indicate mean outage hours.

Figure C.3: Average length of an electricity outage

Survey question: How long does a power outage usually last during/outside the rainy season?

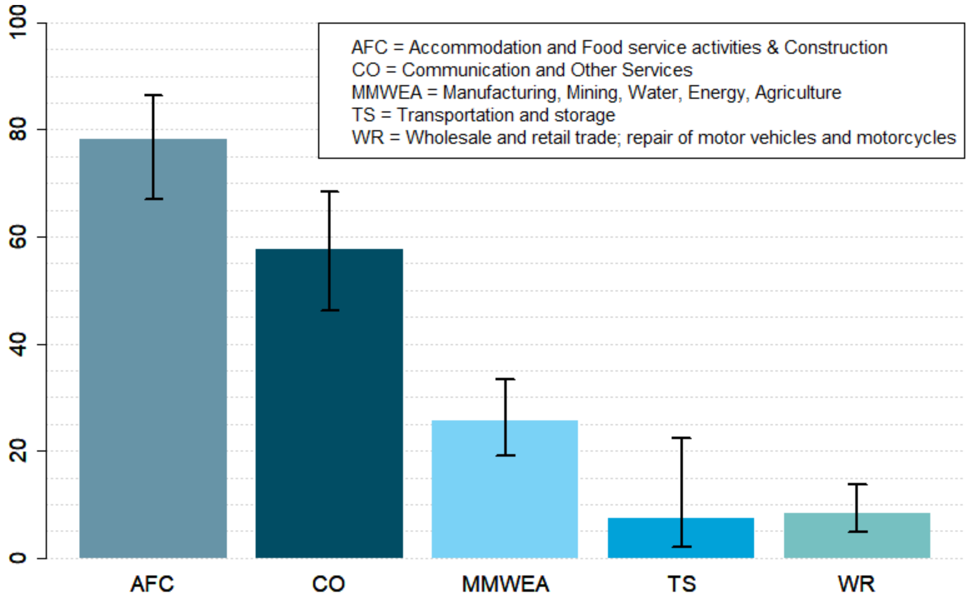


Note: Dotted lines indicate mean outage hours.

Figure C.4: Water dependence, by sector

Percentage of firms that require water for their production.

Survey question: What are you depending on to maintain your firm activity? – Water?



Note: All bars indicate population representative means, taking survey weights into account. Error bars indicate 95 percent confidence intervals after stratification and clustering.

Figure C.5: Source of water, by region

Survey question: What is your main source of water supply?

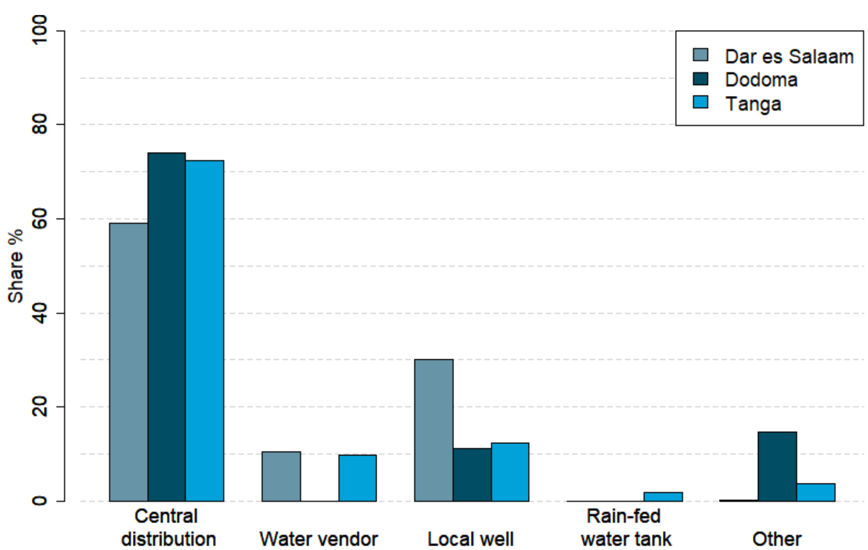
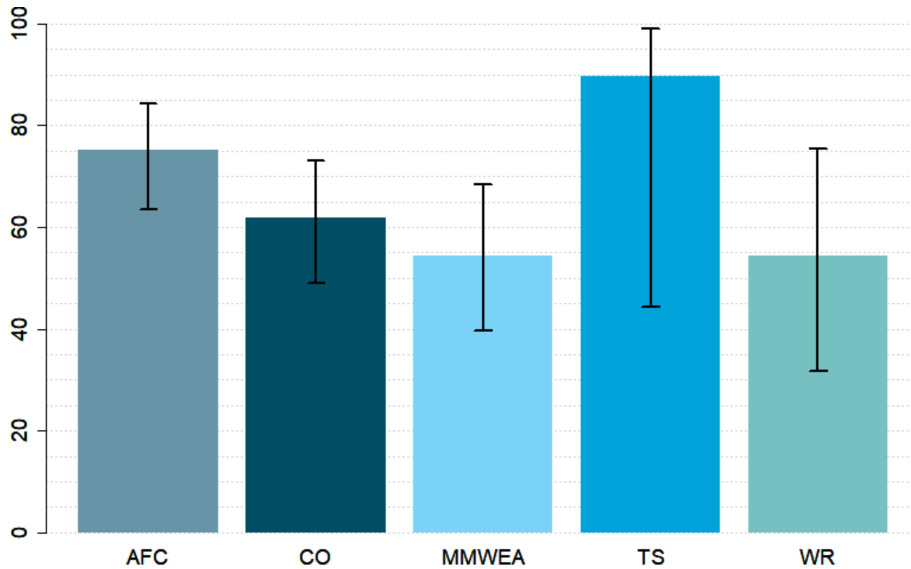


Figure C.6: Water tank ownership, by sector

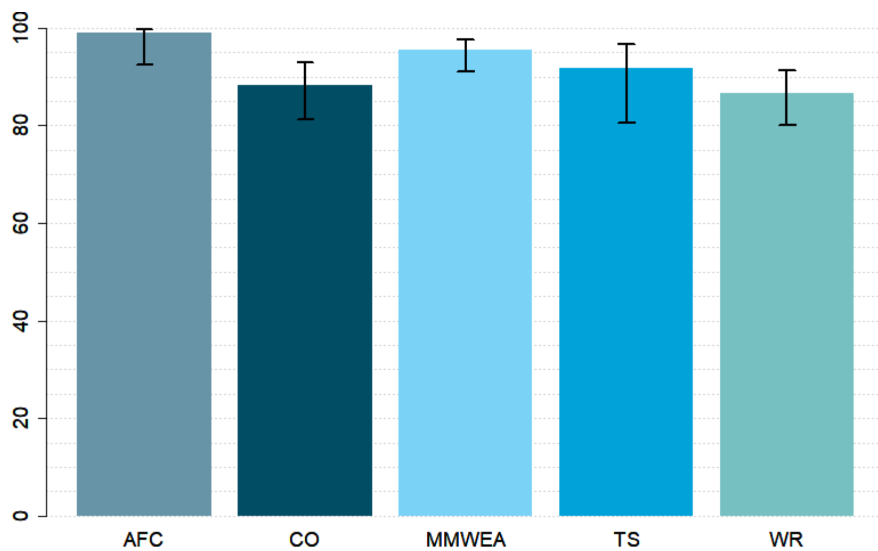
Survey question: Do you have a water tank that enables you to continue firm activity during a disruption?



Note: AFC = Accommodation and food service activities, Construction; CO = Communication and other services; MMWEA = Manufacturing, Mining, Water, Energy, Agriculture; TS = Transportation and storage; WR = Wholesale and retail trade, Repair of motor vehicles and motorcycles.

Figure C.7: Share of firms relying on electricity for their production, by sector

Survey question: Are you depending on electricity to maintain firm activities?



Note: AFC = Accommodation and food service activities, Construction; CO = Communication and other services; MMWEA = Manufacturing, Mining, Water, Energy, Agriculture; TS = Transportation and storage; WR = Wholesale and retail trade, Repair of motor vehicles and motorcycles.

Figure C.8: Cumulative distribution function of a firm's distance to its average supplier

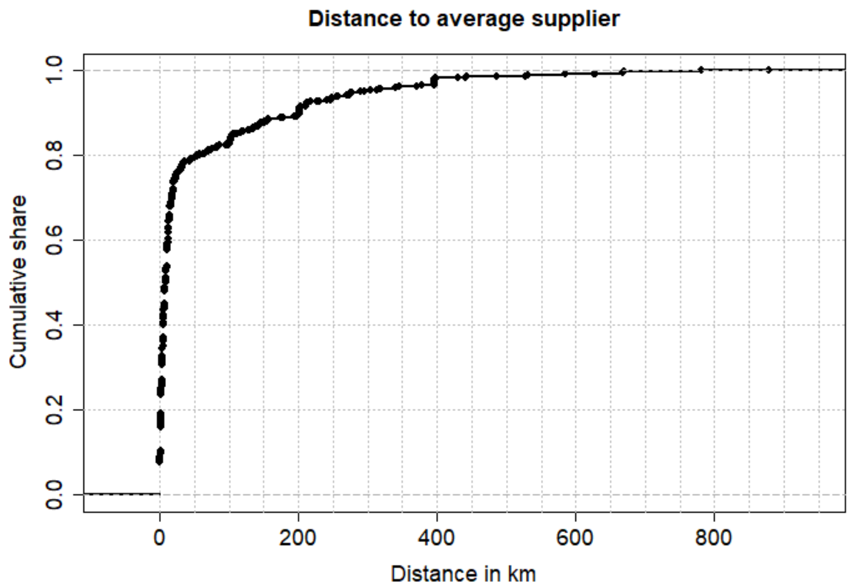


Figure C.9: Distribution of investments across different categories for an average firm, by region

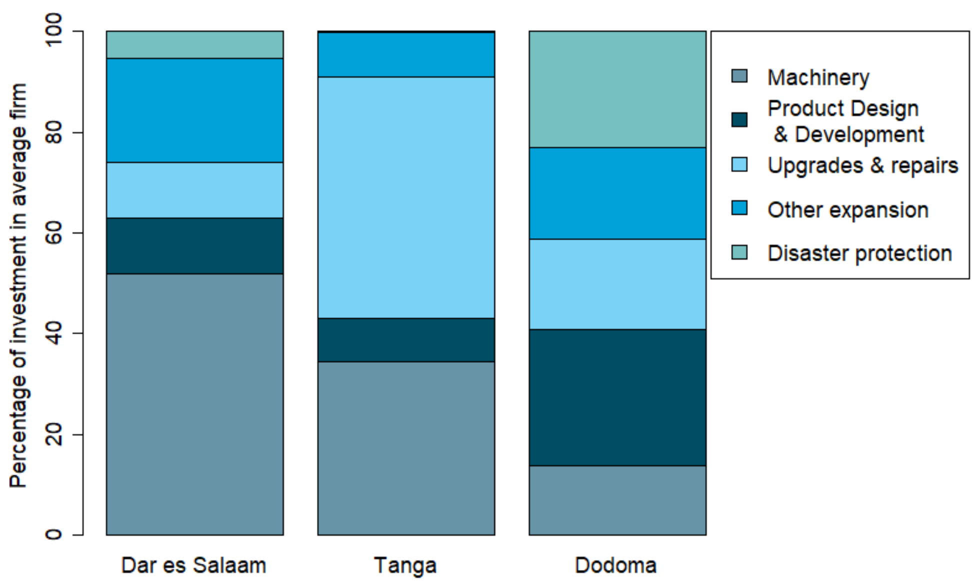


Figure C.10: Primary and secondary reasons for supply disruptions after a disaster

Survey question: Tell me about the most serious shock that affected your firm. What is the most/second most important reason for these supply disruptions?

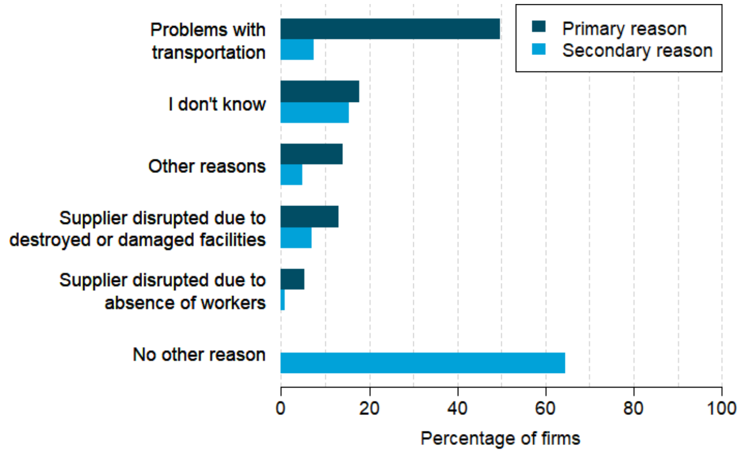


Figure C.11: Reasons for delivery delays by firms' suppliers

Survey question: What is the most important/second most important reason for delivery delays by your suppliers?

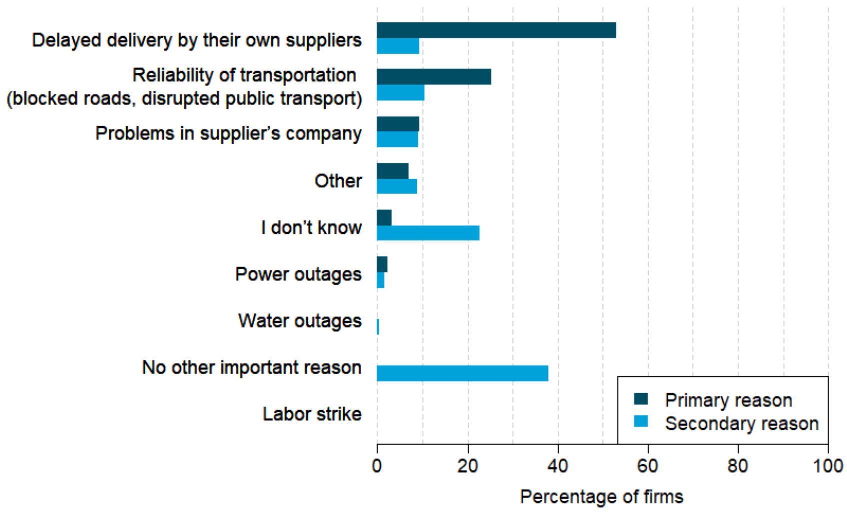
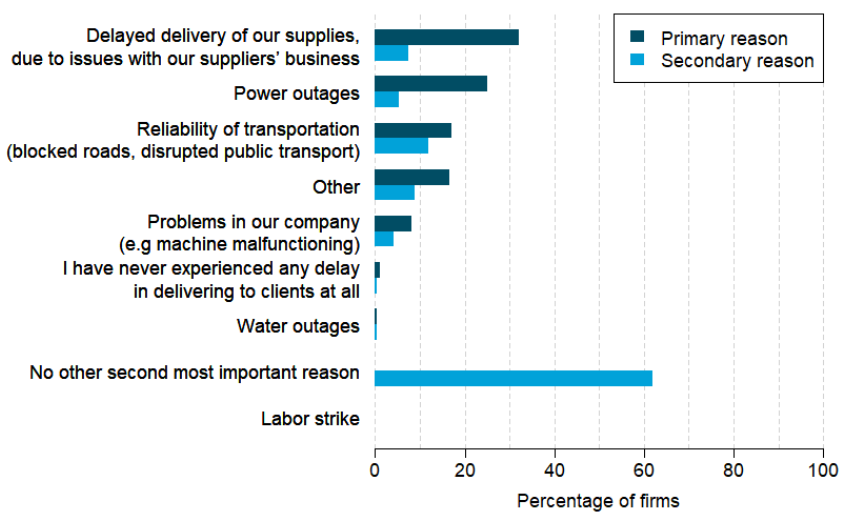


Figure C.12: Reasons for delivery delays to firms' clients

Survey question: What is the most important/second most important reason for your delays in delivering to your clients?



D. Additional regression results

Table D.1: Firms whose employees walk to work are more likely to come to work and be on time compared to employees that use the bus. Informal businesses struggle more with latecomers

	(1)	(2)	(3)	(4)
	Share of workers that are …			
VARIABLES	unable to come to work (rainy season)	unable to come to work (dry season)	late (rainy season)	late (dry season)
Primary mode of transport (bus)				
Train	-0.195***	-0.0185	0.237	-0.0981***
	(0.0372)	(0.0135)	(0.253)	(0.0182)
Walk	-0.0957***	-0.0144***	-0.126***	-0.0561***
	(0.0210)	(0.00527)	(0.0321)	(0.0124)
Bike	-0.0620	0.0109	-0.176**	-0.0210
	(0.0675)	(0.00986)	(0.0870)	(0.0234)
Motorbike	0.0527	0.00263	0.0196	0.00158
	(0.0605)	(0.0142)	(0.0658)	(0.0273)
Car	-0.0310	-0.0154	0.00293	-0.0654***
	(0.0569)	(0.0115)	(0.0972)	(0.0180)
Other	-0.129***	0.0374	-0.322***	-0.0593***
	(0.0485)	(0.0327)	(0.0818)	(0.0200)
Share of employee types				
Seasonal	-0.0451	-0.0114	-0.00167	-0.0532***
	(0.0370)	(0.00973)	(0.0476)	(0.0195)
Daily	0.0246	-0.0290***	-0.0533	-0.0317
	(0.0535)	(0.0101)	(0.0483)	(0.0335)
Family	0.134**	0.0101	0.262***	0.0246
	(0.0619)	(0.0212)	(0.0794)	(0.0288)
Total number of employees	-2.45e-05***	-6.99e-06**	-5.46e-05***	-2.26e-05**
	(9.07e-06)	(3.13e-06)	(2.01e-05)	(8.76e-06)
Fixed effects	YES	YES	YES	YES
Observations	752	755	752	756
R-squared	0.085	0.038	0.189	0.071

Note: Fixed effects include region and sector-specific fixed effects. For categorical variables, base categories are mentioned in parentheses. The low R-squared indicates that results should be interpreted cautiously.
Standard errors are clustered on the ward level: *p<0.1 **p<0.05 ***p<0.01

Table D.2: Regression results for input inventory sizes, using region interactions

	(1)	(2)
	Input inventories	Input inventories
VARIABLES		
Risk perception # region:	**Direct risk**	**Indirect risk**
Dar es Salam (no risk)		
Low risk	-1.268 (9.034)	-0.543 (5.317)
Moderate risk	-8.514 (6.518)	-3.392 (4.730)
High risk	-11.58 (7.169)	-5.049 (4.866)
Very high risk	-16.21** (7.1)	5.992 (13.82)

Dodoma (no risk)		
Low risk	0.0367 (5.553)	-14.85 (13.19)
Moderate risk	2.223 (8.459)	-7.760 (13.80)
High risk	0.0032 (7.184)	-13.88 (12.77)
Very high risk	12.70 (12.16)	1.813 (14.57)
Tanga (no risk)		
Low risk	13.54 (17.02)	10.62* (5.888)
Moderate risk	1.477 (7.758)	15.46** (7.36)
High risk	2.971 (18.03)	24.81** (11.1)
Very high risk	-18.2*** (5.5)	*empty*
Region (Dar es Salaam)		
Dodoma	-2.552 (9.423)	10.01 (13.63)
Tanga	2.657 (7.357)	-7.372 (5.974)
Firm age	0.310* (0.186)	0.278 (0.184)
Number of employees	0.01***(0.001)	0.0105***(0.00124)
Log (total operational costs, in $/month)	-1.001 (1.014)	-0.891 (1.071)
Time since last serious disaster (>12 months)		
<2 month	-10.17* (5.15)	-10.12 (6.332)
2–12 months	-0.588 (3.539)	0.473 (3.571)
Sector (Accommodation and food service activities, Construction)		
Communication and other services	15.87*** (4.3)	17.22*** (3.693)
Manufacturing, Mining, Water, Energy, Agriculture	2.869 (3.056)	1.386 (2.845)
Transportation and storage	19.31*** (7.6)	20.73** (8.113)
Wholesale and retail trade, Repair of motor vehicles and motorcycles	17.54***(3.58)	17.62***(3.373)
Constant	17.73*(9.618)	12.74 (8.244)
Observations	576	576
R-squared	0.091	0.083

Note: Standard errors are clustered on the ward level in parentheses: *** p<0.01 ** p<0.05 * p<0.1

Table D.3: Regression results for supply network extent

	Distance to average supplier (km)			
	(1)	(2)	(3)	(4)
Direct risk perception (no risk)				
Low risk	12.543			9.837
	(8.622)			(8.407)
Moderate risk	-1.081			-3.603
	(8.926)			(10.731)
High risk	6.013			6.843
	(13.444)			(15.098)
Very high risk	20.469			13.486
	(20.067)			(17.414)
Indirect risk perception (no risk)				
Low risk		15.462		12.774
		(10.636)		(9.872)
Moderate risk		14.596		12.777

		(12.406)		(13.333)
High risk		0.226		-5.145
		(13.152)		(13.918)
Very high risk		34.475		28.242
		(22.465)		(21.922)
Experienced flooding on business premises: Yes			6.293	6.691
			(8.638)	(10.804)
Region				
Dar es Salam	-6.670	-13.724	-0.664	-16.643
	(10.830)	(12.373)	(8.665)	(12.718)
Dodoma	79.724***	65.343***	92.392***	62.301***
	(18.285)	(22.399)	(19.276)	(22.574)
Tanga	67.414***	55.627***	71.338***	55.797***
	(15.270)	(18.100)	(14.952)	(18.281)
Sector (Accommodation and food service activities, Construction):				
Communication and other services	5.194	7.133	4.263	7.198
	(8.537)	(8.970)	(8.692)	(8.939)
Manufacturing, Mining, Water, Energy, Agriculture	26.134*	26.336*	25.572*	26.492*
	(15.686)	(15.788)	(15.432)	(15.930)
Transportation and storage	37.905	37.963	35.906	38.542
	(27.076)	(27.032)	(27.277)	(27.060)
Wholesale and retail trade, Repair of motor vehicles and motorcycles	55.073***	55.895***	55.734***	54.987***
	(12.431)	(12.482)	(12.672)	(12.259)
Observations	765	765	763	763
Controls	YES	YES	YES	YES
Log likelihood	-4,734.909	-4,733.514	-4,724.925	-4,720.550

Note: Controls include number of employees, firm age and time since last disaster. All coefficients refer to a standard linear regression model.
Standard errors are clustered on the ward level and take sampling weights into account: *p<0.1 **p<0.05 ***p<0.01

Table D.4: Logistic regression results for probability of water tank ownership

	P (water tank ownership = 1)			
VARIABLES	(1)	(2)	(3)	(4)
Region (Dar es Salaam)				
Dodoma	0.063	0.059	0.161	0.444
	(0.639)	(0.650)	(0.637)	(0.696)
Tanga	0.641	0.310	0.598	0.888
	(0.483)	(0.555)	(0.558)	(0.571)
Direct disaster risk perception (no risk)				
Low risk	0.701			0.712
	(0.651)			(0.696)
Moderate risk	0.905			1.174
	(0.640)			(0.786)
High risk	1.767*			1.686
	(0.969)			(1.278)
Very high risk	0.979			1.005
	(0.798)			(0.965)
Indirect disaster risk perception (no risk)				

Low risk		1.601*		1.362
		(0.829)		(0.986)
Moderate risk		1.267		0.330
		(0.775)		(0.966)
High risk		1.659*		0.554
		(0.946)		(0.981)
Very high risk		1.167		0.397
		(0.880)		(1.122)
Experienced flooding on business premises: Yes			2.059**	1.959**
			(0.948)	(0.908)
Log (water usage, liters/month)	0.192*	0.195*	0.129	0.170
	(0.100)	(0.102)	(0.091)	(0.107)
Log (costs of water, $/liter)	0.156**	0.140*	0.103	0.154*
	(0.075)	(0.083)	(0.072)	(0.080)
Firm age (years)	0.017	0.018	0.012	0.021
	(0.016)	(0.017)	(0.017)	(0.017)
Number of employees	0.002	0.004	-0.000	0.002
	(0.008)	(0.009)	(0.007)	(0.008)
Log (total operational costs, $/month)	0.400***	0.396**	0.520***	0.507***
	(0.151)	(0.154)	(0.182)	(0.171)
Main water source (central distribution)				
Water vendor	-1.209	-1.221	-1.071	-1.173
	(0.815)	(0.811)	(0.836)	(0.914)
Other	-1.288	-0.898	-0.868	-1.084
	(0.816)	(0.783)	(0.762)	(0.805)
Constant	-2.995**	-3.638***	-2.969**	-4.717***
	(1.373)	(1.215)	(1.319)	(1.579)
Observations	167	167	165	165
Sector fixed effects	YES	YES	YES	YES

Note: All coefficients refer to the linear predictor in a logistic regression model. Effects cannot be interpreted as a linear effect on probabilities but state the effect on log odds ratios. Reference levels of categorical variables in parentheses.
Standard errors are clustered on the ward level in parentheses: *** p<0.01 ** p<0.05 * p<0.1

Table D.5: Regression results for generator ownership

	(1)	(2)	(3)	(4)
VARIABLES		P (generator ownership = 1)		
Direct disaster risk perception (no risk)				
Low risk	-0.313			-0.290
	(0.346)			(0.380)
Moderate risk	0.019			0.202
	(0.394)			(0.418)
High risk	-0.483			0.059
	(0.434)			(0.486)
Very high risk	0.390			0.849
	(0.515)			(0.581)
Indirect disaster risk perception (no risk)				
Low risk		-0.242		-0.175
		(0.496)		(0.515)
Moderate risk		-0.189		-0.210
		(0.503)		(0.527)
High risk		-0.512		-0.572

		(0.520)		(0.556)
Very high risk		0.070		-0.187
		(0.578)		(0.627)
Experienced flooding on business premises: Yes			-0.559	-0.744*
			(0.340)	(0.400)
Log (electricity usage, kWh/month)	0.661***	0.650***	0.676***	0.681***
	(0.111)	(0.115)	(0.111)	(0.115)
Log (electricity costs, $/kWh)	0.305**	0.313**	0.343**	0.315**
	(0.142)	(0.144)	(0.141)	(0.147)
Firm age (years)	0.012	0.014	0.015	0.015
	(0.011)	(0.011)	(0.011)	(0.011)
Number of employees	0.002	0.002	0.003	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Log (total operational costs, $/month)	0.204**	0.196**	0.171*	0.188*
	(0.095)	(0.096)	(0.095)	(0.100)
Time until firm needs to halt production without electricity (no halt)				
Less than 6 hours	-0.167	-0.193	-0.203	-0.194
	(0.400)	(0.395)	(0.383)	(0.402)
More than 6 hours	-0.408	-0.359	-0.353	-0.344
	(0.438)	(0.440)	(0.427)	(0.440)
Immediate	0.747**	0.776**	0.750**	0.696*
	(0.344)	(0.357)	(0.346)	(0.365)
Time since last serious disaster (<2 months)				
2–12 months	1.071	1.033	1.145	0.998
	(0.781)	(0.749)	(0.760)	(0.813)
> 12 months	0.574	0.556	0.657	0.475
	(0.750)	(0.717)	(0.720)	(0.793)
Region (Dar es Salaam)				
Dodoma	-0.464	-0.474	-0.410	-0.815
	(0.528)	(0.508)	(0.544)	(0.543)
Tanga	-0.981***	-0.871**	-0.991***	-1.038***
	(0.364)	(0.362)	(0.362)	(0.386)
Sector (Accommodation and food service activities, Construction):				
Communication and other services	-0.405	-0.445	-0.525	-0.373
	(0.410)	(0.422)	(0.406)	(0.417)
Manufacturing, Mining, Water, Energy, Agriculture	-1.927***	-1.943***	-2.012***	-1.932***
	(0.452)	(0.465)	(0.474)	(0.451)
Transportation and storage	0.130	0.067	0.125	0.187
	(0.694)	(0.736)	(0.696)	(0.748)
Wholesale and retail trade, Repair of motor vehicles and motorcycles	-0.982**	-1.034***	-1.079***	-1.028***
	(0.381)	(0.394)	(0.390)	(0.378)
Constant	-5.230***	-4.994***	-5.080***	-4.892***
	(1.006)	(0.969)	(0.975)	(1.038)
Observations	606	606	604	604

Note: All coefficients refer to the linear predictor in a logistic regression model. Effects cannot be interpreted as a linear effect on probabilities but state the effect on log odds ratios. Reference levels of categorical variables in parentheses.
Standard errors are clustered on the ward level in parentheses: *** p<0.01 ** p<0.05 * p<0.1

Table D.6: Logistic regression results for probability of investment, by investment category			
	(1)	(2)	(3)
VARIABLES	P (total investment >0)	P (disaster-related investment >0)	P (disaster-unrelated investment >0)
Region (Dar es Salaam)			
Dodoma	2.301***	3.253***	1.247***
	(0.391)	(0.384)	(0.317)
Tanga	0.145	1.326***	-0.363
	(0.286)	(0.362)	(0.253)
Direct disaster risk perception (no risk)			
Low risk	-0.139	-0.087	-0.156
	(0.272)	(0.380)	(0.271)
Moderate risk	-0.310	0.290	-0.273
	(0.314)	(0.418)	(0.323)
High risk	-0.640*	0.515	-0.374
	(0.368)	(0.482)	(0.383)
Very high risk	-1.294***	0.447	-0.593
	(0.458)	(0.534)	(0.443)
Indirect risk perception (no risk)			
Low risk	0.076	0.109	0.228
	(0.395)	(0.573)	(0.401)
Moderate risk	-0.099	0.040	0.136
	(0.443)	(0.612)	(0.466)
High risk	0.733	0.281	0.623
	(0.480)	(0.683)	(0.497)
Very high risk	0.909*	-0.405	0.760
	(0.481)	(0.761)	(0.536)
Experienced flooding on business premises:			
Yes	0.460	0.515	0.171
	(0.297)	(0.384)	(0.274)
Firm age (years)	-0.012	0.007	-0.011
	(0.009)	(0.009)	(0.008)
Number of employees	0.033***	0.012	0.000
	(0.013)	(0.009)	(0.000)
Log (total operational costs, $/month)	0.253***	0.276***	0.299***
	(0.067)	(0.092)	(0.060)
Time since last serious disaster (months)	0.008*	0.005	0.006*
	(0.005)	(0.004)	(0.003)
Sector (Accommodation and food service activities, Construction):			
Communication and other services	-0.053	-0.528	0.301
	(0.389)	(0.418)	(0.338)
Manufacturing, Mining, Water, Energy, Agriculture	-0.174	-0.871*	0.421
	(0.310)	(0.462)	(0.283)
Transportation and storage	-0.952*	-2.365**	-0.290
	(0.490)	(0.923)	(0.561)
Wholesale and retail trade, Repair of motor vehicles and motorcycles	-0.656**	-0.918**	-0.265
	(0.303)	(0.389)	(0.292)
Constant	-1.590***	-3.769***	-2.415***
	(0.564)	(0.809)	(0.521)

Observations	688	688	688

Note: All coefficients refer to the linear predictor in a logistic regression model. Effects cannot be interpreted as a linear effect on probabilities but state the effect on log odds ratios. Reference levels of categorical variables in parentheses.
Standard errors are clustered on the ward level in parentheses: *** p<0.01 ** p<0.05 * p<0.1

Table D.7: Mean marginal effects for probability of investment, by investment category

VARIABLES	(1) P (total investment >0)	(2) P (disaster related investment >0)	(3) P (disaster unrelated investment >0)
Region (Dar es Salaam)			
Dodoma	0.399***	0.577***	0.271***
	(0.047)	(0.060)	(0.063)
Tanga	0.030	0.184***	-0.077
	(0.060)	(0.056)	(0.052)
Direct disaster risk perception (no risk)			
Low risk	-0.026	-0.010	-0.033
	(0.051)	(0.044)	(0.057)
Moderate risk	-0.058	0.036	-0.057
	(0.059)	(0.051)	(0.067)
High risk	-0.120*	0.066	-0.078
	(0.068)	(0.061)	(0.079)
Very high risk	-0.232***	0.056	-0.121
	(0.072)	(0.069)	(0.087)
Indirect disaster risk perception (no risk)			
Low risk	0.015	0.013	0.047
	(0.076)	(0.068)	(0.082)
Moderate risk	-0.019	0.005	0.028
	(0.085)	(0.073)	(0.095)
High risk	0.143	0.035	0.132
	(0.092)	(0.084)	(0.103)
Very high risk	0.176*	-0.045	0.162
	(0.091)	(0.084)	(0.112)
Experienced flooding on business premises:			
Yes	0.088	0.066	0.036
	(0.056)	(0.051)	(0.058)
Firm age (years)	-0.002	0.001	-0.002
	(0.002)	(0.001)	(0.002)
Number of employees	0.006***	0.001	0.000
	(0.002)	(0.001)	(0.000)
Log (total operational costs, $/month)	0.048***	0.034***	0.063***
	(0.012)	(0.011)	(0.012)
Time since last serious disaster (months)	0.001*	0.001	0.001*
	(0.001)	(0.000)	(0.001)
Sector (Accommodation and food service activities, Construction)			
Communication and other services	-0.010	-0.077	0.065
	(0.076)	(0.063)	(0.073)
Manufacturing, Mining, Water, Energy, Agriculture	-0.034	-0.121*	0.091
	(0.061)	(0.066)	(0.060)
Transportation and storage	-0.183**	-0.258***	-0.060
	(0.090)	(0.078)	(0.114)
Wholesale and retail trade, Repair of motor vehicles and motorcycles	-0.128**	-0.127**	-0.055
	(0.059)	(0.059)	(0.061)

Observations	688	688	688

Note: All coefficients refer to the mean marginal effects—that is, the effects for an average firm—based on the logistic regression model presented in Table D.6. Reference levels of categorical variables in parentheses.
Standard errors are clustered on the ward level in parentheses: *** p<0.01 ** p<0.05 * p<0.1

Table D.8: Regression results for investment volumes

VARIABLES	(1) Log (total investment)	(2) Log (disaster related investment)	(3) Log (disaster unrelated investment)
Region (Dar es Salaam)			
Dodoma	0.604**	-0.465	0.626**
	(0.272)	(0.320)	(0.273)
Tanga	1.091***	0.455	0.859**
	(0.296)	(0.424)	(0.336)
Direct disaster risk perception (no risk)			
Low risk	0.341	-0.246	0.378
	(0.256)	(0.382)	(0.334)
Moderate risk	0.757**	1.017**	0.752**
	(0.296)	(0.482)	(0.325)
High risk	0.671*	0.052	0.712*
	(0.396)	(0.520)	(0.421)
Very high risk	0.891**	-0.183	1.048**
	(0.365)	(0.482)	(0.415)
Indirect disaster risk perception (no risk)			
Low risk	0.099	0.715*	-0.047
	(0.352)	(0.387)	(0.430)
Moderate risk	0.431	0.731*	0.283
	(0.380)	(0.398)	(0.481)
High risk	-0.091	0.310	-0.310
	(0.381)	(0.473)	(0.494)
Very high risk	0.026	0.818*	-0.102
	(0.393)	(0.485)	(0.469)
Experienced flooding on business premises: Yes	-0.037	-0.729*	0.032
	(0.258)	(0.431)	(0.269)
Firm age (years)	0.018*	0.003	0.012
	(0.009)	(0.008)	(0.013)
Number of employees	- 3.64e-04***	-3.79e-04***	-3.05e-04 **
	(9.30e-05)	(8.86e-05)	(1.20e-4)
Log (total operational costs, $/month)	0.732***	0.585***	0.750***
	(0.0504)	(0.0781)	(0.0554)
Time since last serious disaster (months)	-9.69e-04	7.19e-03**	-1.15e-03
	(3.36e-03)	(3.22e-03)	(3.28e-03)
Constant	0.198	1.348**	0.148
	(0.486)	(0.623)	(0.592)
Sector fixed effects	YES	YES	YES
Observations	361	168	309
R-squared	0.507	0.519	0.504

Note: As all regressions are run in logs; coefficients around 0 can directly be interpreted as percentage changes. For coefficients deviating sufficiently from 0, effects should be calculated as exp(β)—for example, a coefficient of 0.7 means that with every unit increase in the respective variable, investment volumes increase by about 200 percent (that is, *exp(0.7) ≈ 2 = 200%).*
Standard errors are clustered on the ward level in parentheses: *** p<0.01 ** p<0.05 * p<0.1

Table D.9: Regression results for probability of obtaining governmental support

	(1)	(2)	(3)	(4)
	P (any governmental support)			
VARIABLES	Regression coefficients	Mean marginal effects	Regression coefficients	Mean marginal effects
Region (Dar es Salaam)				
Dodoma	0.660*	0.0551	0.664	0.0557
	(0.396)	(0.0387)	(0.409)	(0.0401)
Tanga	1.458***	0.167***	1.455***	0.167***
	(0.361)	(0.0529)	(0.369)	(0.0537)
Firm age (years)	-0.00903	-0.000825	-0.00898	-0.000823
	(0.00762)	(0.000712)	(0.00731)	(0.000687)
Number of employees	0.000106	9.69e-06	0.000102	9.38e-06
	(0.000174)	(1.59e-05)	(0.000174)	(1.60e-05)
Log (total operational costs, $/month)	-0.0571	-0.00521	-0.0631	-0.00578
	(0.0850)	(0.00773)	(0.0868)	(0.00792)
Total damages ($)			7.04e-06	6.45e-07
			(8.39e-06)	(7.62e-07)
Experienced flooding on business premises = Yes			0.00194	0.000178
			(0.472)	(0.0434)
Time since last serious disaster (months)	0.00769*	0.000702**	0.00711*	0.000652*
	(0.00390)	(0.000355)	(0.00416)	(0.000382)
Sector (Accommodation and food service activities, Construction):				
Communication and other services	0.188	0.0197	0.181	0.0191
	(0.430)	(0.0445)	(0.431)	(0.0447)
Manufacturing, Mining, Water, Energy, Agriculture	-0.583	-0.0465	-0.585	-0.0470
	(0.492)	(0.0407)	(0.495)	(0.0412)
Transportation and storage	-0.653	-0.0509	-0.633	-0.0500
	(0.712)	(0.0492)	(0.722)	(0.0507)
Wholesale and retail trade, Repair of motor vehicles and motorcycles	-0.00813	-0.000796	-0.0179	-0.00176
	(0.431)	(0.0423)	(0.437)	(0.0431)
Constant	-2.203***		-2.149***	
	(0.673)		(0.705)	
Observations	690	690	686	686

Note: Standard errors in parentheses: *** p<0.01 ** p<0.05 * p<0.1