When Trade Dries Up: Infrastructure Constraints and Firm Performance*

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Abstract

This paper investigates how natural resources can affect firms and supply chains by constraining capacity in critical infrastructure. Combining granular data on firms' maritime shipping and exogenous variation in the capacity of a major trade route caused by drought, I analyze the effects of disruption on the operations and profitability of U.S. firms. A one-standard deviation increase in water scarcity at a choke point decreases revenues and operating income by approximately 3%. Operating expenses increase with constraints, with the incidence of costs determined by firms' market power. Using data on vessel movement and transportation costs, I show that these effects are likely driven by shipping delays and increases in freight rates. Investors do not appear to fully anticipate the effects, since earnings surprises become more negative even when information was publicly available. Since many economies rely on waterways increasingly constrained by drought, these findings underscore that exacerbating natural capacity constraints can pose significant risks to the economy.

Keywords: Climate Change, Corporate Finance, Supply Chains
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1 Introduction

Climate change poses growing risks to global trade and supply chains, exposing firms to disruptions beyond their immediate operations. Although much attention has been paid to how idiosyncratic disturbances can translate into aggregate fluctuations [Acemoglu et al., 2012, Baqaee and Farhi, 2019, Barrot and Sauvagnat, 2016, Carvalho et al., 2021] and how supply chains adjust around extreme weather [Balboni et al., 2023, Barrot and Sauvagnat, 2016, Pankratz and Schiller, 2024], a less examined risk could arise from natural capacity constraints in critical infrastructure. If key trade routes become unreliable due to climate change, firms could face rising costs, unpredictable delivery times, and increased financial uncertainty.

With large shares of firms relying on individual routes, transportation bottlenecks could have far-reaching financial effects. Climate-induced infrastructure constraints are not just hypothetical. In recent years, low-water episodes have disrupted shipping along the Yangtze [European Space Agency, 2022], Rhine [CNBC, 2023], the Mississippi River [NASA Earth Observatory, 2022], and the Panama Canal [U.S. Energy Information Administration, 2024]. These events are frequently described as reducing cargo capacity through draft restrictions, congestion, rerouting, and raising transportation costs. However, systematic evidence on the financial effects of hydrological bottlenecks on firms remains limited. For firms in the United States (U.S.), the Panama Canal is of particular importance with around 40% of U.S. container traffic routed through the canal each year [FreightWaves, 2024].

In this paper, I examine the role of disruptions that arise when drought constrains supply-chain infrastructure. To do so, I focus on the Panama Canal as a major trade route and a critical node that sits between firms in production networks, a source of vulnerability that is comparatively understudied relative to firm- or supplier-specific shocks. Using granular data on local precipitation, supply-chain relationships, shipping routes, and firms' financial performance, I analyze how capacity constraints affect firms' inventories and financial performance. I find that rainfall anomalies around the watershed of the canal reduce inventory buffers and leads to economically significant losses of revenues and operating income. Additionally, earnings surprises become more negative in response to drought-induced supply-chain bottlenecks. This effect holds even when information on drought conditions was widely available to investors, consistent with the interpretation that climate risks

related to supply-chain infrastructure and choke point risk more broadly may be underestimated in financial markets.

The Panama Canal is an ideal empirical setting not only because of its economic significance but also because its operations are highly sensitive to rainfall. The canal operates a lock system that lifts and lowers vessels between the Atlantic and Pacific using freshwater drawn from Gatun Lake. Each transit consumes on the order of 200,000 to 300,000 cubic metres of water, which is discharged through the locks and cannot be recaptured. As a result, rainfall shortfalls reduce the effective supply of daily transits. The canal is operated by the Panama Canal Authority (PCA), which sets toll schedules and allocates transit slots through a mix of reservations and market-based mechanisms. When demand exceeds available capacity during times of drought, the PCA can use sealed-bid auctions for priority passage rights. In addition, the PCA manages capacity by restricting transits and imposing operational constraints, most prominently draft limits that reduce the maximum allowable vessel depth and therefore force carriers to lighten loads or adjust routing and schedules. These measures can amplify congestion and raise effective shipping costs both directly and indirectly. Higher tolls and auction premia to reduce wait times have reportedly reached several million dollars for a single slot [Bloomberg, 2023]. However, indirect losses from delays, rerouting, and inventory disruptions could loom even larger.

The incidence of costs between importers, exporters, and carriers is nuanced. Under long-term fixed-rate contracts, shippers pay scheduled tolls while carriers decide whether to bid for priority slots. This arrangement can create agency conflict because the party paying the auction premium may not be the party bearing the full cost of delay in downstream production. By contrast, under spot-linked pricing or contracts with explicit auction or congestion clauses, incentives are more closely aligned. Carriers bid for slots and pass surcharges through to cargo owners with caps or sharing rules. In this setting, drought-driven scarcity is more likely to translate into higher transportation charges for importing and exporting firms.

For the analyses, I combine data on firms' reliance on trade routes from customs records from S&P Panjiva, financial performance data from Compustat, earnings announcements and surprises from IBES, and granular local information on precipitation over the watershed of the Panama Canal from ERA5 by the European Centre for Medium-Range Weather Forecasts (ECMWF) [Hersbach, 2016]. To estimate rainfall anomalies, I use watershed shapefiles from the Smithsonian Tropical Re-

search Institute [Smithsonian Tropical Research Institute, 2025]. I then aggregate over grid cells to obtain total precipitation across the watershed. In addition to rainfall anomalies, I calculate a series of alternative measures of drought conditions for robustness tests. Specifically, I use the natural logarithm of total rainfall aggregated over the Lake Gatun watershed, drought days, defined as the number of days in which watershed-average rainfall falls below the 10^{th} percentile of the historical distribution for the same calendar month, and standardized drought indices, including the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) [Mishra and Singh, 2010]. These indices normalize precipitation (SPI) and precipitation net of atmospheric water demand (SPEI) relative to historical distributions.

Information on firms' reliance on the canal is derived from customs records including shipment-level information on ports of origin and destination. Using the Python package SEAROUTE.PY [Halili, 2022] and taking into account all U.S. ports that are recorded as a part of a vessel's voyage, I determine the most efficient container shipping routes and whether this route uses the canal. Before analyzing the effects of capacity constraints on firms, I document stylized facts on firms' exposure to the Panama Canal. Exposure is widespread, and among firms with recorded imports, roughly 78% have some inbound exposure to the canal, with an average exposure of about 28% and a median around 16%. For exporting firms, about 65% exhibit outbound exposure, though the export sample is smaller and exposures are lower on average. Exposure varies across industries but is not confined to a single sector, and firms all across the United States rely on the canal for inbound shipments.

Using exogenous variation in capacity constraints from rainfall, I document three key results. First, drought conditions at the Panama Canal materially affect firms' operations and financial performance. Revenues decline more strongly for firms with higher reliance on the canal, consistent with a cross-sectional gradient in exposure. This effect is robust across alternative measures of firms' dependence on the canal as well as a range of proxies of drought conditions including total rainfall, drought days, and precipitation and evaporation indices. Operating income also deteriorates, with evidence that bottom-line effects can extend beyond the most heavily exposed firms. The effects are economically meaningful: a one standard deviation increase in water scarcity is associated with a 2.82% decline in revenues relative to assets and a 2.84% decline in operating income relative to assets.

Second, the results show that drought constraints in supply chains affect firms' operational expenses. In periods of drought, firms' costs rise, likely reflecting a combination of higher transportation charges and the cost responses to disruption such as rescheduling, inventory management, and sourcing adjustments. Importantly, the incidence of the documented cost increases is heterogeneous and aligns with market power considerations. Firms operating in more competitive industries exhibit stronger expense pass-through, whereas firms in more concentrated markets and firms with greater market power experience smaller increases in operating expenses. This observation would be consistent with firms' greater ability to renegotiate terms, shift costs within the supply chain, or cushion shocks through margins and contractual advantages. This heterogeneity drought-driven shipping cost surges depends on bargaining power and the structure of product markets.

The documented patterns on firm performance and costs are consistent with a model of firm production and the idea that reduced water supply coincides with logistical bottlenecks. Using data on vessel movements, I show that drought episodes are associated with adjustments in shipping such as shifts towards smaller vessels and reductions in vessel load. In addition, I find that freight-rate indicators rise when water scarcity intensifies, indicating that these physical constraints translate into higher transportation costs.

Third, I examine whether investors anticipate drought-driven choke point risk by studying analyst forecast errors around earnings announcements. Using IBES forecasts, I find that surprises become systematically more negative during drought episodes, indicating that analysts do not fully incorporate the implications of reduced canal capacity into their expectations. The effect is strongest and most robust for revenue-based surprises and increases with firms' reliance on the canal, consistent with an underestimation of climate-sensitive supply-chain infrastructure risk even when information about water scarcity is publicly available.

Taken together, the results point towards the relevance of infrastructure vulnerabilities for firms and supply chains. The estimates suggest that natural constraints to shipping affect firm profitability and translate into earnings surprises in financial markets. These findings connect to the literature on finance and infrastructure, the economics of production networks, as well as climate finance. First, previous research in economics has documented the welfare effects of infrastructure investments [Donaldson and Hornbeck, 2016, Hummels and Schaur, 2013] and the literature in finance has studied infrastructure as an asset. Andonov et al. [2021] study the investments of

institutional investors in infrastructure and find returns comparable to other private equity assets. In their data, transportation infrastructure ranks second behind energy assets in terms of deal numbers. Howell et al. [2022] study the privatization of transportation infrastructure focusing on airports and find that private equity involvement improves operations, whereas other types of owners do not appear to have a positive impact. Connecting to these studies, this paper examines the effects of infrastructure constraints on firms, and documents adverse economic effects on a large share of publicly listed firms in the U.S.

Second, the paper relates to the literature on firms and production networks. Previous research in this area often focuses on firm-to-firm connections and the endogenous formation of supply chains [e.g., Acemoglu and Azar, 2020, Antràs et al., 2017, Lim, 2018, Oberfield, 2018]. For instance, multiple studies have highlighted the propagation of shocks between customers and suppliers, documenting that firms can be indirectly exposed to hazards due to their global supply chain network [Barrot and Sauvagnat, 2016, Boehm et al., 2019, Carvalho et al., 2021, Custodio et al., 2022]. Instead of the propagation of shocks between firms, this paper focuses on vulnerabilities in transportation infrastructure. These shocks could potentially pose larger and systematic risks relative to the propagation of idiosyncratic shocks [Cohen and Frazzini, 2008, Herskovic, 2018] due to correlations across firms when economies rely on a few prominent shipping routes.

Third, through the possible role of extreme weather in reinforcing capacity constraints, this paper is linked to research on climate change and finance. In this literature, related works have documented the direct effects of weather shocks on firm profitability [Addoum et al., 2020, Pankratz et al., 2023, Ponticelli et al., 2023, Zhang et al., 2018]; stock returns [Addoum et al., 2020, Kumar et al., 2019] and financial markets [Acharya et al., 2022, Bansal et al., 2016, Sautner et al., 2023, Schlenker and Taylor, 2019]. The results in this paper align with these studies in indicating that firm performance is sensitive to a variety of climate-related hazards, and that not all of them are particularly salient. The most closely related paper might be Hong et al. [2019], who find that drought trends affect profit growth and produce predictable returns as a possible sign of under-reaction of the market to climate risk. Instead of the direct effects of drought on firm profitability, this paper documents disruptions caused by droughts elsewhere through bottlenecks in transportation channels. These types of bottlenecks exists in many regions of the world and cannot be directly managed by firms.

2 Data

For the analyses, I combine data on the maritime trade routes used in supply chains, records of firms' financial performance, and information on earnings announcements with measures of drought conditions at the Panama Canal. The following sections describe the data and explain how individual datasets are linked. Table 1 summarizes the key variables.

[Insert Table 1 here.]

2.1 Supply-Chain Relationships

To determine firms' exposure to trade routes, I use records of firm-to-firm shipments from S&P Panjiva. The data has been increasingly used in academic research [Ayyagari et al., 2025, Ganapati et al., 2024, Smirnyagin and Tsyvinski, 2022] and is described in detail by Flaaen et al. [2023]. It is derived from customs records of maritime imports and exports, and coverage begins in 2007. The data includes the universe of maritime shipments to and from the U.S.. However, firms can request redaction of their own and their suppliers' identity by the U.S. Customs and Border Protection. Schafhäutle and Sran [2024] study redaction patterns and find that about 16% of shipment records from 2013 through 2023 have redacted identities. Redaction requests are fulfilled for two years before requiring renewal. As a result, data for companies that request redaction can briefly appear before the renewal of requests. I follow Ayyagari et al. [2025] and exclude firms with large shipment-count spikes in shipments, defined as variations exceeding three times the sample standard deviation.

Since redaction is possible, I observe a subset of firms relying on maritime shipping. However, given that redactions are requested at the firm level, it is not possible for firms to selectively redact supply-chain relationships based on whether or not major trade routes are traversed. In the data, redacted identities are either empty or filled with the names of the executing ocean transport intermediary (OTI), which are either freight forwarders (FF) or non-vessel operating common carriers (NVOCC). To remove these observations, I obtain lists of FFs and NVOCCs operating in the U.S. [Federal Maritime Commission, a,b], embed their names, and determine matches with company names entered in Panjiva. I remove observations where the name similarity exceeds 90%. In addition, I drop logistics companies and freight forwarders (SIC 4412, 4424, 4432, 4449, 4731).

I also drop companies from the financial industry (SIC 6000–6999).

Each observation in Panjiva includes the addresses of consignees and shippers of goods as well as the port of origin and destination, the vessel, an identifier for the specific voyage, the arrival date, names of the shipping and receiving firms, product designations by container, and information on shipped quantities. Panjiva also provides a company identifier that links firms to their associated companies in S&P Capital IQ.

2.2 Exposure to Drought-Constrained Shipping Routes

Using ports of origin and destination, I estimate firms' reliance on specific trade routes. To do so, I first geocode the locations of ports in the U.S. and abroad using the Google Maps API. Second, I use the obtained coordinates to determine the most efficient shipping route between two container ports with the Python package searoute.py [Halili, 2022]. Since voyages of container ships usually run on schedules and load and unload in multiple ports in the U.S. and abroad, I aggregate data by vessel and voyage. When the most efficient route includes a passage for a fraction of legs, I consider passages as traversed when more than half of the legs of a voyage would require a passage. Next, I aggregate the share of volume, value, weight, and the fraction of shipments at the level of U.S. firms.

Panel (a) and (b) of Figure 1 shows the share of passages traversed across all supply-chain relationships. The Panama Canal has the largest share above 25% for incoming and outgoing shipments, followed by Gibraltar and the Suez Canal. Panel (c) and (d) of Figure 1 show the share of relationships with routing through the Panama Canal for U.S. firms. The share of firms without any exposure is low both for firms with any record of incoming shipments in Panel (c), and for firms recording outgoing shipments in Panel (d). Table 1 describes the distribution of firms' exposures. For incoming shipments, 78.1% of observed firms have some exposure to the canal, with an average of 27.5% and a median of 16% of shipments traversing the canal. For outgoing shipments, the sample is more limited in line with U.S. trade patterns. 64.9% of observed firms have some exposure to the canal, with an average of 19.8% and a median of 6.2% of shipments traversing the canal.

Heterogeneity across industries is illustrated in Figure 2. Exposures across industries do not vary substantially except for the agricultural industry, which shows the highest exposure with over

60% for incoming shipments. Figure 3 shows geographic variation in firms' exposure. Firms across the U.S. rely on the canal for incoming shipments in Panel (a), both inland and along the coasts. However, in the Western U.S. zip codes without any exposure are predominant. Panel (b) shows the distribution of the more sparse sample of outgoing shipments. Inland areas in the Western U.S. seem particularly reliant on exporting through the canal, with more dispersed usage across the Eastern U.S..

2.3 Water Scarcity and Shipping Capacity

To measure route constraints, I use weather information from ERA5, a re-analysis dataset provided by the European Centre for Medium-term Weather Forecasts (ECMWF). Re-analyses are generated by interpolating local weather records using atmospheric models. ERA5 provides global hourly estimates of total precipitation and evaporation on a 0.25° grid starting in 1940 (Hersbach et al. 2020). I use watershed shapefiles from the Smithsonian Tropical Research Institute [Smithsonian Tropical Research Institute, 2025] to aggregate precipitation and evaporation across the area. Figure 4 illustrates the approach.

As the main measure, I use rainfall anomalies calculated as the total rainfall across the watershed minus the average rainfall recorded in the same month over the period from 1980 to 2010 as a WMO climatological standard normal period [World Meteorological Organization, 2022], divided by the average rainfall in the standard normal period. For ease of interpretation, I invert the scale of the anomaly so that an increase coincides with drier conditions. In addition, I compile drought indices including the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) for robustness tests [Mishra and Singh, 2010], and measure dry days in which rainfall is less than the 10^th percentile of the distribution in rainfall for the same calendar month between 1970 and 1980. I aggregate all monthly data at the quarterly level for alignment with firms' reporting schedules.

Figure 5 shows rainfall and drought trends over time for three different measures. Since Panama has a distinct rainy and dry season, trends are plotted separately: The rainfall anomaly in percent in Panel (a) and (b), total rainfall in cubic meters aggregated across the area in Panel (c) and (d), and the number of dry days in Panel (e) and (f). Across all three measures, conditions have become drier in the period since 2007 covered by Panjiva.

In addition, I obtain historical information on daily water levels in the canal to understand how often constraints bind from the website of the Panama Canal Authority PCA [Panama Canal Authority, 2025]. The data is plotted in Figure 6. Panel (a) shows the time series of minimum water levels since the PCA began reporting it. Minimum levels of the reservoir are visibly becoming more volatile approximately in 2011. Panel (b) zooms in on the time period covered by shipment records in Panjiva. In 2016, a major expansion of the lock system of the Panama Canal was completed. The expansion introduced a new set of larger locks and increased capacity by allowing wider and heavier ships to transit. The colored lines indicate when the PCA imposes draft limitations, with the green line indicating limits on the draft of vessels using the newer Neopanamax locks, and the blue line indicating binding constraints on the original Panamax locks. The plot shows that the conditions for draft limitations on the Neopanamax locks are triggered frequently, whereas restrictions for the smaller Panamax locks are rare. Yet, it is important to note that congestion can occur without a drop of water levels below critical limits, since the PCA can restrict the number of transits before constraints become binding.

2.4 Firm Characteristics and Accounting Performance

To measure effects on firms' performance, I obtain financial data from 2000 to 2024 for all U.S. firms covered by Compustat. As the main measures, I use standardized quarterly revenues and operating income as well as revenues and operating income scaled by lagged total assets. I focus on these measures, since they are narrowly defined metrics at the top of the income statement and therefore should be relatively less distorted by accounting choices as compared to metrics further down the income statement. Subsequently, I match information on drought conditions taking firms' financial reporting schedules into account. I also collect data on employees, asset tangibility, operating margins, inventories, accounts receivables and accounts payable, cost of goods sold (COGS), sales, general, and administrative expenses, and short and long-term investments. To remove outliers, I trim all variables above (below) the 99th (1st) percentile. Further, I construct measures of industry competitiveness as the Herfindahl-Hirschman Index (HHI) of revenues in a given 4-digit NAICS industry, the market share of revenues of the largest four firms, and the market share per firm.

To be able to conduct the analyses, the sample only includes listed firms with financial data

available. Therefore, the data captures a subsample of predominantly large and liquid firms. When capacity constraints occur, the PCA uses an auction system to determine passages. Hence, smaller, private firms with financial constraints limiting their ability to use shipping contracts including provisions to advance passage by bidding in auctions if slots become restricted. Therefore, firms not included in the analyses may be more strongly affected, and the effects estimated in this paper likely represent a lower bound.

Table 1 includes descriptive statistics on firms' financial performance. The total asset values in this sample lie between 35 and 1877 million U.S. dollars between the 25^{th} and the 75^{th} percentile, with a median of 303 million U.S. dollars in firms' total assets. The average sales turnover measured as revenues over lagged assets is 20.7%. Profitability in the covered time period is low with an of average -4% in operating income before depreciation scaled by lagged assets.

Within the sample of covered firms, Table A.1 compares the characteristics of firms that rely on the canal with those that do not, or to a lesser extent. Panel (a) compares firms with zero to firms with non-zero exposures. Firms with non-zero exposures are significantly larger in revenues, assets, and cash holdings and record higher sales turnover and profitability. Panel (b) splits firms above and below the sample mean. Firms are still significantly larger, though differences in sales turnover and profitability are more limited economically. Panel (c) reports difference above and below the median. Around the median, size differences become insignificant. Across all three panels, upstreamness as an indicator of the position of firms in the supply chain and measures of market concentration are relatively similar in economic terms but at times statistically significant.

2.5 Earnings Announcements and Surprises

To study if investors anticipate infrastructure risks tied to drought in supply chains, I collect data from IBES on analyst forecasts. To align analyses, I focus on analysts' projections and realizations of revenues and income. In addition, I use data on earnings per share. Across all measures, I calculate earnings surprises in percent as the difference between actuals and the mean (median) estimate scaled by the mean (median estimate). To remove outliers, I trim all variables above (below) the 95th (5th) percentile.

2.6 Aggregate Freight Rates

To investigate mechanisms underlying the potential effects on firms, I draw on two monthly indices from the Federal Reserve Economic Data (FRED), maintained by the Federal Reserve Bank of St. Louis to capture a high-level proxy of freight-rate dynamics. First, the Producer Price Index by Industry for Deep Sea Freight Transportation records changes in ocean-freight service prices. Second, the Cass Freight Rates Index measures total dollars paid on shipping bills, capturing base rates, fuel surcharges, and accessorial charges across all major domestic modes, adjusting for seasonality.

2.7 Vessel Movements and Characteristics

In addition, I build a monthly vessel-level panel using records of vessel entrances and clearances from the U.S. Army Corps of Engineers' National Data Center for the years 2013 to 2022. I extract each voyage's entry port, exit port, origin, destination, date of journey, and vessel flag. I restrict the sample to pure container and bulk cargo vessels—dropping any vessels designated as carrying passengers, tug boats, or fishing vessels. At the voyage level, I calculate the time between sea legs and the duration spent in port. The data contains information on vessel size in net tonnage as well as the voyage-specific draft. To investigate responses of the shipping industry to route constraints, I classify ships as suited for the smaller Panamax or newer and larger Neopanamax locks based on vessel length and beam dimensions. I obtain this additional information on vessel characteristics by matching the records in Panjiva with the Eikon Cargo registry via the vessel IMO numbers.

3 Water Scarcity and Shipping Patterns

I begin by validating if drought conditions cause natural capacity constraints of the Panama Canal. Testing if shipping patterns adjust when rainfall declines, I use plausibly exogenous variation in precipitation over the watershed of the Panama Canal conditional on season. The canal operates using a lock system that depends on freshwater from Gatun Lake, which is replenished by rainfall. Each vessel transit requires a substantial amount of freshwater as part of the lock operations, which is discharged into the ocean. Hence, precipitation is the main determinant of the number of ships that can pass the canal. Rainfall is also exogenous to the decisions of the canal authority

and independent of the demand for canal passages. The geographic distance between the canal and U.S. firms limits the possibility of confounding direct effects of extreme weather on the U.S.. Precipitation over the Panama Canal is influenced by El Niño and Atlantic Ocean climate variability. To the extent that these same large-scale patterns also affect U.S. weather, some correlation is possible. However, prior work suggests that El Niño's impacts on U.S. precipitation are localized and heterogeneous across regions [Downey et al., 2023].

When water levels drop, the PCA imposes draft restrictions, reducing the maximum allowable depth for vessels. The minimum water level triggering restrictions is predetermined and differs for the two types of locks the canal operates. In the past, the PCA curtailed allowable drafts in the larger Neopanamax locks while leaving the original Panamax chambers unchanged [Panama Canal Authority, 2023]. When restriction are imposed, they force container ships and bulk carriers to either lighten their loads or seek alternative routes. To manage water shortages before draft restrictions bind, the PCA can proactively restrict transits.

I test whether water constraints affect shipping dynamics such as a re-allocation across smaller and larger vessels and adjustment of draft levels of vessels to be able to navigate the canal despite restrictions. To do so, I estimate the following equation:

$$\begin{aligned} y_i = \beta\, Drought_{m(i)} + \theta Drought_{m(i)} \times PC\ Route_i + \mu_{p(i)\times m(i)} \\ + \gamma_{yr(i)} + \delta_{r(i)} + \eta_{\text{type}(i)} + \kappa_{\text{flag}(i)} + \varepsilon_i. \end{aligned} \tag{1}$$

where i indexes voyages. The dependent variable y_i is alternatively vessel size, voyage-specific vessel draft, or an indicator for whether the vessel's dimensions satisfy the requirements of the Panamax or Neopanamax locks. $Drought_{m(i)}$ measures rainfall anomalies or drought intensity in the calendar month $m(i)$ in which voyage i occurs. $PC\ Route_i$ is an indicator equal to 1 if the most efficient route between the origin and destination ports for voyage i implies a passage through the Panama Canal. The coefficient β captures the association between drought conditions and outcomes for voyages whose efficient route does not require canal passage while θ captures the differential sensitivity for canal-routed voyages.

The specification includes passage-time-by-month fixed effects $\mu_{p(i)\times m(i)}$ to control for seasonal-

ity and other time-varying factors common to major trade routes at a given passage time. Passages include the Panama Canal, Gibraltar, Suez, Bab-al-Mandab, Hormuz, Bosporus, Cape of Good Hope, Strait of Magellan, and Sunda. Year fixed effects $\gamma_{yr(i)}$ absorb aggregate trends, and route fixed effects $\delta_{r(i)}$ (origin $\times$ destination port) control for time-invariant differences across port pairs. Finally, vessel-type fixed effects $\eta_{\text{type}(i)}$ and flag fixed effects $\kappa_{\text{flag}(i)}$ account for systematic differences across vessel classes and registries. All observations are at the voyage level. Since treatment variation is time-based, standard errors are clustered by year-month.

[Insert Table 2 here.]

Table 2 shows the results for these tests. Columns (1) to (4) in Panel (a) show the effects on the size of vessels in use as the net tonnage. The interaction between water constraints and the Panama Canal passage indicator is negative and significant for vessels entering and clearing U.S. ports. In column (1), a one standard deviation decrease (i.e., a rainfall anomaly of 62.11%) in canal-area rainfall decreases the size of inbound vessels by roughly 2.5%. Columns (5) to (8) show that vessels also reduce cargo entering and leaving the U.S.. In column (6) and (8), decreases of one standard deviation in precipitation lead to a lower draft of canal-transiting vessels.

Panel (b) of Table 2 shows Poisson estimates of the effect of water-supply shocks at the Canal on the reallocation of vessel types around lock restrictions. Column (1) to (4) show that Panamax-compliant vessels are more frequently entering U.S. ports from routes relying on the canal when the canal is affected by drier conditions. According to column (2), the likelihood of observing Panamax-compliant vessels increases by 11.18%. The positive interaction and baseline effects could indicate spillovers and be driven by observations of vessels that continue their voyage without a Panama Canal crossing within the U.S.. Column (5) to (8) show a matching negative effect of declines in rainfall on the usage of larger Neopanamax vessels as well as no effect on vessels leaving U.S. ports. These effects are consistent with the interpretation that shipments can be reallocated to smaller vessels, since draft restrictions to the Panamax chambers are imposed less frequently (see Panel (b) of Figure 6.

These effects suggest that shipping companies respond to restrictions and use smaller vessels to traverse the canal when water supply is scarce. Through these frictions, drought-driven water shortages could thus translate directly into lower volumes of goods entering and clearing the U.S..

In addition to the effects of limited throughput, shipping delays could drag down output. Through the production function, a delay in the arrival of inputs reduces output and lowers the marginal products of capital and labor.

Using the same panel of vessel movements and following equation 1, I estimate whether rainfall and drought days affect voyage duration.

[Insert Table 3 here.]

Table 3 shows the results broken down by vessel type. Columns (1) to (4) document the coefficients for the tests on time spent on voyages, and columns (5) to (8) show the effects on idle time in ports. Regressing the time between port calls as a proxy of voyage duration on canal-area precipitation, I find that the duration of trips decreases with water supply and increases with water scarcity for container ships, tankers, and roll-on roll-off vessels. At a one standard deviation increase in rainfall anomalies over three months (-62.103% in rainfall compared to WMO baselines), these effects translate into an increase in travel time of 4.2 days for container ships and 7.9 days for tankers. For vessels transporting dry bulk, the effects are of a similar magnitude but statistically muted. In addition, columns (6) shows that a decline in precipitation increases the extent to which tankers idle in ports. For other types of vessels, wait times do not appear affected. In the event of delayed deliveries, firms can cushion small slowdowns by drawing on inventories. However, under just-in-time stocking or when inputs are highly specialized [Barrot and Sauvagnat, 2016], delays that exhaust buffers can halt production and cause non-linear output declines.

4 Natural Capacity Constraints and Inventory Buffers

If the observed changes in vessel size, draft, and time between trips translate into delivery frictions, they may affect firms' inventory buffers. On the one hand, inventories could decrease through delayed replenishment and forced drawdowns. On the other hand, precautionary stocking could increase inventories in the short run. These possibility can be tested by running firm-level panel regressions with fixed effects. As in the previous tests, I again rely on variation in precipitation over the watershed of the Panama Canal conditional on season. However, in contrast to route-level tests, exposure to the Panama Canal is aggregated at the firm level over the period with available

data from 2007 to 2024. To compare firms with and without exposure to the constraints, I restrict the sample to observations where firms appear in Panjiva with zero or non-zero usage of the canal.

Thereby, it is important to caution that firm-level $PC\ Exposure_j$ is measured with error: First, firms may select into using the canal. Second, the main specifications use an exposure measure aggregated over the full 2007–2024 period and may not reflect firms' current routing choices. The alternative choice of constructing a contemporaneous measure, however, is equally complicated since firms may endogenously re-route shipments or otherwise adapt their supply chains in response to shocks. Third, even firms with similar measured exposure may ship inputs with different economic relevance, implying heterogeneous sensitivity to canal disruptions. Taken together, these concerns mean there is no cleanly identified dose–response effect of exposure. Nonetheless, estimating whether outcomes vary systematically with their import exposure and testing for a slope with respect to firms' estimated exposure seems relevant.

With this restriction in mind, I test whether drought as a cause of constraints depletes inventories, and whether the observed effects increase with firms' reliance on the canal:

$$\begin{aligned} y_{jq} = \beta\, \text{Drought}_q^{(0:2)} + \theta\big(\text{Drought}_q^{(0:2)} \times \text{PC Exposure}_j\big) \\ + \mu_{js(q)} + \gamma_{g(j)\tau(q)} + \delta_{h(j)\tau(q)} \\ + \kappa^{\text{size}}_{p(j)\tau(q)} + \kappa^{\text{age}}_{a(j)\tau(q)} + \kappa^{\text{prof}}_{r(j)\tau(q)} + \varepsilon_{jq}. \end{aligned} \tag{2}$$

where y_{jq} represents measures of inventories for firm j in financial quarter q. $\text{Drought}_q^{(0:2)}$ captures rainfall anomalies in quarter q and the two preceding quarters.[1] Exposure_j is the proxy of the reliance of firm j on the Panama Canal for imports. Further, the specification includes firm-by-season fixed effects ($\mu_{js(q)}$) to prevent coincidental correlations between seasonal differences in firm operations and rainier and drier times of year in Panama from confounding the effects. NAICS 3-digit industry-by-year fixed effects ($\gamma_{g(j)\tau(q)}$) control for simultaneous industry trends.

Figure 3 shows no extreme regional concentration in exposure. Nevertheless, region-by-year fixed effects ($\delta_{h(j)\tau(q)}$) are included to absorb macroeconomic shocks based on geography. Since Table A.1 shows differences in firm characteristics with varying exposure to the canal, I sort firms

[1] In line with related works on the effects of weather on firms' operations [Addoum et al., 2023, Barrot and Sauvagnat, 2016, Pankratz and Schiller, 2024, Ponticelli et al., 2023], it is likely that effects set in with some delay. However, the correct aggregation is unclear ex-ante, and I present alternative specifications in robustness tests.

into size, age, and profitability terciles to introduce additional size-, age-, and profitability-time fixed effects ($\kappa^{\text{size}}_{p(j)\tau(q)}$, $\kappa^{\text{age}}_{a(j)\tau(q)}$, and $\kappa^{\text{prof}}_{r(j)\tau(q)}$) to absorb common variation of different firm profiles [Barrot and Sauvagnat, 2016]. Standard errors are clustered by year-quarter, as the identifying variation in water supply as the treatment variable is time-based.

[Insert Table 4 here.]

Table 4 reports how rainfall shortfalls in the Lake Gatun watershed relate to firms' inventories. Columns (1)–(5) use inventories scaled by lagged assets as the outcome and interact rainfall anomalies with measures of firms' import reliance on the canal. The baseline effect in column (1) is zero, but the interaction specifications indicate that more canal-reliant importers' inventories drop, with the negative association showing up most clearly when exposure is measured continuously or when focusing on firms above the mean and median thresholds. Columns (6)–(10) switch the outcome to the quarterly change in inventories and apply analogous interactions for export reliance. Here, the rainfall anomaly coefficients are more consistently negative and statistically significant in the baseline, suggesting that drought conditions could coincide with inventory draw-downs both for exposed and unexposed firms.

The effect on inventories for exporting firms is more complex. In the data, most firms relying on the Panama Canal for exports also use it for imports. Therefore, the negative effects on firm production could affect exporting firms, depleting inventories. At the same time, concerned customers might cancel orders in the face of shipping constraints, leading to opposite pressures. Table A.2 presents estimates of how rainfall shortfalls relate to inventory across varying levels of export reliance on the canal. Consistent with the idea of opposing forces, the coefficient on rainfall anomalies is small and generally not distinguishable from zero in most specifications using log inventories as the dependent variable, and the interaction terms with export-intensity measures are likewise imprecisely estimated. For changes in inventories, some estimates suggest that a negative effect prevails.

5 Drought-Induced Bottlenecks and Firm Performance

Based on these validation exercises, I turn to testing if natural capacity constraints of the Panama Canal have a measurable effect on U.S. firm performance. To estimate the effects, I use equation 2 but substitute inventories with revenues and operating income, standardized or scaled by lagged assets. Table 5 shows the effects on revenues. In Panel (a), the measure of rainfall anomalies is interacted with measures of firms' reliance on the canal for imports. Panel (b) restricts to firms with records of exports in Panjiva, and tests for a slope with respect to the share of volume of exports shipped outbound through the canal.

[Insert Table 5 here.]

In Panel (a), rainfall shortfalls are associated with weaker firm revenues across all tests, including for all firms covered by Compustat regardless of Panjiva coverage in column (1). The coefficients also indicate a negative baseline for all firms across the sample except for column (3). This effect could be explained by noise in the measure of exposure, spillovers, or indirect exposures through connections to directly exposed firms. Across columns (2) to (5), the magnitudes of the effect increase when firms rely on the canal. In column (4), the combined effect of the rainfall anomaly is -0.0009 for a one-unit increase in water scarcity. Scaling by the empirical dispersion of rainfall anomalies (SD= 40.575), a one-standard deviation rainfall shortfall corresponds to a -0.037 SD change. In dollar terms, this effect is economically meaningful: Converting this effect into revenue (SD= 1544.405), the implied decrease at the sample mean is roughly -56.4m for firms above-mean. At the sample median, the effect still amounts to approximately 2.09m. Table A.3 corroborates the results with revenues scaled by assets. The effect of water scarcity in the canal is negative across firms and the slope for the proxies of exposure are negative in all specifications. In column (3), a one–standard deviation increase in water scarcity implies ≈ -0.584 for above-mean exposure firms. Relative to the sample mean, these effects correspond to roughly a 2.82% decline in sales turnover. Relative to the median, sales turnover declines by 4.07%.

Panel (b) mirrors this structure for outbound exposure: the rainfall-anomaly main effect is negative in the full sample, but also increases in magnitude for firms with substantive outbound dependence on the canal canal. The latter sample is more restrictive, since fewer firms export goods.

In addition, exporting firms usually also import goods. Therefore, the cross-sectional sensitivity to reliance on the canal for exports cannot be cleanly separated from simultaneous import exposures.

Panel (b) of 5 shows similar effects when we restrict to exporters and focus on the slope of the effects relative to outbound exposure, as increases in export dependence are associated with larger decreases in revenues. As a key difference, the baseline effect is only significant in column (1) and (2) but negative and consistent in magnitude throughout. As exporting firms usually also rely on the canal for important in the data, the cross-sectional sensitivity has to be interpreted with some caution.

In addition to the alternative dependent variable, Table A.4 shows the robustness of the effects to using alternative proxies of precipitation and drought conditions. The effects hold when I use the natural logarithm of the total amount of rainfall, the number of drought days, the standardized precipitation index (SPI), or the standardized precipitation and evaporation index (SPEI).

Overall, the table supports the interpretation that scarce canal capacity can matter for firm outcomes such as revenues. However, effects on firms' bottom lines could be muted despite distortions in supply chains, e.g., if firms are able to adjust expenses in the short-run, or if they financially hedge or insure themselves against losses.

[Insert Table 6 here.]

Table 6 shows the effects of drought-induced constraints on standardized operating income.. In Panel (a), the effects indicate that operating income decreases with drought, and that the magnitude of the effects varies with import exposures. Except for column (4), there is a negative slope in column (2) and larger effects for firms with non-zero and above median exposures. In column (5), the total effect on above-median exposed firms is -0.0028. A one-standard deviation increase in water scarcity corresponds to -0.114. Relative to the sample mean (median) operating-income-to-assets ratio of -0.040 (0.006), this corresponds to roughly a 2.84% (19%) change in magnitude. Thus, while the effect is small compared with the mean level of profitability, it is sizeable when benchmarked against the median firm. Table A.6 shows the robustness of the effects to using alternative proxies of precipitation and drought conditions. The effects hold using the natural logarithm of the total amount of rainfall, the number of drought days, the standardized precipitation index (SPI), or the standardized precipitation and evaporation index (SPEI).

6 Capacity Constraints, Expenses, and Market Concentration

These results indicate that the operations and earnings of firms in the U.S. are sensitive to water supply to the Panama Canal, and the capacity of a crucial supply-chain choke point. The earlier tests are consistent with the idea that in a framework of firm production, reduced water supply could matter because it induces logistical bottlenecks. In addition to limited input availability and delays, transportation costs could drive adverse effects on firms. In a production function, transportation costs enter by raising the effective price of intermediate inputs and reducing their optimal usage, and thereby decreasing output.

To understand the potential magnitude of increases in transportation costs, the auction mechanism to allocate slots and the scope of fees are relevant. To reduce wait times, bids for auction slots have reached up to $4 million. In addition, contract structures are important: Firms on long-term fixed-rate charters are insulated from auctions, paying only the scheduled tolls. However, this structure gives rise to an agency conflict: shippers, who bear auction costs, are unlikely to bid aggressively although the value of a faster passage might exceed potential damages from delays for firms. Under spot-linked or auction-clause contracts, incentives are more likely to be aligned. Carriers bid for slots, and pass surcharges straight through to the firm. Alternatively, carriers can cap their maximum auction exposure, with any excess fees absorbed by the receiving firm.

Historical data on fees paid for canal passages is not publicly available, and route-level freight rates are equally challenging to obtain. To test if there is evidence of increases in costs with water scarcity in the canal, we therefore use four data series provided by FRED of the Federal Reserve Bank of St. Louis: the producer price index for deep sea freight transportation prices and the Cass Index for implied freight rates across all modes including sea, air, and land. I estimate the following OLS regressions:

$$y_t = \beta Drought_m t + \mu_{m(t)} + \gamma_{y(t)} + \epsilon_{mt}, \tag{3}$$

with rainfall anomalies as the independent variable as well as month fixed effects $m(t)$ to condition on season and year fixed effects $y(t)$ to absorb seasonality and general trends.

[Insert Table 7 here.]

Table 7 shows the results. Columns (1) to (4) use the full sample. The dependent variable is the Producer Price Index (PPI) for Deep Sea Freight Transportation in columns (1) and (2) and (5) and (6), and the Cass Freight Rates Index (CFRI) in columns (3) and (4) and (7) and (8). Odd-numbered columns include only the contemporaneous anomaly; even-numbered columns additionally include one- and two-month lags of the anomaly (m-1, m-2). Across specifications, drier conditions are associated with higher measures of transportation costs, with the strongest and most consistent evidence for the deep-sea freight PPI and for the CFRI at short horizons. The contemporaneous rainfall anomaly is positive and statistically significant for the PPI Deep Sea index, indicating that months with unusually low rainfall coincide with higher ocean-freight service prices. The lag structure in column (2) suggests that the contemporaneous association remains similar in magnitude, while the one-month lag is small and imprecisely estimated and the two-month lag is negative and not statistically distinguishable from zero. For the CFRI, the contemporaneous coefficient is close to zero and statistically insignificant with evidence of a delayed response: the one-month lag of the rainfall anomaly is positive and statistically significant in the distributed-lag specification. Excluding crisis periods yields qualitatively similar patterns.

Overall, the estimates are consistent with water scarcity at the canal translating into higher freight-rate indicators. The next question is how these cost pressures map into firm-level outcomes. Two notes are important. First, the relevant margin does need not be limited to posted transportation rates: canal-related disruptions can also raise effective trade costs through longer transit times, congestion, rerouting, and associated working-capital and inventory-holding costs. Second, the incidence of higher trade costs is an empirical question, much like the incidence of tariffs: depending on contract terms and market structure, cost increases may be absorbed by carriers, passed on to shippers and downstream firms, or ultimately transmitted to consumer prices.

Adjusting the dependent variables in equation 2, I test if natural constraints of the Panama Canal affect firm operations by increasing expenses. Taking the question of incidence into consideration, I interact firms' exposure to the canal with measures of market concentration in triple interactions. Table 8 presents regressions testing this effect. Across specifications, the average association between rainfall anomalies and expenses is small in the baseline but significant for firms with above-median canal exposure. This effect is consistent with canal-related disruptions raising input and logistics costs for more exposed firms. Further, the triple interactions of rainfall

anomalies, firms' exposure, and industry concentration and firm market power are relevant. These terms are negative and significant. This result indicates that the expense response among highly exposed firms is attenuated when market power is higher. Interpreting the coefficients through a tariff-incidence lens, the pattern is consistent with the idea that increases in transportation costs are more likely to be borne by firms with less market power.

7 Water Scarcity, Supply Chains, and Earnings Surprises

Taken together, the results indicate that drought-induced capacity constraints at a major maritime chokepoint translate into weaker firm earnings. Yet, markets may not fully price such risks. Supply-chain infrastructure and bottlenecks like canals, straits, and key ports are sources of systemic disruption, but investors may systematically underweight them because their consequences only become salient when capacity abruptly binds. Moreover, the climate dimension adds an additional layer of uncertainty. Shifting precipitation patterns and the increasing likelihood of extremes can alter constraints and complicate reliance on historical experience. Motivated by these considerations, I next test whether investors anticipate drought risk in supply chains by examining forecast errors around firms with greater reliance on the Panama Canal.

Analogous to the earlier analyses, I exploit plausibly exogenous variation in drought intensity at the Panama Canal measured by rainfall anomalies over the Lake Gatun watershed. The identifying assumption is that precipitation is quasi-random conditional on temporal fixed effects and seasonality and orthogonal to firms' contemporaneous demand shocks except through canal capacity. The null hypothesis is that analysts update forecasts based on publicly observable information about water scarcity and firms' reliance on the canal, such that forecast errors should not systematically covary with drought exposure. However, if analysts underestimate risk related to supply-chain infrastructure or climate, surprises could become more negative when drought conditions intensify.

To align the tests with the previous analyses, I consider analyst projections and realizations for revenues, income, and earnings per share. Rather than estimating cumulative effects of drought over multiple quarters, I focus on the effects of drought realized in the contemporaneous quarter. I construct the timing so that information about canal conditions is publicly observable with sufficient lead time for analysts to incorporate it into their projections. Figure A.1 illustrates this setup.

Analysts issue forecasts for a given fiscal quarter. During that period, the Panama Canal is subject to a realized level of water scarcity captured by rainfall anomalies over the watershed. Firm performance is subsequently revealed on the announcement date, which occurs after the close of the fiscal quarter with a reporting lag. This reporting lag provides a window for analysts to update their forecasts near the end of or immediately after the fiscal period once realized canal conditions are known. If canal constraints affect firms with a lag, analysts have additional time to update their expectations before the announcement of subsequent quarters. Equation 4 shows the regression specification matching this test:

$$\begin{aligned} Performance\ Surprise_{jq} = \beta\, \text{Drought}_q + \theta \left(\text{Drought}_q \times \text{Exposure}_j\right) \\ + \mu_{js(q)} + \gamma_{g(j)\tau(q)} + \delta_{h(j)\tau(q)} + \varepsilon_{jq}, \end{aligned} \tag{4}$$

where $Performance\ Surprise_{jq}$ denotes the forecast error for firm j for fiscal quarter q, measured as the difference between realized performance and the consensus analyst forecast (mean or median for revenues, income, or earnings per share), scaled by the consensus forecast. Drought_q captures quarterly rainfall anomalies over the Panama Canal watershed and higher values indicate drier conditions. Exposure_j measures firm j's reliance on the Panama Canal for imports as the share of total shipping volume. The interaction terms $\text{Drought}_q \times \text{Exposure}_j$ test whether forecast errors become systematically more negative for firms with higher canal exposure during drought episodes.

The specification includes firm-by-season fixed effects $\mu_{j\times s(q)}$, where $s(q) \in \{1, 2, 3, 4\}$ indexes the calendar quarter, to absorb firm-specific seasonal patterns in forecast errors and operations that may coincide with Panama's wet and dry seasons. $\gamma_{g(j)\times\tau(q)}$ are NAICS 3-digit industry-by-year fixed effects that control for time-varying shocks common to an industry. Standard errors are clustered by calendar quarter, reflecting that the identifying variation in Drought is common within a given year-quarter.

[Insert Table 10 here.]

Table 10 shows the results for these tests, and drier conditions in the Lake Gatun watershed are associated with systematically more negative earnings surprises. This result indicates that analysts may underestimate the repercussions of canal-related capacity constraints. Panel (a) uses revenue-based surprises as the dependent variable. The coefficient of the rainfall anomaly is negative and

highly statistically significant across all specifications for both mean- and median-based surprises (columns (1)–(10)). Moreover, the sensitivity of revenue surprises becomes more negative with firms' reliance on the canal. The interaction terms between the rainfall anomaly and the import-exposure measures are negative and statistically significant across alternative exposure definitions.

Panel (b) reports analogous tests for earnings-per-share surprises. Here, the main effect of rainfall anomaly is again negative and statistically significant in most specifications indicating that drought conditions coincide with more negative EPS surprises on average. However, unlike in Panel (a), the interaction terms with the exposure measures are small and statistically insignificant, and are not consistently negative. This pattern is corroborated by robustness tests with alternative measures of water scarcity including total rainfall, and the standardized precipitation and standardized precipitation and evaporation index in Table A.7 and A.8. The difference suggests that the differential underestimation of drought-related impacts is much clearer in revenue forecasts than in EPS forecasts, potentially because EPS incorporates additional margins such as cost adjustments and accounting components that weaken the translation from canal exposure to forecast errors.

8 Conclusion

This study analyzes how capacity constraints at a major trade route caused by drought shape U.S. firm performance and financial responses. Focusing on the Panama Canal and exploiting exogenous variation in water scarcity, I document that rainfall anomalies affect shipping patterns and contribute to bottlenecks in supply chains. I find that inventories decrease in response to constraints, and revenues and operating income are adversely affected. Analyses of aggregate freight rates point to increasing costs of transportation as a mechanism in addition to delivery delays and input shortages. In line with the idea that the incidence of increased shipping costs varies with market power, operational expenses increase for firms but less so when markets are more concentrated and when firms have more market power. Analysts do not appear to fully anticipate these effects, since earnings surprises become more negative after periods of drought, even when information on weather conditions is publicly available.

These results underscore the potential risks arising from infrastructure and climate risk in supply-chain operations. First, a large literature in economics and finance studies how idiosyn-

cratic shocks propagate through production networks and under which conditions idiosyncratic disturbances can translate into aggregate fluctuations [e.g., Acemoglu et al., 2012, Baqaee and Farhi, 2019, Barrot and Sauvagnat, 2016, Carvalho, 2014, Carvalho et al., 2021, Gabaix, 2011]. Yet, much of this work abstracts from infrastructure-based vulnerabilities that sit between firms, such as canals, straits, ports, and inland waterways. The stylized facts in this paper highlight why this omission matters: nearly 80% of firms in the sample rely on the Panama Canal to some degree. Hence, shocks to capacity at this node are unlikely to remain firm-specific. Second, a growing literature investigates whether investors anticipate climate-related risks. Some evidence suggests that climate risk is reflected in asset prices and risk premia [e.g., Bolton and Kacperczyk, 2021, Giglio et al., 2021, Ilhan et al., 2021, Krüger et al., 2018], while other work points to limited attention and heterogeneous beliefs that can lead to underreaction and mispricing [e.g., Baldauf et al., 2020, Hong et al., 2019, Murfin and Spiegel, 2020]. The findings in this paper speak to both debates: they show that supply-chain risks beyond firm boundaries can be financially material, and they suggest that investors may not fully incorporate climate risk from supply-chain infrastructure.

The findings are likely relevant beyond the specific geographic context. The Panama Canal is a critical node in U.S. trade, and its sensitivity to drought poses risks to U.S. supply chains. However, risks from natural constraints in capacity extend to other geographies. Anecdotes report that the magnitude of droughts has increasingly led to water scarcity and affected shipping along the Yangtze [European Space Agency, 2022], Rhine [CNBC, 2023], and the Mississippi River [NASA Earth Observatory, 2022].

From a managerial perspective, these findings highlight the need for firms to develop flexible supply-chain strategies and that considerations about adaptation go beyond revising production networks [Pankratz and Schiller, 2024]. For instance, firms could benefit from diversifying transportation networks, securing alternative suppliers, or increasing buffer inventory levels to hedge against trade disruptions. While each of these strategies offers potential relief, open questions remain around the cost–benefit tradeoffs of these approaches. The findings also speak to how financial markets process supply-chain disruptions and related considerations about improved disclosure and measurement to reduce informational frictions.

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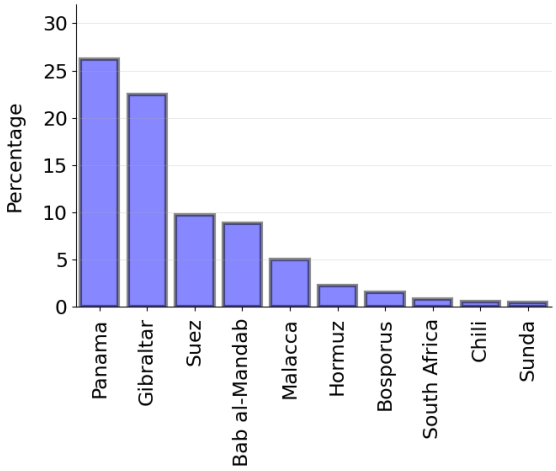
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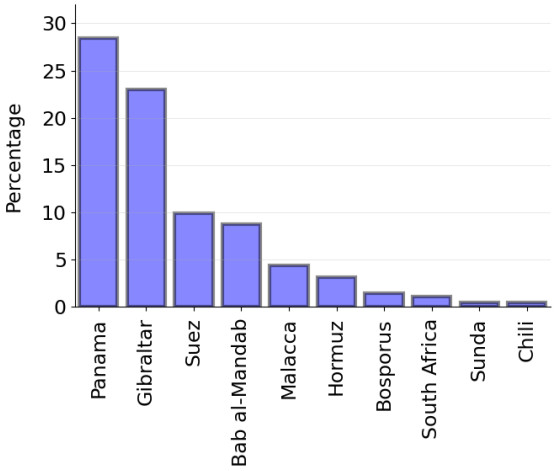
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Tables and Figures

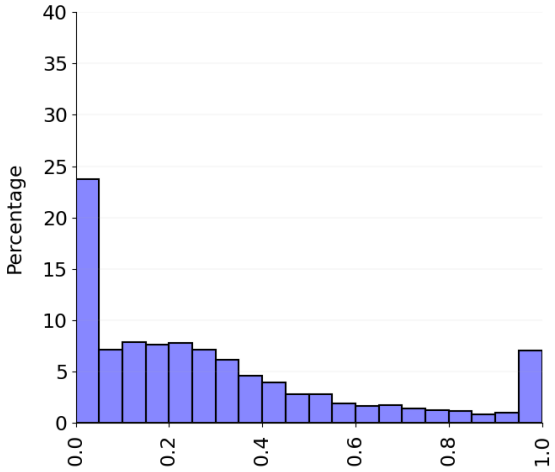
Figure 1: Economic Reliance on Trade Routes of US Firms



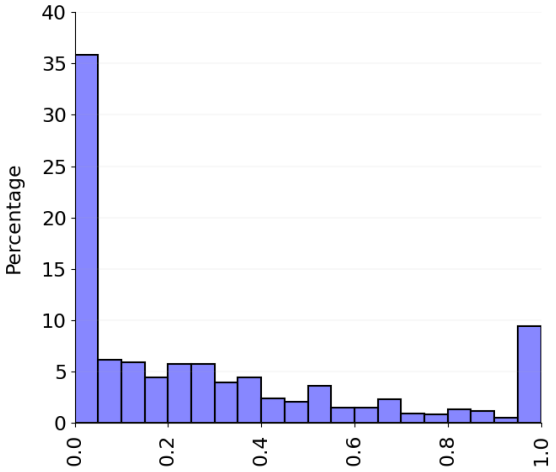
(a) Passages Traversed for Incoming Shipments



(b) Passages Traversed for Outgoing Shipments



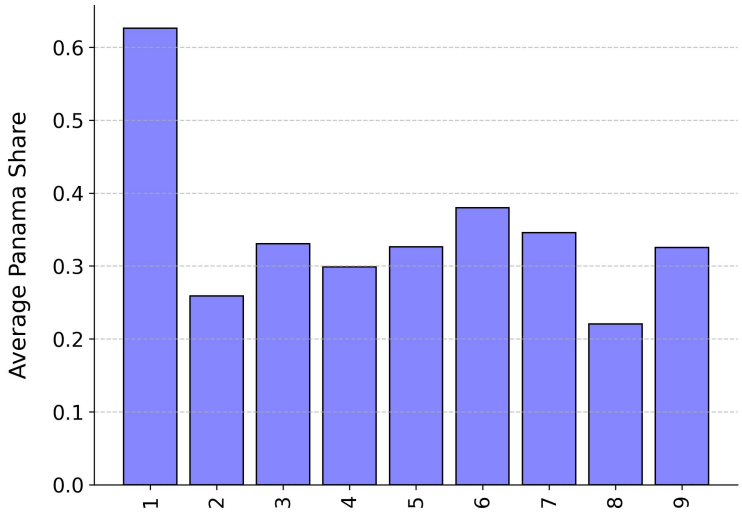
(c) Share of Incoming Shipments by Volume



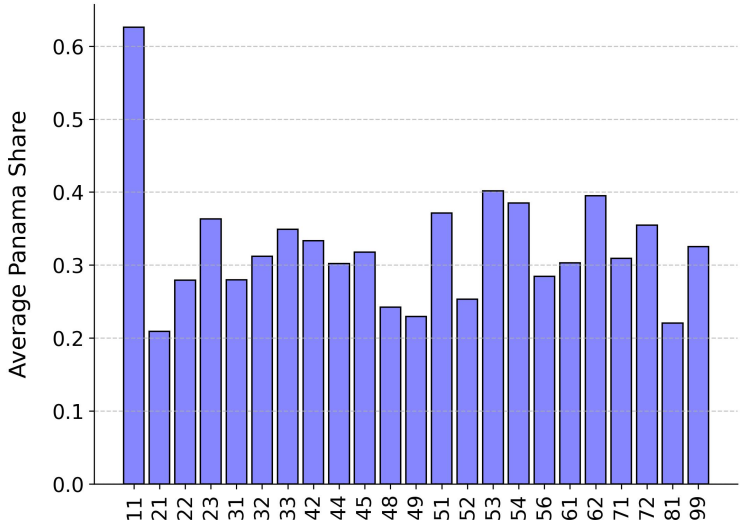
(d) Share of Outgoing Shipments by Volume

Notes: This figure shows the distribution of traversed passages and exposure to the Panama Canal estimated based on ports of origin and destination in S&P Panjiva. The most efficient route between two ports is inferred using the Python package searoute.py. Figure (a) and (b) show exposures for incoming shipments across all major trade routes. Figure (c) and (d) zoom in on the Panama Canal and show the distribution of the share of volume shipped through canal relative to the total shipping volume for incoming and outgoing shipments, respectively.

Figure 2: Route Exposure of Listed Firms by Industry



(a) Share by Industry (NAICS 1)

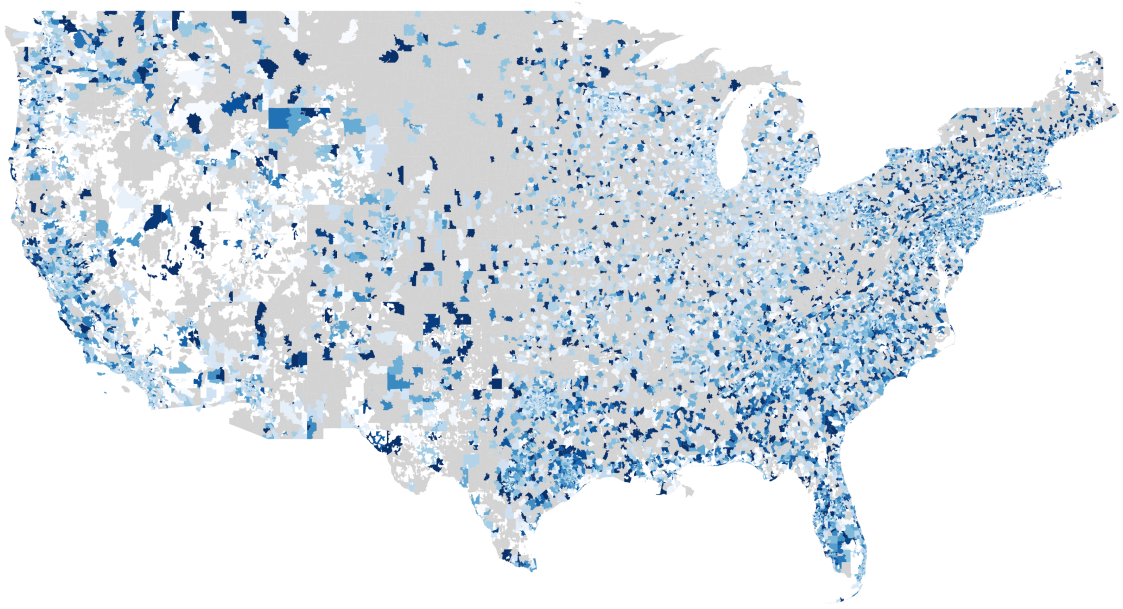


(b) Share by Industry (NAICS 2)

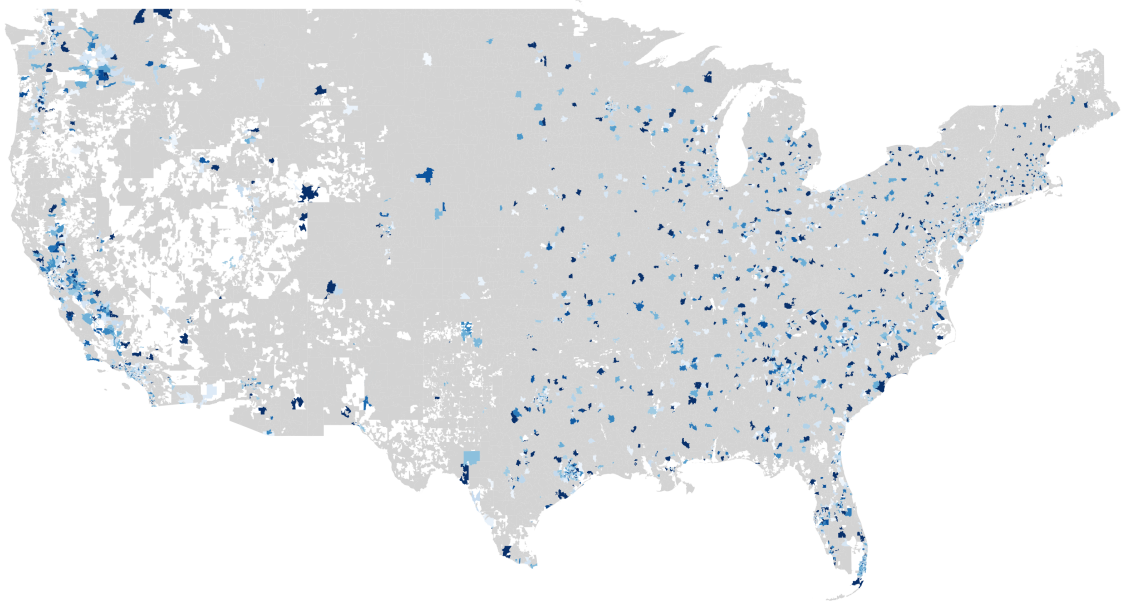
Notes: This figure shows the average share of shipment volume routed through the Panama Canal by industry. Panel (a) shows shares for incoming shipments across broad industry groups assigned based on the first digit of the NAICS code. Figure (b) shows the distribution assigning groups based on the second digit of the NAICS code.

Figure 3: Geographic Variation in Route Exposure

(a) Inbound Shipments



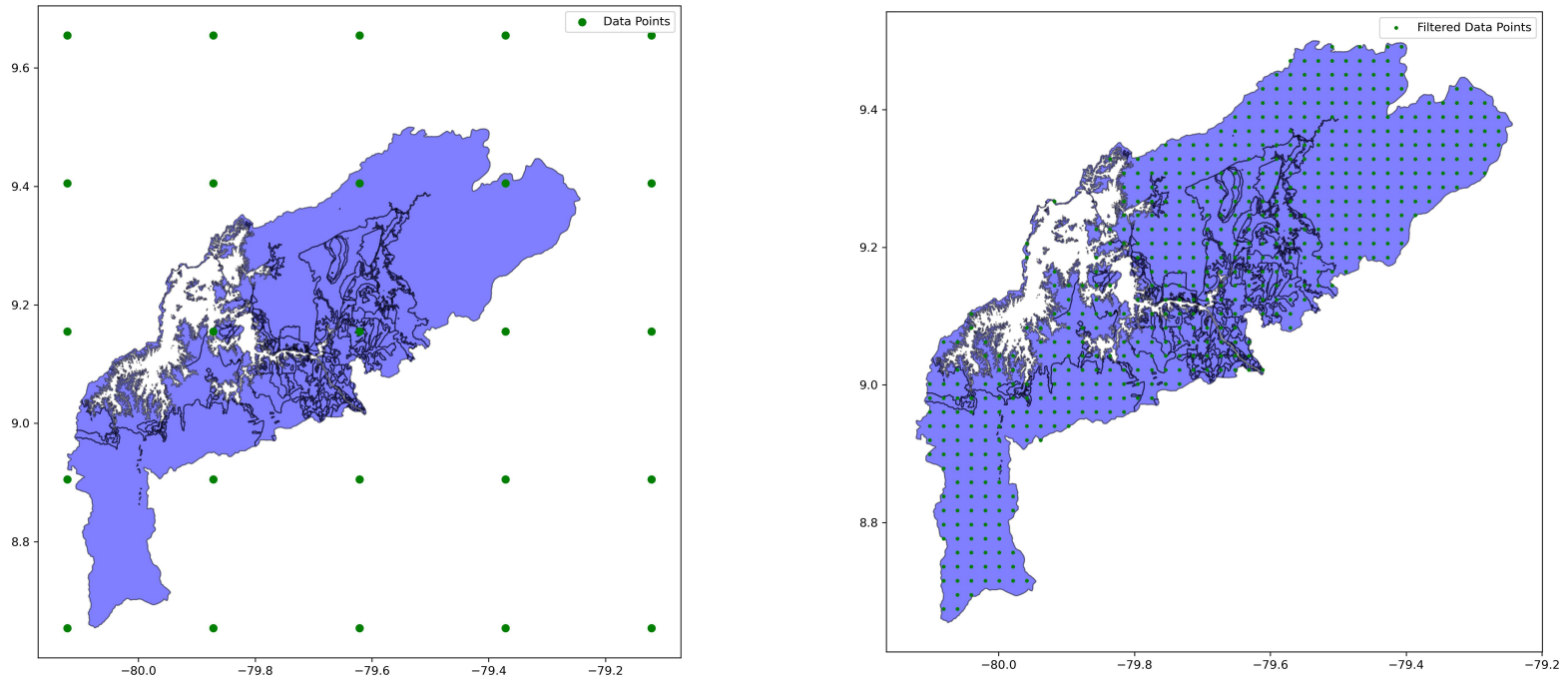
(b) Outbound Shipments





Notes: This figure shows the geographic distribution of route exposure, obtained by aggregating the share of shipments traversing the Panama Canal at the zip code level. Observations where ocean transportation intermediaries, freight forwarders, or non-vessel operating common carriers are entered as the US firm are excluded. Panel (a) shows the exposure of inbound shipments, Panel (b) refers to outbound shipments.

Figure 4: Aggregation of Precipitation Data over the Watershed of the Panama Canal

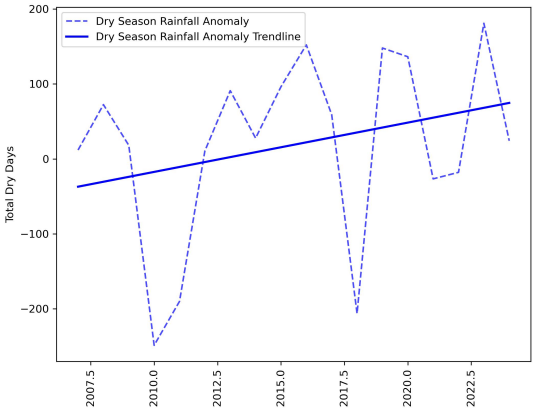


(a) Gatun Lake watershed and ERA5 grid nodes

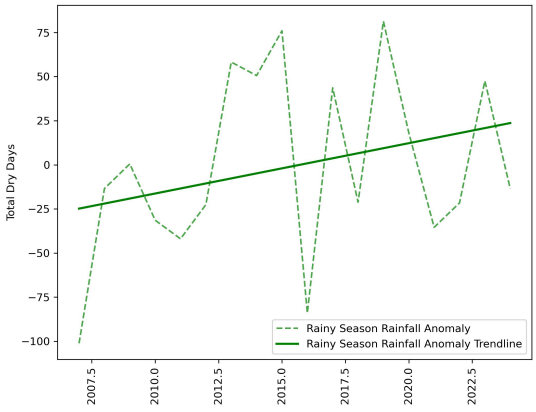
(b) Aggregation of ERA5 data points

Notes: This figure shows the aggregation of data on precipitation and evaporation from ERA5. The shapefile in Figure (a) marks the boundaries of the watershed of Gatun Lake. Green dots indicate ERA5 grid nodes. Precipitation and evaporation are aggregated by area-weighted averaging over grid cells. Figure (b) shows interpolated observations of precipitation masked by the area of the watershed.

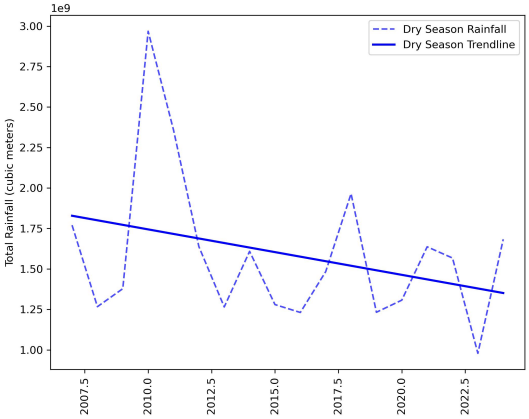
Figure 5: Drought Trends by Season over Time



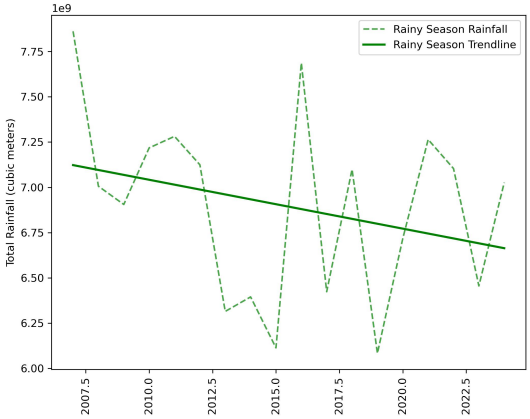
(a) Anomaly in the Dry Season



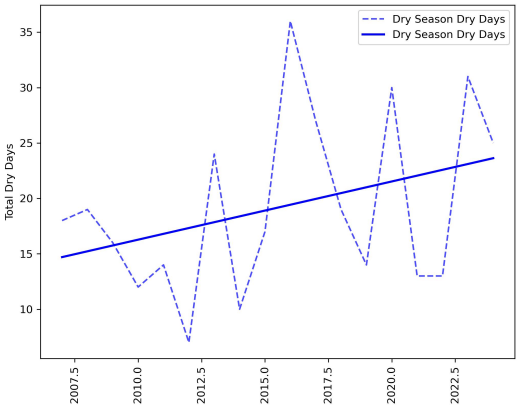
(b) Anomaly in the Rainy Season



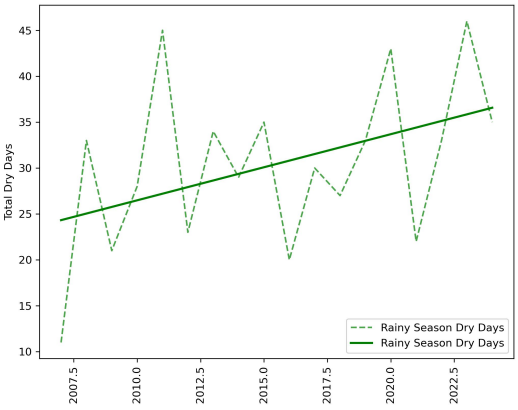
(c) Rainfall in the Dry Season



(d) Rainfall in the Rainy Season



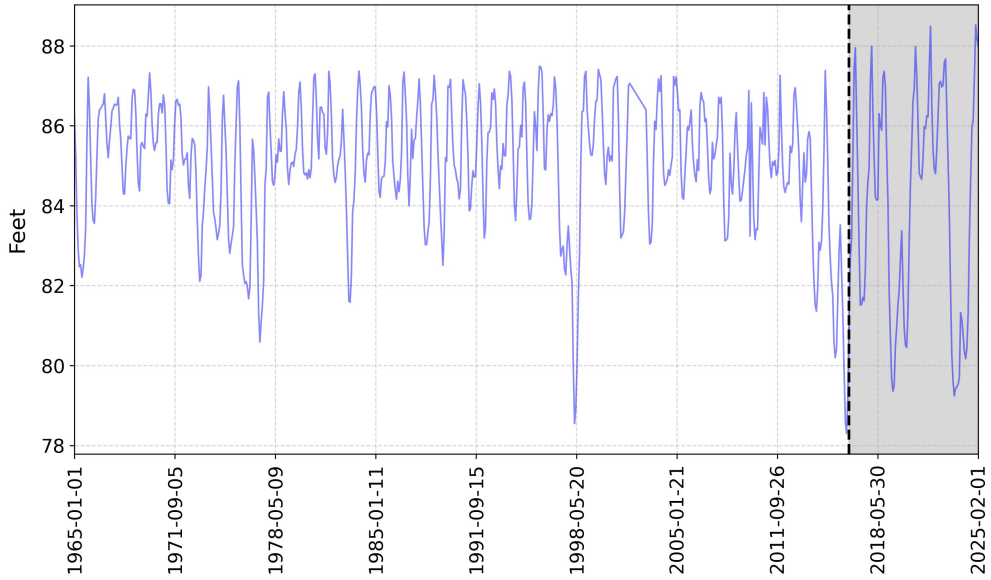
(e) Dry Days in the Dry Season



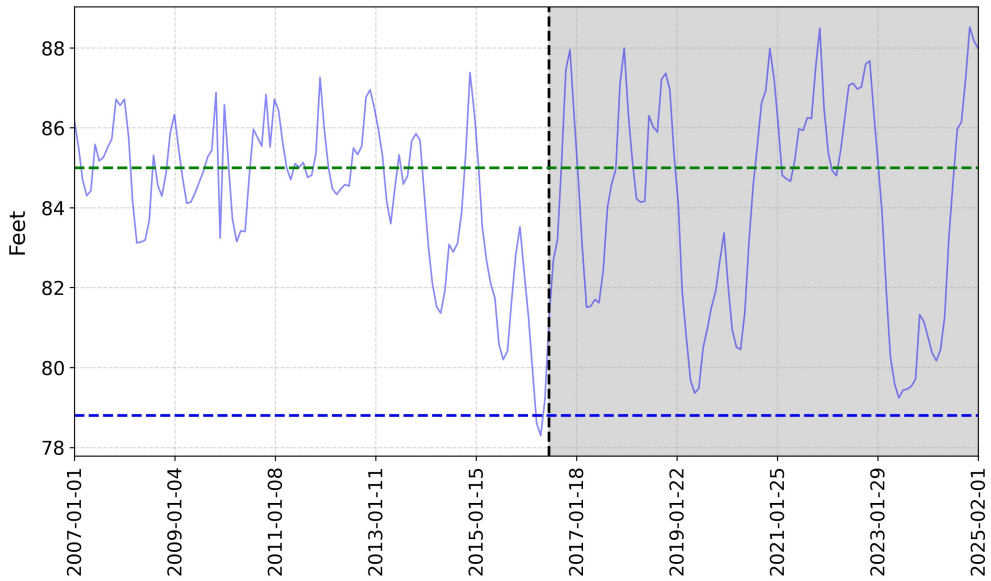
(f) Dry Days in the Rainy Season

Notes: This figure shows precipitation trends over the watershed of Gatun Lake over time. The aggregation is illustrated in Figure 4. Figure (a) shows the trend in the dry season from December to April. Figure (b) shows the trend in the rainy season from May to November.

Figure 6: Historical Water Levels in Lake Gatun



(a) Available Data – Gatun Lake Minimum Water Level



(b) Sample Period – Gatun Lake Minimum Water Level

Notes: This figure shows minimum water levels in Gatun Lake, an artificial freshwater lake that forms a major part of the Panama Canal. Locks allow ships to pass from the Atlantic to the Pacific ocean. In June 2016, a major expansion of the canal was completed, doubling capacity of the Panama Canal by adding a new traffic lane (Neopanamax). Panel (a) shows all available records. Panel (b) focuses on the period beginning in 2007 when Panjiva data is available. When water levels fall below the green (blue) line, the Panama Canal Authority (PCA) imposes draft restrictions for the Neopanamax (Panamax) locks. Before these restrictions bind, the number of passages can be capped.

Table 1: **Summary Statistics**

Notes: This table shows the summary statistics for the measures of precipitation, drought, and firm performance. The sample covers the years 2000 to 2024. Financial and accounting measures are shown in million U.S. dollar, ratios are unitless. All observations of financial and accounting performance are at the year-quarter level.

	N	Mean	StDev	p25	Median	p75
Rainfall Anomaly (%)	1158125	0.975	20.645	-7.178	1.781	13.129
Rainfall Anomaly within Quarter (%)	1158125	0.000	20.313	-8.009	2.576	12.242
Rainfall Anomaly over three Quarters (%)	1158125	2.235	40.754	-18.531	2.669	32.848
Rainfall Anomaly within three Quarters (%)	1158125	0.000	40.575	-20.659	0.772	30.424
Precipitation (m cubicm)	1158125	2127.421	988.219	1238.424	2361.448	2928.089
Precipitation within Quarter (m cubicm)	1158125	0.000	327.571	-198.625	-38.251	135.820
Drought Days	1158125	11.911	5.845	7.000	11.000	16.000
Drought Days within Month	1158125	0.000	5.816	-4.295	-1.018	3.982
Minimum Water Level of Gatun Lake	1113902	84.019	4.381	83.207	84.997	85.963
Maximum Water Level of Gatun Lake	1123383	84.947	5.823	84.213	86.033	87.000
Revenues over Lagged Assets	679869	20.723	22.616	4.049	14.366	29.412
Revenues	703068	552.054	1544.405	7.534	56.602	316.000
Operating Income over Lagged Assets	715593	-0.040	0.197	-0.023	0.006	0.023
Operating Income	855047	59.074	206.577	-0.773	1.402	24.264
Assets	847473	4254.293	14643.580	35.496	303.936	1877.439
Cost of Goods Sold	873361	291.178	926.640	1.458	14.941	126.870
Sales, General, Administrative Expenses	702593	76.834	241.022	1.769	7.953	39.367
Inventories	835591	151.680	541.154	0.000	1.467	42.221
Depreciation	793119	26.098	80.916	0.101	1.234	11.610
Accounts Payable	844209	483.836	2013.801	1.404	12.036	129.900
Accounts Receivable	834165	677.677	2812.499	1.478	25.271	225.671
>0 Exposed Volume of Incoming Shipments	247242	0.781	0.413	1.000	1.000	1.000
% Exposed Volume of Incoming Shipments	247242	0.275	0.309	0.019	0.160	0.420
>0 Exposed Volume of Outgoing Shipments	65993	0.649	0.477	0.000	1.000	1.000
% Exposed Volume of Outgoing Shipments	65993	0.198	0.278	0.000	0.062	0.306

Table 2: **Mechanisms – Drought-Related Adjustments in Shipping**

Notes. This table reports estimates of how water scarcity in the Lake Gatun watershed translates into observable adjustments in vessel movements at U.S. ports, using the U.S. Army Corps of Engineers data on vessel entrances and clearances. The sample period is 2013 to 2022. Columns (1)–(4) use entrances and columns (5)–(8) use clearances of US ports. *Panama Canal* takes a value of one when routes traverse the passage. Panel (a) shows OLS estimates with net registered tonnage and draft in inches as the dependent variable. Panel (b) shows Poisson estimates on the usage of Panamax and Neopanamax vessel classes. Included fixed effects are indicated in the table. Robust standard errors clustered at year-month level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Vessel Size and Draft

	Ln(Net Registered Tonnage)				Ln(Draft)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Entering US Ports		Clearing US Ports		Entering US Ports		Clearing US Ports	
Rainfall Anomaly × Panama Canal	-0.0004***		-0.0003**		-0.0342**		-0.0161	
	(0.00)		(0.00)		(0.01)		(0.01)	
Rainfall Anomaly (m to m-2) × Panama Canal		-0.0004***		-0.0003***		-0.0244**		-0.0196**
		(0.00)		(0.00)		(0.01)		(0.01)
Rainfall Anomaly	-0.0000		-0.0000		0.0053		0.0076	
	(0.00)		(0.00)		(0.01)		(0.01)	
Rainfall Anomaly (m to m-2)		-0.0000		-0.0000		-0.0008		0.0011
		(0.00)		(0.00)		(0.00)		(0.00)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	167256	167256	167839	167839	165053	165053	167135	167135
R^2	.81	.811	.805	.805	.708	.708	.681	.681

(b) Vessel Types

	Panamax				Neo-Panamax			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Entering US Ports		Clearing US Ports		Entering US Ports		Clearing US Ports	
Rainfall Anomaly × Panama Canal	0.0016***		0.0009***		-0.0010***		-0.0009***	
	(0.00)		(0.00)		(0.00)		(0.00)	
Rainfall Anomaly (m to m-2) × Panama Canal		0.0017***		0.0009***		-0.0011***		-0.0009***
		(0.00)		(0.00)		(0.00)		(0.00)
Rainfall Anomaly	0.0002**		0.0002***		-0.0002***		-0.0003***	
	(0.00)		(0.00)		(0.00)		(0.00)	
Rainfall Anomaly (m to m-2)		0.0001**		0.0001***		-0.0001**		-0.0001***
		(0.00)		(0.00)		(0.00)		(0.00)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165304	165304	163438	163438	139586	139586	143382	143382

Table 3: **Mechanisms – Effects of Infrastructure Constraints on Shipping Time**

Notes. This table shows OLS regressions on the effects of water supply in the Lake Gatun watershed on the timing of vessel movements into and out of US ports using data on entrances and clearances from the US Army Corps of Engineers. The sample period is 2013 to 2022. Columns 1 to 4 show the effects on days spent on voyages outside of ports, and columns 5 to 8 shows the effects on time spent in ports. Included fixed effects are indicated in the table. Robust standard errors clustered at the year-month level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Days Between Voyages				Days in U.S. Port			
	(1) Containers	(2) Tankers	(3) Dry Bulk	(4) Ro-Ros	(5) Containers	(6) Tankers	(7) Dry Bulk	(8) Ro-Ros
Rainfall Anomaly (m to m-2) × Panama Canal	0.0702**	0.1312**	0.1063	0.1281*	0.0001	0.0086***	0.0177	0.0049
	(0.03)	(0.06)	(0.15)	(0.07)	(0.00)	(0.00)	(0.02)	(0.00)
Rainfall Anomaly (m to m-2)	0.0492	0.0053	-0.0780	0.0335	-0.0006	-0.0019	-0.0031	-0.0017
	(0.04)	(0.07)	(0.08)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144264	64972	32238	36363	167011	100878	65497	48800
R^2	.135	.305	.378	.293	.167	.194	.254	.157

Table 4: **Effects of Drought-Induced Infrastructure Constraints on Inventory**

Notes. This table shows OLS regressions on the effects of rainfall declines in the Lake Gatun watershed on inventories. The results show the effects interacted with intensity measures of import reliance on the canal. The dependent variable is inventory over lagged assets in column (1) to (4), and the quarterly change in inventories in column (5) to (8). The sample period is 2000 to 2024. Included fixed effects are indicated in the table. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Inventories/Assets					Change in Inventories				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall Anomaly (q,q+2)	-0.0013	-0.0004	-0.0009	-0.0009	-0.0008	-0.0102***	-0.0289**	0.0105	-0.0284**	-0.0221**
	(-1.63)	(-0.25)	(-0.20)	(-0.58)	(-0.51)	(-2.67)	(-2.61)	(0.59)	(-2.60)	(-2.14)
Rainfall Anomaly (q,q+2) × % Volume		-0.0064**					0.0081			
		(-2.42)					(0.97)			
Rainfall Anomaly (q,q+2) × >0 Volume			-0.0012					-0.0377**		
			(-0.28)					(-2.14)		
Rainfall Anomaly (q,q+2) × > Mean Volume				-0.0034***					0.0047	
				(-2.79)					(0.97)	
Rainfall Anomaly (q,q+2) × > Median Volume					-0.0022**					-0.0080
					(-2.17)					(-1.64)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311302	86128	86128	86128	86128	339806	85642	85642	85642	85642
Firms	9421	1281	1281	1281	1281	10036	1275	1275	1275	1275
R^2	.839	.837	.837	.837	.837	.396	.388	.388	.388	.388

Table 5: **Effects of Infrastructure Capacity Constraints on US Firm Revenues**

Notes. This table shows OLS regressions on the effects of water scarcity in the Panama Canal on the performance of firms in the United States. Revenues are standardized. Rainfall anomalies are defined as monthly rainfall minus average rainfall over a WMO base period, scaled by average base period rainfall. The measure is inverted so that an increase coincides with drier conditions. Panel (a) shows sensitivity to an exposure measure calculated based on incoming shipments. Panel (b) shows interactions with a measure of exposure based on outgoing shipments. The sample period is 2000 to 2024. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Inbound Exposure

	Z Revenues				
	(1)	(2)	(3)	(4)	(5)
Rainfall Anomaly (q,q+2)	-0.0003**	-0.0004**	0.0003	-0.0005***	-0.0004**
	(-2.08)	(-2.43)	(0.52)	(-2.75)	(-2.27)
Rainfall Anomaly (q,q+2) × % Volume		-0.0006***			
		(-2.87)			
Rainfall Anomaly (q,q+2) × >0 Volume			-0.0009*		
			(-1.78)		
Rainfall Anomaly (q,q+2) × > Mean Volume				-0.0004***	
				(-4.58)	
Rainfall Anomaly (q,q+2) × > Median Volume					-0.0003***
					(-3.15)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	341200	94237	94237	94237	94237
Firms	9723	1287	1287	1287	1287
R^2	.353	.501	.501	.501	.501

(b) Outbound Exposure

	Z Revenues				
	(1)	(2)	(3)	(4)	(5)
Rainfall Anomaly (q,q+2)	-0.0003**	-0.0003*	-0.0003	-0.0003	-0.0003
	(-2.08)	(-1.66)	(-1.27)	(-1.30)	(-1.53)
Rainfall Anomaly (q,q+2) × % Volume		-0.0010***			
		(-3.31)			
Rainfall Anomaly (q,q+2) × >0 Volume			-0.0004***		
			(-2.92)		
Rainfall Anomaly (q,q+2) × > Mean Volume				-0.0008***	
				(-4.53)	
Rainfall Anomaly (q,q+2) × > Median Volume					-0.0004***
					(-2.64)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	341200	46410	46410	46410	46383
Firms	9723	571	571	571	570
R^2	.353	.551	.551	.551	.551

Table 6: **Effects of Infrastructure Capacity Constraints on US Firm Operating Income**

Notes. This table shows OLS regressions on the effects of water scarcity in the Panama Canal on the performance of firms in the United States. Operating income is standardized. Rainfall anomalies are defined as monthly rainfall minus average rainfall over a WMO base period, scaled by average base period rainfall. The measure is inverted so that an increase coincides with drier conditions. Panel (a) shows sensitivity to an exposure measure calculated based on incoming shipments. Panel (b) shows interactions with a measure of exposure based on outgoing shipments. The sample period is 2000 to 2024. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Inbound Exposure

	Z Operating Inc.				
	(1)	(2)	(3)	(4)	(5)
Rainfall Anomaly (q,q+2)	0.0010	-0.0014*	0.0042	-0.0021***	-0.0019**
	(1.41)	(-1.97)	(1.19)	(-3.14)	(-2.61)
Rainfall Anomaly (q,q+2) × % Volume		-0.0039**			
		(-2.58)			
Rainfall Anomaly (q,q+2) × >0 Volume			-0.0067*		
			(-1.91)		
Rainfall Anomaly (q,q+2) × > Mean Volume				-0.0009	
				(-1.63)	
Rainfall Anomaly (q,q+2) × > Median Volume					-0.0009*
					(-1.96)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	292473	84135	84135	84135	84135
Firms	9179	1284	1284	1284	1284
R^2	.67	.643	.643	.643	.643

(b) Outbound Exposure

	Z Operating Inc.				
	(1)	(2)	(3)	(4)	(5)
Rainfall Anomaly (q,q+2)	0.0010	0.0000	-0.0005	-0.0006	-0.0005
	(1.41)	(0.01)	(-0.58)	(-0.86)	(-0.67)
Rainfall Anomaly (q,q+2) × % Volume		-0.0087***			
		(-3.64)			
Rainfall Anomaly (q,q+2) × >0 Volume			-0.0016*		
			(-1.90)		
Rainfall Anomaly (q,q+2) × > Mean Volume				-0.0031***	
				(-3.90)	
Rainfall Anomaly (q,q+2) × > Median Volume					-0.0020**
					(-2.38)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	292473	42381	42381	42381	42291
Firms	9179	574	574	574	573
R^2	.67	.624	.624	.624	.624

Table 7: **Mechanisms – Effects of Capacity Constraints on Transportation Costs**

Notes. This table shows OLS regressions on the effects of rainfall in the Lake Gatun watershed on indicators of transportation costs of firms in the United States. The dependent variable in column (1) to (4) is the FRED producer price index on deep sea freight transportation. In column (5) to (8), the dependent variable is the Cass Freight Index on implied freight rates. The sample period is 2000 to 2024. Included fixed effects are indicated in the table. Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	PPI Deep Sea		Cass Rates		PPI Deep Sea		Cass Rates	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample				excl. Financial Crisis Covid			
Rainfall Anomaly	0.0456*	0.0442*	0.0003	0.0003	0.0425*	0.0413	0.0003*	0.0003*
	(0.02)	(0.02)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)
Rainfall Anomaly (m-1)		0.0081		0.0005**		0.0074		0.0004**
		(0.02)		(0.00)		(0.03)		(0.00)
Rainfall Anomaly (m-2)		-0.0257		0.0002		-0.0281		0.0002
		(0.02)		(0.00)		(0.03)		(0.00)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	300	300	300	300	264	264	264	264
R^2	.97	.97	.982	.983	.974	.974	.983	.983

Table 8: **Effects of Drought-Induced Infrastructure Constraints on Firm Expenses**

Notes. This table shows OLS regressions on the effects of rainfall in the Lake Gatun watershed on the costs of goods sold (COGS) and sales, general, and administrative expenses (SGA) of firms in the United States. COGS (columns 1-4) and SGA (columns 5-8) are scaled by assets lagged by one year. The sample period is 2000 to 2024. Included fixed effects are indicated in the table. Robust standard errors clustered at the firm and year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Precipitation

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Anomaly (q,q+2)	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
	(1.47)	(1.42)	(0.68)	(0.56)	(0.97)	(1.08)
Rainfall Anomaly (q,q+2) × > Median Volume	0.0001*	0.0001*	0.0001***	0.0001***	0.0001***	0.0001***
	(1.68)	(1.77)	(3.76)	(3.42)	(3.54)	(3.41)
Rainfall Anomaly (q,q+2) × NAICS4 HHI	-0.0001					
	(-1.02)					
Rainfall Anomaly (q,q+2) × > Median Volume × NAICS4 HHI	0.0000					
	(0.21)					
Rainfall Anomaly (q,q+2) × NAICS4 HHI		-0.0002				
		(-0.93)				
Rainfall Anomaly (q,q+2) × > Median Volume × NAICS4 HHI		-0.0000				
		(-0.12)				
Rainfall Anomaly (q,q+2) × Top 5 Market Share			0.0000			
			(0.43)			
Rainfall Anomaly (q,q+2) × > Median Volume × Top 5 Market Share			-0.0001***			
			(-2.82)			
Rainfall Anomaly (q,q+2) × Top 5 Market Share				0.0000		
				(0.69)		
Rainfall Anomaly (q,q+2) × > Median Volume × Top 5 Market Share				-0.0002***		
				(-2.72)		
Rainfall Anomaly (q,q+2) × Firm Market Share					-0.0000	
					(-0.33)	
Rainfall Anomaly (q,q+2) × > Median Volume × Firm Market Share					-0.0003**	
					(-2.49)	
Rainfall Anomaly (q,q+2) × Firm Market Share						-0.0000
						(-0.27)
Rainfall Anomaly (q,q+2) × > Median Volume × Firm Market Share						-0.0003**
						(-2.38)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93335	93335	93335	93335	92258	93025
Firms	1284	1284	1284	1284	1279	1281
R^2	.648	.648	.648	.648	.652	.648

Table 10: **Effects of Drought-Induced Capacity Constraints on Earnings Surprises**

Notes. This table shows OLS regressions on the effects of rainfall in the Lake Gatun watershed on earnings surprises. The sample period is 2000 to 2024. Included fixed effects are indicated in the table. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Forecasts of Revenues

	Mean Surprise					Median Surprise				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall Anomaly	-0.0056***	-0.0049***	-0.0048***	-0.0049***	-0.0048***	-0.0056***	-0.0049***	-0.0048***	-0.0049***	-0.0048***
	(-3.71)	(-3.38)	(-3.46)	(-3.41)	(-3.46)	(-3.76)	(-3.49)	(-3.56)	(-3.52)	(-3.56)
Rainfall Anomaly × % Volume		-0.0023***					-0.0030***			
		(-2.65)					(-3.38)			
Rainfall Anomaly × >0 Volume			-0.0016**					-0.0021***		
			(-2.21)					(-2.62)		
Rainfall Anomaly × > Mean Volume				-0.0017**					-0.0021***	
				(-2.45)					(-2.89)	
Rainfall Anomaly × > Median Volume					-0.0016**					-0.0021***
					(-2.21)					(-2.62)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76825	91437	91437	91437	91437	92695	91446	91446	91446	91446
Firms	1600	1992	1992	1992	1992	2016	1992	1992	1992	1992
R^2	.194	.199	.199	.199	.199	.198	.199	.199	.199	.199

(b) Forecasts of Earnings per Share

	Mean Surprise					Median Surprise				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall Anomaly	-0.0063	-0.0100**	-0.0088*	-0.0086*	-0.0088*	-0.0111**	-0.0125**	-0.0117**	-0.0117**	-0.0117**
	(-1.34)	(-2.04)	(-1.84)	(-1.80)	(-1.84)	(-2.30)	(-2.25)	(-2.10)	(-2.12)	(-2.10)
Rainfall Anomaly × % Volume		0.0083					0.0056			
		(1.07)					(0.73)			
Rainfall Anomaly × >0 Volume			0.0022					0.0016		
			(0.46)					(0.30)		
Rainfall Anomaly × > Mean Volume				0.0016					0.0016	
				(0.31)					(0.30)	
Rainfall Anomaly × > Median Volume					0.0022					0.0016
					(0.46)					(0.30)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77233	92259	92259	92259	92259	93604	92249	92249	92249	92249
Firms	1649	2061	2061	2061	2061	2086	2061	2061	2061	2061
R^2	.172	.176	.176	.176	.176	.18	.179	.179	.179	.179

Appendix

Figure A.1: **Construction of the Tests on Earnings Surprises**

Notes: This figure shows the timeline of the tests on forecast errors which is constructed to ensure that information on realized drought conditions was available to analysts before earnings were announced. *Drought* measures rainfall anomalies in a given quarterly fiscal period t, labeled $Affected\ Fiscal\ Period$. The earnings of the respective fiscal period are announced with a lag at time t. The time window available to analysts and investor to adjust their expectations depends on how quickly the effects on firms' materialize. If there is an instant effect of drought in t on firm performance in t, analysts and investors have the opportunity to update forecasts in the time between the end of the fiscal period and the announcement date ($Adjustment\ Time\ (a)$). Even in this most extreme case, information on drought is publicly available to analysts and investors, and would allow for adjustment. If there is a longer lag until the effects on performance materialize, the window widens and investors have more time to process information, e.g., if there are significant effects lagged by one quarter [two quarters], the adjustment time window grows to $Adjustment\ Time\ (b)$ [(c)].

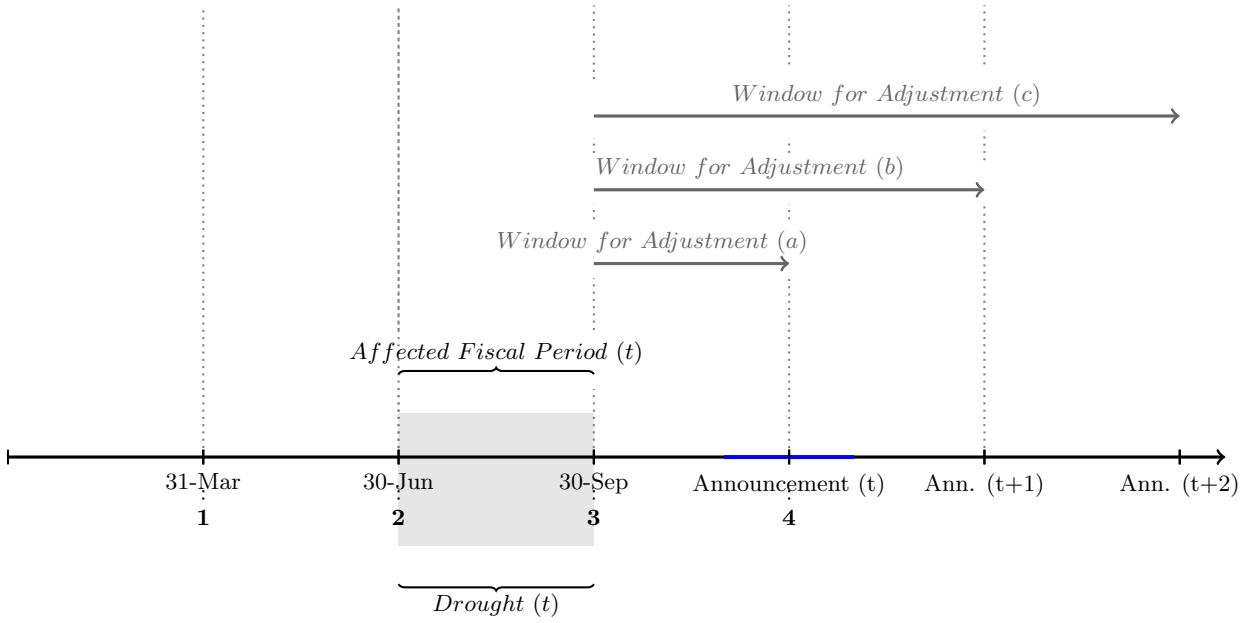


Table A.1: **Firm Characteristics and Bottleneck Exposure**

Notes. This table describes the characteristics of the firms in the sample and compares them based on their exposure to the Panama Canal measured as the share of the volume of incoming shipments through the canal relative to all other shipments. The sample covers the years 2000 to 2024. In Panel (a), firms are split depending on whether their exposure is zero (columns 1 and 2) or non-zero (columns 3 and 4). In Panel (b), firms are split below and above the mean of exposure. In Panel (c), the split is below and above the median. Financial and accounting measures are shown in million U.S. dollar, ratios are unitless, age is in years, and shipment shares are in [0,1] or percent. All observations of financial and accounting performance are averaged at the firm level. Column 5 and 6 show the difference between sample means as well as t-statistics.

(a) Zero vs. Non-Zero Exposure

	N (Exp. = Zero)	Mean (Exp. = Zero)	N (Exp. > Zero)	Mean (Exp. > Zero)	Diff (1–0)	t-stat
Revenues	908	579.08	2,656	986.16	-407.08	-6.32
Assets	952	4,286.18	2,716	6,915.17	-2,628.99	-4.64
Operating Income/Assets	937	-0.06	2,679	-0.02	-0.04	-6.27
Operating Income/Assets (Alt)	845	-0.01	2,548	0.01	-0.01	-6.14
Revenues/Assets	922	0.23	2,636	0.29	-0.05	-7.31
Cash Holdings	890	288.82	2,593	436.95	-148.13	-4.36
Firm Age	958	25.64	2,740	31.35	-5.71	-9.99
% Value of Panama Shipments	958	0.00	2,740	0.35	-0.35	-56.16
Upstreamness	713	2.05	2,247	1.96	0.09	4.26
Market Share in NAICS4 Industry	719	0.05	2,293	0.08	-0.03	-5.43
HHI in NAICS 4 Industry	759	0.17	2,355	0.20	-0.03	-5.51

(b) Below vs. Above-Mean Exposure

	N (Exp. < Mean)	Mean (Exp. < Mean)	N (Exp. > Mean)	Mean (Exp. > Mean)	Diff (1–0)	t-stat
Revenues	1,471	1,139.20	1,185	796.20	343.00	4.28
Assets	1,500	7,788.54	1,216	5,837.82	1,950.72	2.71
Operating Income/Assets	1,477	-0.01	1,202	-0.03	0.03	5.28
Operating Income/Assets (Alt)	1,423	0.01	1,125	0.00	0.01	4.57
Revenues/Assets	1,456	0.29	1,180	0.28	0.01	1.09
Cash Holdings	1,433	502.14	1,160	356.43	145.71	3.63
Firm Age	1,514	32.41	1,226	30.06	2.35	3.87
% Value of Panama Shipments	1,514	0.11	1,226	0.65	-0.55	-70.48
Upstreamness	1,233	1.95	1,014	1.98	-0.03	-1.36
Market Share in NAICS4 Industry	1,265	0.08	1,028	0.07	0.01	1.72
HHI in NAICS 4 Industry	1,290	0.21	1,065	0.19	0.01	1.65

(c) Below vs. Above-Median Exposure

	N (Exp. < Median)	Mean (Exp. < Median)	N (Exp. > Median)	Mean (Exp. > Median)	Diff (1–0)	t-stat
Revenues	948	984.94	1,707	986.94	-1.99	-0.02
Assets	971	7,051.95	1,744	6,840.62	211.33	0.28
Operating Income/Assets	957	-0.01	1,721	-0.02	0.01	3.06
Operating Income/Assets (Alt)	919	0.01	1,628	0.01	0.00	2.39
Revenues/Assets	939	0.29	1,696	0.28	0.00	0.50
Cash Holdings	920	438.45	1,672	436.15	2.30	0.05
Firm Age	976	32.14	1,763	30.91	1.23	1.91
% Value of Panama Shipments	976	0.06	1,763	0.51	-0.45	-61.38
Upstreamness	803	1.95	1,443	1.96	-0.01	-0.59
Market Share in NAICS4 Industry	822	0.08	1,470	0.08	-0.01	-0.90
HHI in NAICS 4 Industry	841	0.20	1,513	0.20	0.00	0.23

Table A.2: **Effects Drought-Induced Constraints on Inventory**

Notes. This table shows OLS regressions on the effects of rainfall declines in the Lake Gatun watershed on inventories. The results show the effects interacted with intensity measures of export reliance on the canal. The dependent variable is inventory over lagged assets in column (1) to (4), and the quarterly change in inventories in column (5) to (8). The sample period is 2000 to 2024. Included fixed effects are indicated in the table. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Inventories/Assets					Change in Inventories				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall Anomaly (q,q+2)	-0.0013	-0.0024	-0.0046*	-0.0026	-0.0035*	-0.0102***	-0.0305*	-0.0259	-0.0306*	-0.0303*
	(-1.63)	(-1.30)	(-1.89)	(-1.46)	(-1.79)	(-2.67)	(-1.79)	(-1.58)	(-1.81)	(-1.79)
Rainfall Anomaly (q,q+2) × % Volume		-0.0028					-0.0188			
		(-1.10)					(-1.12)			
Rainfall Anomaly (q,q+2) × >0 Volume			0.0025					-0.0122		
			(1.35)					(-1.29)		
Rainfall Anomaly (q,q+2) × > Mean Volume				-0.0009					-0.0106	
				(-0.74)					(-1.17)	
Rainfall Anomaly (q,q+2) × > Median Volume					0.0012					-0.0074
					(0.85)					(-1.01)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311302	42887	42887	42887	42848	339806	41320	41320	41320	41301
Firms	9421	568	568	568	567	10036	564	564	564	563
R^2	.839	.838	.838	.838	.838	.396	.384	.384	.384	.384

Table A.3: **Robustness of the Effects to Different Measures of Revenue**

Notes. This table shows OLS regressions on the effects of water scarcity in the Panama Canal on the performance of firms in the United States. Instead of standardizing, revenues are scaled by lagged assets. Rainfall anomalies are defined as monthly rainfall minus average rainfall over a WMO base period, scaled by average base period rainfall. The measure is inverted so that an increase coincides with drier conditions. Panel (a) shows sensitivity to an exposure measure calculated based on incoming shipments. Panel (b) shows interactions with a measure of exposure based on outgoing shipments. The sample period is 2000 to 2024. Fixed effects included in the regression are indicated below the table. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Revenues/Assets (t-1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Import Exposure				Export Exposure			
Rainfall Anomaly (q,q+2)	-0.0070**	-0.0070	-0.0082***	-0.0073**	-0.0085***	-0.0093***	-0.0100***	-0.0085***
	(-2.43)	(-0.71)	(-3.00)	(-2.40)	(-3.08)	(-2.85)	(-3.77)	(-3.00)
Rainfall Anomaly (q,q+2) × % Volume	-0.0132***							
	(-3.49)							
Rainfall Anomaly (q,q+2) × >0 Volume		-0.0035						
		(-0.37)						
Rainfall Anomaly (q,q+2) × > Mean Volume			-0.0062***					
			(-3.50)					
Rainfall Anomaly (q,q+2) × > Median Volume				-0.0056***				
				(-3.45)				
Rainfall Anomaly (q,q+2) × % Volume					-0.0100**			
					(-2.10)			
Rainfall Anomaly (q,q+2) × >0 Volume						-0.0016		
						(-0.76)		
Rainfall Anomaly (q,q+2) × > Mean Volume							-0.0012	
							(-0.59)	
Rainfall Anomaly (q,q+2) × > Median Volume								-0.0037**
								(-2.17)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87567	87567	87567	87567	43462	43462	43462	43439
Firms	1280	1280	1280	1280	570	570	570	569
R^2	.771	.771	.771	.771	.814	.814	.814	.813

Table A.4: **Robustness of the Effects on Revenues to Different Measure of Drought**

Notes. This table shows OLS regressions on the effects of water scarcity in the Panama Canal on the performance of firms in the United States. Revenues are scaled by lagged assets. Instead of rainfall anomalies, the table shows the effects for four alternative measures including the log of total rainfall, the number of drought days, the standardized precipitation index, and the standardized precipitation and evaporation index. The measure is inverted so that an increase coincides with drier conditions. Panel (a) shows sensitivity to an exposure measure calculated based on incoming shipments. Panel (b) shows interactions with a measure of exposure based on outgoing shipments. The sample period is 2000 to 2024. Fixed effects included in the regression are indicated below the table. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Revenues/Assets (t-1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Import Exposure				Export Exposure			
Ln Precip. (q,q+2)	0.7965**				0.9200***			
	(2.20)				(2.66)			
Ln Precip. (q,q+2) × > Median Volume	0.5418***							
	(2.84)							
Drought Days (q,q+2)		-0.0264**				-0.0254**		
		(-2.41)				(-2.25)		
Drought Days (q,q+2) × > Median Volume		-0.0098						
		(-1.46)						
SPI (q,q+2)			0.2742**				0.2563**	
			(2.56)				(2.53)	
SPI (q,q+2) × > Median Volume			0.1581***					
			(2.97)					
SPI (q,q+2)				0.2786**				0.2724***
				(2.59)				(2.71)
SPI (q,q+2) × > Median Volume				0.1619***				
				(3.04)				
Ln Precip. (q,q+2) × > Median Volume					0.2387			
					(1.10)			
Drought Days (q,q+2) × > Median Volume						-0.0031		
						(-0.38)		
SPI (q,q+2) × > Median Volume							0.1513**	
							(2.57)	
SPI (q,q+2) × > Median Volume								0.1428**
								(2.42)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87567	87567	87567	87567	43439	43439	43439	43439
Firms	1280	1280	1280	1280	569	569	569	569
R^2	.771	.771	.771	.771	.813	.813	.813	.813

Table A.5: **Robustness of the Effect to Different Measures of Operating Income**

Notes. This table shows OLS regressions on the effects of water scarcity in the Panama Canal on the performance of firms in the United States. Instead of standardizing, operating income is scaled by lagged assets. Rainfall anomalies are defined as monthly rainfall minus average rainfall over a WMO base period, scaled by average base period rainfall. The measure is inverted so that an increase coincides with drier conditions. Panel (a) shows sensitivity to an exposure measure calculated based on incoming shipments. Panel (b) shows interactions with a measure of exposure based on outgoing shipments. The sample period is 2000 to 2024. Fixed effects included in the regression are indicated below the table. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Operating Income/Assets (t-1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Import Exposure				Export Exposure			
Rainfall Anomaly (q,q+2)	-0.0014*	0.0042	-0.0021***	-0.0019**	0.0000	-0.0005	-0.0006	-0.0005
	(-1.97)	(1.19)	(-3.14)	(-2.61)	(0.01)	(-0.58)	(-0.86)	(-0.67)
Rainfall Anomaly (q,q+2) × % Volume	-0.0039**							
	(-2.58)							
Rainfall Anomaly (q,q+2) × >0 Volume		-0.0067*						
		(-1.91)						
Rainfall Anomaly (q,q+2) × > Mean Volume			-0.0009					
			(-1.63)					
Rainfall Anomaly (q,q+2) × > Median Volume				-0.0009*				
				(-1.96)				
Rainfall Anomaly (q,q+2) × % Volume					-0.0087***			
					(-3.64)			
Rainfall Anomaly (q,q+2) × >0 Volume						-0.0016*		
						(-1.90)		
Rainfall Anomaly (q,q+2) × > Mean Volume							-0.0031***	
							(-3.90)	
Rainfall Anomaly (q,q+2) × > Median Volume								-0.0020**
								(-2.38)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84135	84135	84135	84135	42381	42381	42381	42291
Firms	1284	1284	1284	1284	574	574	574	573
R^2	.643	.643	.643	.643	.624	.624	.624	.624

Table A.6: **Robustness of the Effect on Operating Income to Different Measures of Drought**

Notes. This table shows OLS regressions on the effects of water scarcity in the Panama Canal on the performance of firms in the United States. Operating income is scaled by lagged assets. Instead of rainfall anomalies, the table shows the effects for four alternative measures including the log of total rainfall, the number of drought days, the standardized precipitation index, and the standardized precipitation and evaporation index. The measure is inverted so that an increase coincides with drier conditions. Panel (a) shows sensitivity to an exposure measure calculated based on incoming shipments. Panel (b) shows interactions with a measure of exposure based on outgoing shipments. The sample period is 2000 to 2024. Fixed effects included in the regression are indicated below the table. Robust standard errors clustered at the year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Operating Income/Assets (t-1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Import Exposure				Export Exposure			
Ln Precip. (q,q+2)	0.7965**				0.9200***			
	(2.20)				(2.66)			
Ln Precip. (q,q+2) × > Median Volume	0.5418***							
	(2.84)							
Drought Days (q,q+2)		-0.0264**				-0.0254**		
		(-2.41)				(-2.25)		
Drought Days (q,q+2) × > Median Volume		-0.0098						
		(-1.46)						
SPI (q,q+2)			0.2742**				0.2563**	
			(2.56)				(2.53)	
SPI (q,q+2) × > Median Volume			0.1581***					
			(2.97)					
SPI (q,q+2)				0.2786**				0.2724***
				(2.59)				(2.71)
SPI (q,q+2) × > Median Volume				0.1619***				
				(3.04)				
Ln Precip. (q,q+2) × > Median Volume					0.2387			
					(1.10)			
Drought Days (q,q+2) × > Median Volume						-0.0031		
						(-0.38)		
SPI (q,q+2) × > Median Volume							0.1513**	
							(2.57)	
SPI (q,q+2) × > Median Volume								0.1428**
								(2.42)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87567	87567	87567	87567	43439	43439	43439	43439
Firms	1280	1280	1280	1280	569	569	569	569
R^2	.771	.771	.771	.771	.813	.813	.813	.813

Table A.7: **Effects of Drought-Induced Capacity Constraints on Surprises in Revenues**

Notes. This table shows OLS regressions on the effects of rainfall in the Lake Gatun watershed on surprises in firms' sales. Instead of using rainfall anomalies, water scarcity is measured as the natural logarithm of total precipitation, the Standardized Precipitation Index (SPI), or the Standardized Precipitation and Evaporation Index (SPEI). The sample period is 2000 to 2024. Included fixed effects are indicated in the table. Robust standard errors clustered at the firm and year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Log of Total Rainfall

	Mean Surprise					Median Surprise				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln Precipitation	0.6733***	0.6050***	0.6035***	0.6098***	0.6035***	0.6874***	0.6158***	0.6144***	0.6222***	0.6144***
	(3.38)	(3.17)	(3.30)	(3.26)	(3.30)	(3.59)	(3.38)	(3.52)	(3.47)	(3.52)
Ln Precipitation × % Volume		0.2653**					0.3208***			
		(2.52)					(2.99)			
Ln Precipitation × >0 Volume			0.1755**					0.2112**		
			(1.99)					(2.23)		
Ln Precipitation × > Mean Volume				0.1705**					0.2044**	
				(2.06)					(2.30)	
Ln Precipitation × > Median Volume					0.1755**					0.2112**
					(1.99)					(2.23)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76825	91437	91437	91437	91437	92695	91446	91446	91446	91446
Firms	1600	1992	1992	1992	1992	2016	1992	1992	1992	1992
R^2	.195	.199	.199	.199	.199	.199	.2	.2	.2	.2

(b) Standardized Precipitation Index (SPEI)

	Mean Surprise					Median Surprise				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stand. Precipitation Index (q,q+2)	0.2105***	0.1928***	0.1927***	0.1952***	0.1927***	0.2197***	0.1951***	0.1945***	0.1975***	0.1945***
	(3.75)	(3.56)	(3.71)	(3.66)	(3.71)	(4.10)	(3.74)	(3.89)	(3.85)	(3.89)
Stand. Precipitation Index (q,q+2) × % Volume		0.0757**					0.0990***			
		(2.19)					(2.88)			
Stand. Precipitation Index (q,q+2) × >0 Volume			0.0489*					0.0657**		
			(1.86)					(2.42)		
Stand. Precipitation Index (q,q+2) × > Mean Volume				0.0453*					0.0615**	
				(1.77)					(2.33)	
Stand. Precipitation Index (q,q+2) × > Median Volume					0.0489*					0.0657**
					(1.86)					(2.42)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76825	91437	91437	91437	91437	92695	91446	91446	91446	91446
Firms	1600	1992	1992	1992	1992	2016	1992	1992	1992	1992
R^2	.195	.2	.2	.2	.2	.199	.2	.2	.2	.2

(c) Standardized Precipitation and Evaporation Index (SPEI)

	Mean Surprise					Median Surprise				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stand. Precip. Evaporation Index (q,q+2)	0.2066***	0.1894***	0.1895***	0.1918***	0.1895***	0.2166***	0.1923***	0.1918***	0.1947***	0.1918***
	(3.67)	(3.50)	(3.65)	(3.61)	(3.65)	(4.02)	(3.69)	(3.85)	(3.80)	(3.85)
Stand. Precip. Evaporation Index (q,q+2) × % Volume		0.0759**					0.0979***			
		(2.22)					(2.87)			
Stand. Precip. Evaporation Index (q,q+2) × >0 Volume			0.0489*					0.0647**		
			(1.85)					(2.36)		
Stand. Precip. Evaporation Index (q,q+2) × > Mean Volume				0.0458*					0.0610**	
				(1.79)					(2.31)	
Stand. Precip. Evaporation Index (q,q+2) × > Median Volume					0.0489*					0.0647**
					(1.85)					(2.36)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76825	91437	91437	91437	91437	92695	91446	91446	91446	91446
Firms	1600	1992	1992	1992	1992	2016	1992	1992	1992	1992
R^2	.195	.2	.2	.2	.2	.199	.2	.2	.2	.2

Table A.8: **Effects of Drought-Induced Capacity Constraints on Surprises in Earnings Per Share**

Notes. This table shows OLS regressions on the effects of rainfall in the Lake Gatun watershed on surprises in the earnings per share. Instead of using rainfall anomalies, water scarcity is measured as the natural logarithm of total precipitation, the Standardized Precipitation Index (SPI), or the Standardized Precipitation and Evaporation Index (SPEI). The sample period is 2000 to 2024. Included fixed effects are indicated in the table. Robust standard errors clustered at the firm and year-quarter level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Log of Total Rainfall

	Mean Surprise					Median Surprise				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln Precipitation	0.8980*	1.2148**	1.1309**	1.0514**	1.1309**	1.3988***	1.5476***	1.4928***	1.4414**	1.4928***
	(1.75)	(2.28)	(2.19)	(2.03)	(2.19)	(2.74)	(2.70)	(2.63)	(2.53)	(2.63)
Ln Precipitation × % Volume		-0.7037					-0.7110			
		(-0.74)					(-0.76)			
Ln Precipitation × >0 Volume			-0.2236					-0.3098		
			(-0.38)					(-0.48)		
Ln Precipitation × > Mean Volume				-0.0017					-0.1787	
				(-0.00)					(-0.27)	
Ln Precipitation × > Median Volume					-0.2236					-0.3098
					(-0.38)					(-0.48)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77233	92259	92259	92259	92259	93604	92249	92249	92249	92249
Firms	1649	2061	2061	2061	2061	2086	2061	2061	2061	2061
R^2	.172	.176	.176	.176	.176	.18	.179	.179	.179	.179

(b) Standardized Precipitation Index (SPEI)

	Mean Surprise					Median Surprise				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stand. Precipitation Index (q,q+2)	0.2471*	0.3494**	0.3311**	0.3050**	0.3311**	0.3973***	0.4451***	0.4309***	0.4137***	0.4309***
	(1.77)	(2.35)	(2.29)	(2.10)	(2.29)	(2.76)	(2.86)	(2.81)	(2.67)	(2.81)
Stand. Precipitation Index (q,q+2) × % Volume		-0.1738					-0.2037			
		(-0.63)					(-0.73)			
Stand. Precipitation Index (q,q+2) × >0 Volume			-0.0617					-0.0931		
			(-0.35)					(-0.49)		
Stand. Precipitation Index (q,q+2) × > Mean Volume				0.0118					-0.0481	
				(0.06)					(-0.25)	
Stand. Precipitation Index (q,q+2) × > Median Volume					-0.0617					-0.0931
					(-0.35)					(-0.49)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77233	92259	92259	92259	92259	93604	92249	92249	92249	92249
Firms	1649	2061	2061	2061	2061	2086	2061	2061	2061	2061
R^2	.172	.176	.176	.176	.176	.18	.179	.179	.179	.179

(c) Standardized Precipitation and Evaporation Index (SPEI)

	Mean Surprise					Median Surprise				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stand. Precip. Evaporation Index (q,q+2)	0.2317	0.3393**	0.3181**	0.2923**	0.3181**	0.3839***	0.4316***	0.4158***	0.3990**	0.4158***
	(1.65)	(2.30)	(2.22)	(2.02)	(2.22)	(2.66)	(2.78)	(2.71)	(2.57)	(2.71)
Stand. Precip. Evaporation Index (q,q+2) × % Volume		-0.1908					-0.2112			
		(-0.70)					(-0.76)			
Stand. Precip. Evaporation Index (q,q+2) × >0 Volume			-0.0652					-0.0933		
			(-0.37)					(-0.49)		
Stand. Precip. Evaporation Index (q,q+2) × > Mean Volume				0.0073					-0.0499	
				(0.04)					(-0.26)	
Stand. Precip. Evaporation Index (q,q+2) × > Median Volume					-0.0652					-0.0933
					(-0.37)					(-0.49)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77233	92259	92259	92259	92259	93604	92249	92249	92249	92249
Firms	1649	2061	2061	2061	2061	2086	2061	2061	2061	2061
R^2	.172	.176	.176	.176	.176	.18	.179	.179	.179	.179