When Trade Dries Up: Infrastructure Constraints and Firm Performance*

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Abstract

This paper investigates how drought affects firms and supply chains by constraining capacity in critical trade infrastructure. Combining granular data on firms' maritime shipping and exogenous variation in the capacity of a major trade route caused by water scarcity, I analyze the effects of disruption on the performance of U.S. firms. A one-standard-deviation decrease in available water reduces revenues by 1–2% and operating income by 3–4% relative to the sample median for firms with above-mean import or export exposure. Inventories decrease and operating expenses increase with constraints, while the incidence of costs varies with firms' market power. Analyses of vessel movement and freight indexes indicate that the effects coincide with vessel reallocation and increases in transportation costs. Compared to disruptions at individual suppliers, the risks of drought-related choke points are opaque and affect many firms at once. In line with opacity, mentions of drought and supply chain pressure increase only marginally in earnings calls. Sophisticated investors respond to information on realized constraints in water supply by increasing shorting, but analysts do not fully anticipate the effects, and earnings surprises tend to become more negative. Since many economies rely on waterways increasingly constrained by drought, the findings highlight how local physical climate shocks can spread through supply-chain infrastructure, generating non-local losses that can be challenging to observe.

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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. Significant attention has been paid to how idiosyncratic shocks to suppliers can cause aggregate fluctuations [Acemoglu et al., 2012, Baqaee and Farhi, 2019, Barrot and Sauvagnat, 2016, Carvalho et al., 2021] and how supply chains adjust to extreme weather [Balboni et al., 2026, Barrot and Sauvagnat, 2016, Pankratz and Schiller, 2024]. A less examined source of climate risk could lie in firms' logistics and supply-chain infrastructure. If key trade routes become less reliable, firms could face rising costs and increased financial uncertainty.

Climate-induced infrastructure constraints are not just hypothetical. Low-water episodes have increasingly disrupted shipping along the Yangtze [European Space Agency, 2022], Rhine [CNBC, 2023], Mississippi River [NASA Earth Observatory, 2023], and Panama Canal [U.S. Energy Information Administration, 2023]. News articles report reduced cargo capacity through draft restrictions, congestion, rerouting, and raised transportation costs [Associated Press, 2022a,b, Hirtzer, 2023, Reuters, 2026]. With large shares of companies relying on the same routes, transportation bottlenecks could have far-reaching financial implications for firms and investors. However, systematic evidence is limited.[1]

This paper examines how capacity constraints affect firms' inventories and financial performance, and studies the awareness of these risks across executives and different types of participants in financial markets. I focus on a major trade route as a source of vulnerability that is comparatively understudied relative to firm- or supplier-specific shocks. Using granular data on local drought conditions, supply-chain relationships, shipping routes, vessels, and firms' financial performance, I find that localized water scarcity abroad reduces inventory buffers of firms across the U.S. and causes economically significant losses of operating income. These losses are likely opaque while affecting many firms at once: Earnings calls discuss drought and supply chain pressures at slightly increased frequencies, and interest in shorting particularly exposed firms increases marginally. Yet, revenue and earnings surprises become more negative around drought-induced bottlenecks, even when information on drought conditions has been publicly available.

[1] Estimates of the costs of transportation bottlenecks for firms are scarce. For instance, Tran et al. [2025] estimate the direct costs of the 2021 Suez blockage including inventory-carrying costs but without firms' other financial losses, and Jung et al. [2025] carefully document the magnitude of shipping delays caused by drought but not the financial effect on firms.

In addition to concerns about extreme weather, recent geopolitical tensions emphasize the importance of control over trade routes, and the literature on climate and conflict demonstrates that conflict can arise when resources or capacity become scarce [Burke et al., 2015]. To study the nature and magnitude of firms' financial losses related to route disruption, the Panama Canal provides an ideal empirical setting because of its economic significance, and as its operations are directly affected by rainfall in a distinct location. In addition, the setting provides a unique opportunity to study firm risk arising from logistics. Detailed customs records including ports and vessels allow me to track the movement of goods. In contrast, many recent headlines on drought and shipping affect inland waters, where firm exposures are unobservable, and other types of transportation by truck and rail are even more challenging to trace.

The canal operates a lock system that lifts and lowers vessels between the Atlantic and Pacific using freshwater from Gatun Lake. Each transit consumes around 200,000 to 300,000 cubic meters of water, which is discharged through the locks and cannot be recaptured. As a result, rainfall shortfalls limit the number of transits. Since December 1999, the canal has been operated by the Panama Canal Authority (PCA), which sets tolls and allocates transit slots through a combination of reservations and market-based mechanisms. During times of drought, the PCA can use sealed-bid auctions for priority passage rights. Moreover, the PCA manages capacity by restricting transits and imposing operational constraints. For instance, draft limits reduce the maximum allowable vessel depth and force carriers to lighten loads or adjust routing and schedules. These measures raise effective shipping costs both directly and indirectly. Direct costs from higher tolls and auction premia to reduce wait times have reportedly reached several million dollars for a single slot [Bloomberg, 2023]. Indirect losses can result from delays, rerouting, and inventory disruptions. The incidence of costs incurred between importers and exporters, but also between importers or exporters and carriers is not straightforward. Under long-term fixed-rate contracts, shippers pay scheduled tolls but do not cover the costs of auction slots. This arrangement can create agency conflict as the party paying auction premia may not benefit from avoiding delays in downstream distribution or production. By contrast, under contracts with explicit auction or congestion clauses, incentives are more closely aligned.

For the analyses, I derive two measures of firms' reliance on trade routes from customs records from S&P Panjiva. Using information on ports of origin and destination, I determine the most

efficient shipping route using the Python package SEAROUTE.PY [Halili, 2022]. Using vessel names, I determine vessel presence in Panama with hourly Automatic Identification System (AIS) records of vessel locations collected by Global Fishing Watch [Global Fishing Watch, 2026]. I aggregate both types of indicators of route usage at the firm level.

I download firm financial data from Compustat, earnings call transcripts from Capital IQ, short interest from Factset, and revenue and earnings announcements and surprises from IBES. I merge the records with granular information on precipitation over the watershed of the Panama Canal from ERA5 by the European Centre for Medium-Range Weather Forecasts (ECMWF) [Hersbach et al., 2020] and CHIRPS provided by UC Santa Barbara [Funk et al., 2015]. In addition to rainfall anomalies, I calculate a series of alternative measures of drought conditions for robustness tests including total rainfall, 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 such as 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 evaporation (SPEI).

Before analyzing the effects of drought-driven constraints on firms, I document stylized facts on firms' exposure to the Panama Canal. More than 75% of firms show non-zero import exposures to the canal, with an average exposure of 17% and a median of 8% of value shipped through the canal by firm-quarter. Among exporters, the mean (median) is around 12% (1%). Average exposures of firms are similar in different industries and across the U.S. In addition to their direct reliance, firms face indirect exposures through their partners, competitors, domestic suppliers and customers with an average of 20% with positive exposures. Yet, the canal is mentioned in less than 0.2% of earnings calls, at an average rate of 0.001 times per 1,000 words.

Using exogenous variation in capacity constraints from rainfall as well as cross-sectional heterogeneity in firm exposure, I document three key results.First, drought conditions at the Panama Canal materially affect firms' operations and financial performance. Revenues decline for firms with above-mean or above-75th-percentile reliance on the canal. This effect is robust across alternative measures of firms' dependence on the canal as well as a range of proxies of drought conditions. Operating income deteriorates by considerably more than revenues. For firms with above-mean exposure, a one-standard-deviation increase in accumulated water scarcity lowers revenues by 0.26,

0.56, and 0.44 percentage points of lagged assets for import-only, export-only, and two-sided firms, or 1.0%, 2.2%, and 1.7% of the median, and operating income by 0.13, 0.10, and 0.12 percentage points, or 4.1%, 3.3%, and 3.8% of the median. The effect on the bottom line is not confined to the most exposed firms.

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 is heterogeneous, not concentrated in directly exposed firms, and aligns with market power considerations. Firms operating in more competitive industries exhibit stronger expense pass-through, while 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 or shift costs within the supply chain, and illustrates a direct channel through which the financial effects propagate between firms.

The documented patterns on firm performance and costs fit with a conceptual 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, providing suggestive evidence that these physical constraints translate into higher transportation costs.

After describing the effects of drought-driven infrastructure constraints on firms, I examine whether investors anticipate drought-driven choke point risk by studying earnings calls, investors' interest in short-selling firms' stock, and analyst forecast errors. The three sets of tests are broadly in line with the idea that infrastructure risks are financially material but opaque: Neither executives nor analysts discuss the canal or drought concerns related to shipping when water scarcity increases over time, or when their firms are more exposed. However, they appear to discuss the disruptions produced more when constraints become more binding, for instance related to supply chain pressures or concerns related to inventories. Short sellers, in contrast, do seem to act on exposure. I find significant increases in Markit short scores or short interest as a percentage of float. Yet, in economic terms, the magnitudes are modest. In line with limited questioning by

analysts, earnings forecasts tend to not completely anticipate the consequences of canal exposure. This result holds even when water scarcity was realized and information is publicly available.

In sum, risk stemming from the logistics layer in supply chains appears large enough to move earnings, but obscure enough to not be fully registered by professionals tasked with it. This finding connects to the literature on climate finance, the economics of production networks, and finance and infrastructure. First, related works in climate finance 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, Cuculiza et al., 2026], financial markets [Acharya et al., 2022, Bansal et al., 2016, Sautner et al., 2023, Schlenker and Taylor, 2021], and supply chains [Boehm et al., 2019, Custodio et al., 2022, Pankratz and Schiller, 2024]. The results in this paper align with these studies in indicating that firm performance is sensitive to climate-related hazards, and extend them by highlighting that climate risk can threaten firms through strategic transportation infrastructure elsewhere, which is even harder to observe than the already complex geographic footprints of firm locations. One of the most closely related papers might be Hong et al. [2019], who find that drought trends affect the profit growth of agricultural firms and produce predictable returns as a possible sign of under-reaction of the market to climate risk. This paper connects to this work by studying shipping as a different mechanism through which non-localized drought can generate sizeable losses for large shares of firms across the economy. Drought-driven shipping bottlenecks exist in many regions of the world and cannot be directly managed by firms. In addition to Hong et al. [2019], Kruttli et al. [2025] show that options markets underestimate the uncertainty firms face after hurricanes strike their establishments, even though landfall data are public in real time. The results presented here connect to these findings, and indicate that climate risk from transportation might not be particularly salient to investors.

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, Liu et al., 2025]. 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 [Carvalho et al., 2021, Cohen and Frazzini, 2008, Gabaix, 2011, Herskovic, 2018] due to correlations across firms when economies rely on a few prominent shipping routes. Contemporaneous studies have studied this possibility [Bai et al., 2026, Veetil and Vemmarath, 2026]. However, these simultaneous works do not document the financial effects on firms and financial markets, and do not highlight the specific risks related to climate change.

Third, a related literature in economics has studied the welfare gains of infrastructure investments [Brancaccio et al., 2020, Donaldson and Hornbeck, 2016, Heiland et al., 2025] and quantifies the economic value of shipping time and delays [Carreras-Valle, ming, Hummels and Schaur, 2013, Komaromi et al., 2022]. Moreover, the literature in finance examines 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. [2026] 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 documents the financial effects of infrastructure constraints on firms and investors, and documents climate risk affecting a large share of private and publicly listed firms in the U.S.

2 Data

I derive data on firms' reliance on maritime trade routes and combine it with records of firms' financial and accounting performance, transcripts of earnings calls, information on interest in shorting firms' stock, analyst earnings surprises, and measures of drought conditions at the Panama Canal. The core components of the data are described here and summarized in Table 1.

[Insert Table 1 here.]

Supply-Chain Relationships Data on supply chain relationships comes from customs records collected by S&P Panjiva. The data has been increasingly used in academic research [Ayyagari et al., 2024, Ganapati et al., 2024, Liu et al., 2025] and is described in detail by Flaaen et al. [2023].

Coverage begins in 2007 for imports, and late 2009 for exports. 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' identities by the U.S. Customs and Border Protection. Redaction requests are fulfilled for two years before requiring renewal. Schafhäutle and Sran [2025] study redaction patterns and find that about 16% of shipment records from 2013 through 2023 have redacted identities. Therefore, I observe a subset of firms relying on maritime shipping. Yet, it is impossible for firms to redact records selectively for specific trade routes. In the data, redacted identities are either empty or filled with the names of the executing ocean transport intermediary (OTI), freight forwarders (FF), or non-vessel operating common carriers (NVOCC). To remove these observations, I obtain lists of OTIs, FFs, and NVOCCs [Federal Maritime Commission, a,b] and use embeddings to match their names with company names in Panjiva. I remove observations where the name similarity exceeds 90%. I also drop logistics companies and freight forwarders (SIC 4412, 4424, 4432, 4449, 4731).

The data includes the name and addresses of consignees and shippers, the ports of origin and destination, vessel names and identifiers, shipment dates, information on shipped products and quantities, and a company identifier that links firms to their associated companies in S&P Capital IQ. Vessel identifiers are missing for 20-40% of observations per year, and names are frequently misspelled. Therefore, I first build a name-to-International Maritime Organization number (IMO) crosswalk from complete records in Panjiva, U.S. Army Corps of Engineers entrance-and-clearance records, the Global Fishing Watch (GFW) vessel-identity registry, the EU Monitoring, Reporting and Verification emissions registry, ship categories on Wikimedia Commons, and the U.S. Coast Guard PSIX database. I then apply a multi-step matching process to recover identifiers beginning with confirmed exact name-IMO matches, matches on cleaned names, fuzzy matches with a maximum of two to four character edits, web-search of maritime registries, and a large language model typo-correction pass followed by web-search.

Shipment-Level Route Usage To measure firm exposure to the Panama Canal, I determine predicted and confirmed routing at the shipment level. For routing predictions, I geocode the locations of ports in the U.S. and abroad using the Google Maps API. Next, I calculate the most efficient shipping route between ports with the Python package SEAROUTE.PY [Halili, 2022].

For confirmed routing, I use information on vessel movements from AIS data collected by GFW.[2] I download daily vessel presence starting in 2012 for the Exclusive Economic Zone (EEZ) of Panama, which comprises an ocean area extending up to 200 nautical miles from a nation's coast. This area includes the Panama Canal as well as areas where vessels idle awaiting transit. Applying the same process as for vessels in Panjiva, I recover missing IMOs in GFW, and use vessel-level information from Refinitiv to remove vessel types that do not carry merchandise such as offshore vessels, tugs, fishing vessels, cruise liners, yachts, and ferries. I also remove vessels that do not fit the Panama Canal based on physical dimensions (length and beam) as well as vessels that spend most of the year in the Panama EEZ. Out of 98,908 unique vessel names, I am able to link 90,915 to a validated IMO. I flag shipments as transits if the vessels appear in the Panama EEZ within a window of 45 or 60 days before the U.S. arrival date (imports) or after the shipment date (exports).[3] I repeat the confirmed-presence procedure for ten additional maritime routes.[4] Among all routes, the Panama Canal is the most frequent confirmed transit for imports, and ranks third for exports (see Figure 1). Considering efficient routing in Figure A.1, the Panama Canal comes first for both imports and exports, indicating that the canal might be avoided more on outbound voyages.

Firm-Level Route Exposure As a proxy for firms' exposure, I calculate the share of the value shipped through the Panama Canal relative to total shipped value. I aggregate measures for imports and exports as well as the share of shipped weight and volume as alternatives for robustness tests. As an important stylized fact, Figure 2 shows how reliant U.S. firms are on the canal. Panels (a) and (b) highlight that less than 25% (35%) of firms have no import (export) exposure to the canal. Table 1 shows that firms ship 17.4% of the value of their imports and 12.0% of exports through the canal. In terms of mean exposures, heterogeneity across industries is limited in Figure 3 and not particularly concentrated in geographic terms (see Figure 4).[5] Firms across the U.S. rely on

[2]Historic AIS data is not publicly available. GFW is an international non-profit focused on ocean sustainability and transparency, and has collected real-time AIS data since 2012 for all vessel types.

[3]The lag between transit and arrival is this long for three reasons: The window includes queueing, and during drought stretches, anecdotes report two weeks or more. Further, reaching either the East, Gulf Coast, or West Coast ports takes one to three weeks. Lastly, container ships typically call at several ports, so that transit and the particular port call can be separated by several weeks.

[4]For the Suez Canal, Cape of Good Hope route, Strait of Malacca, Strait of Gibraltar, Strait of Hormuz, Bosporus, Strait of Magellan, Bab-el-Mandeb, Sunda Strait, and the Drake Passage, I draw or download boundaries from public sources such as the Marine Regions EEZ and IHO layers, Natural Earth marine polygons, and OpenStreetMaps. I verify each polygon visually on a world map and against known coordinates inside the passage.

[5]Figure A.2 shows exposures aggregated by headquarters.

the canal, both inland and along the coasts.

A challenge for empirical analyses is that the observed shares are a noisy estimate of a firm's true exposure: sub-periods can be redacted and some firms do not ship very often. Therefore, sampling variance falls with the number of shipment records available per firm, and firms with few records frequently show extremes such as 0% or 100%. With the exposure share as an independent variable, this measurement error attenuates the estimated coefficients toward zero. One possible solution is to limit the sample to firms that import and export frequently at the cost of external validity. As an alternative, I keep the sample complete and use an empirical Bayes estimator [Walters, 2024], which shrinks firms' exposure share toward the cross-firm average. To construct it, I assume that the true exposure shares across firms follow a beta-binomial distribution, whose parameters can be estimated from the cross-section of firms. I then use a weighted average of firms' raw share and the cross-firm mean to calculate its posterior mean or adjusted exposure. The weight on the raw share increases with the firm's number of records, so that firms with ample data retain shares close to their raw values, while sparsely observed firms are pulled toward the mean.

Further, the exposure measure pools each firm's shipments across all years available in Panjiva. In most tests, I assign the resulting share to every period in the sample, including years outside Panjiva's coverage. This choice requires the assumption that firms have a structural reliance on the Panama Canal, which changes slowly relative to the variation in drought. With this choice, the measure is not meant as a precise record of canal usage but rather as an indication of where a firm stands in the cross-section of canal dependence. This pooling decision has evident costs: Firms may change their exposure and move within the distribution over time, and because shipments from later years enter the average, the measure assigned to early periods partly reflects later behavior. Both features add measurement error, which attenuates estimates and makes them conservative. There are two natural but less attractive alternatives. First, a time-varying measure solves issues related to look-ahead bias, but greatly thins the sample. Even when lagged, it is also endogenous: past canal usage cannot drive rainfall anomalies, but it relates to later realizations of firm-level financial outcomes. As a second alternative, fixing exposure at the start of the sample avoids endogeneity and look-ahead bias but also has downsides: It shrinks the sample and lowers power, and it excludes firms that have redacted or no early shipment records. It also grows increasingly outdated in the later years of the analysis. On balance, I use the pooled time-invariant share as

the preferred specification, and show results on the thinner samples for robustness.

Water Scarcity To measure constraints, I use weather information from ERA5, a re-analysis dataset provided by the European Centre for Medium-Range 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. For robustness tests, I download Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) from UC Santa Barbara. CHIRPS combines satellite and rain-gauge data at 0.05° resolution, offering an observation-based alternative to model-based re-analysis.

Figure 5 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 from 1981 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. Further, I compile drought indices, counts of exceptionally dry days, and measures of total rainfall and evaporation for robustness tests. Figure 6 shows rainfall and drought trends over time for two different measures. Since Panama has a distinct rainy and dry season, trends are plotted separately: Panels (a) and (b) show the rainfall anomaly, and Panels (c) and (d) show the number of dry days.

To understand how often constraints bind, I also obtain historical information on daily water levels in the canal [Panama Canal Authority, 2025]. Panel (a) of Figure 7 shows the time series of minimum water levels since the PCA began reporting. Minimum levels are visibly becoming more volatile around 2011. Panel (b) covers the time period with Panjiva coverage. The dotted line marks the completion of the Neopanamax locks in 2016, which allow wider and heavier ships to transit.[6] The colored lines indicate when the PCA must impose draft limitations, with the green line indicating triggers for the Neopanamax locks, and the blue line indicating binding constraints on the original Panamax locks. The conditions for draft limitations on the Neopanamax locks are triggered more frequently. Before minimum levels bind, the PCA can restrict transits preemptively.

[6] In principle, year fixed effects absorb changes in capacity. In addition, robustness tests include limitations of the sample to the period after the completion of the expansion.

Firm Characteristics and Accounting Performance Multiple analyses include firm financial and accounting data, which I obtain for 2000 to 2024 for all U.S. firms covered by Compustat. The most relevant variables include revenues, operating income and expenses, inventories, and assets. To remove outliers, I trim variables above (below) the 99th (1st) percentile. I match information on drought conditions taking firms' financial reporting schedules into account. I exclude financial firms and firms in maritime logistics. By design, the analyses are also limited to listed firms with financial data, capturing a subsample of larger and liquid firms. When capacity constraints occur, the PCA uses an auction system to determine passages. Smaller, financially constrained firms might not be able to bid for advance passage. Hence, firms not included in the analyses may be more strongly affected, and the estimates might represent a lower bound.

Table 1 includes descriptive statistics on firms' financial performance. The total asset values in this sample lie between 158 and 3,682 million U.S. dollars between the 25^{th} and the 75^{th} percentile, with a median of 854 million U.S. dollars in firms' total assets. The average sales turnover measured as revenues over lagged assets is 28%. Profitability in the covered time period is 0.7% on average (2.7% at the median) 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. Firms with non-zero exposures are significantly larger in revenues, assets, and cash holdings, are older, and record higher sales turnover and profitability (see Panel (a)). The differences are attenuated or at times reversed when comparing exposed firms above and below the sample mean in Panel (b).

3 Effects of Drought-Driven Infrastructure Constraints on Firms

3.1 Conceptual Framework

To motivate the empirical tests, I outline a brief conceptual framework in which firm production involves imports, and potentially, exports. Firm output is $Y = A\,F(K, L, M)$.

On the import side, canal constraints can cause delays and raise trade costs on raw materials, imported intermediates, finished goods for distribution, and capital goods. Therefore, the effects of drought-driven constraints enter through three terms: efficiency A (i.e., inefficiencies from delays, missing capital goods needed for production), input quantities q_M (delays or scarcity in input

markets), and input prices p_M (higher transport costs and price pressure in input markets).

For the effects of temporary constraints on q_M, related studies show that non-linear losses can occur under just-in-time inventories or if inputs are specific [Alessandria et al., 2023, Barrot and Sauvagnat, 2016, Sanz, 2026]. An important question concerns the incidence of costs such as increases in input prices p_M, which is likely determined by bargaining between firms, i.e., the importer and the exporter, or the importer and the shipping firm [Amiti et al., 2019, Grossman et al., 2024]. Taken together, import constraints likely reduce the inputs available to the firm directly, while higher input prices reduce the inputs the firm chooses to employ. Both lower output, affecting revenues and operating income. Higher input prices additionally compress margins at any given level of production.

Further, export exposure can exacerbate the effects on sales and margins even if production is unaffected. The profit function points to additional channels that become relevant, $\pi = p_Y Y - p_M M - wL - rK$. For one, canal constraints can act as an iceberg cost τ on shipped output [Hummels and Schaur, 2013], lowering the price p_Y received per exported unit due to freight rates, auction fees, and delay penalties. Moreover, drought constraints can affect the quantity q_Y firms can sell if there are delivery limits or lost demand for time-sensitive goods.

Beyond direct effects of constraints, network effects offer predictions for additional channels and mechanisms. The literature on production networks shows that whether firm-level effects aggregate depends on the size and position of the shock. To a first approximation, shock magnitudes scale with the sales weight of exposed sectors [Acemoglu et al., 2012, Hulten, 1978] and the size of exposed firms [Gabaix, 2011]. Beyond first order, the position of the affected sector matters as well, since limited substitutability amplifies the effect of negative shocks [Baqaee and Farhi, 2019]. These conditions tend to apply: Transportation is large in the aggregate with U.S. business logistics costs amounting to 8.8% of GDP in 2024, of which transportation accounts for roughly 5.5% of GDP.[7] Exposure is also concentrated among firms that are individually large: over 75% of firms in the Compustat sample are import-exposed (see Figure 2), and Figure A.3 shows similar exposures for firms with and without affiliations to listed firms. Further, canal exposure appears to be tilted towards larger firms (see Table A.1). Substitution is limited in the short run: Firms facing canal

[7] Gross expenditures rather than value added are a useful analogue since Domar weights are defined as gross sales relative to GDP.

constraints can re-route, ship cargo to the opposite coast and truck, or shift to domestic suppliers. These margins are possible but constrained, and quantities are unlikely to adjust one-for-one.

Additional mechanisms can amplify propagation: Demand linkages can transmit losses from drought-driven constraints and generate Keynesian-type spillovers [Guerrieri et al., 2022]. Emphasizing the potential relevance of this dimension, indirect exposures of firms resemble the direct exposures (see Figure A.5). Financial accelerators could further amplify real effects when tighter cash flows and balance sheets raise external-finance costs [Bernanke et al., 1999, Liu et al., 2025].

Following these considerations, I begin the empirical tests by validating if drought conditions impact shipping in terms of delays and quantities delivered. Next, I test whether there is a reduced form effect alongside matching the import and export-related predictions on profitability and revenues. Subsequently, I depart from the framework's focus on firm production, and examine how analysts and investors respond to supply-chain exposures through the transportation layer.

3.2 Shipping Patterns

Testing whether shipping patterns adjust when rainfall declines relies on three identifying assumptions: exogeneity, relevance, and exclusion. The exogeneity assumption is that, conditional on season, variation in precipitation over the Panama Canal watershed is beyond the control of the Panama Canal Authority, unrelated to the decisions of U.S. firms, and not driven by aggregate trade patterns. The relevance assumption holds because rainfall is a first-order determinant of canal capacity. Each transit through the lock system draws a substantial amount of freshwater from Gatun Lake, which is discharged into the ocean and replenished only by rainfall. The exclusion restriction requires that Panamanian rainfall affects U.S. firms only through the canal. The geographic distance between the canal and U.S. firms limits direct effects. The main threat to exclusion is large-scale climate variability. El Niño shapes weather in both Panama and the U.S., but its effects are heterogeneous across space and time: dry conditions in Panama do not map into uniform weather shocks across the U.S. [Downey et al., 2023]. Nevertheless, I orthogonalize canal rainfall with respect to El Niño indices and show that the results hold for robustness.

Building on these assumptions, I first validate if water scarcity impacts possible margins of adjustment in shipping such as vessel draft,[8] size, and type as outcomes. Since Panjiva is not

[8] More cargo pushes the ship lower into the water, which increases the so called draft. Draft is particularly relevant

aggregated at the voyage level and does not include information on draft, I collect data on vessel entrances and clearances from the U.S. Army Corps of Engineers for the years 2013 to 2022. I extract each voyage's entry port, exit port, origin, destination, date of journey, and vessel flag, and merge records with information on vessel size using Refinitiv. I drop any vessels designated as carrying passengers, tug boats, or fishing vessels. I then estimate the following equation:

$$\begin{aligned} y_i = \beta\, \textit{Rainfall Anomaly}_{t(i)} + \theta\, \textit{Rainfall Anomaly}_{t(i)} \times \textit{Panama Canal}_i + \mu_{p(i)\times m(i)} \\ +\gamma_{yr(i)} + \delta_{r(i)} + \eta_{\text{type}(i)} + \kappa_{\text{flag}(i)} + \varepsilon_i. \end{aligned} \tag{1}$$

where i indexes voyages, y_i is alternatively vessel size, voyage-specific vessel draft, or an indicator for Neopanamax fit. $\textit{Rainfall Anomaly}_{t(i)}$ is the rainfall anomaly over the Panama Canal watershed in the year-month $t(i)$ of the voyage i. $\textit{Panama Canal}_i$ is an indicator equal to 1 if the confirmed route of the voyage includes the Panama Canal. θ (β) captures the association between rainfall conditions and outcomes for canal voyages (others). Passage $\times$ calendar-month fixed effects $\mu_{p(i)\times m(i)}$, where $m(i) \in \{1, \ldots, 12\}$, control for seasonality. Because $\textit{Rainfall Anomaly}_{t(i)}$ varies across years within a calendar month, these fixed effects do not absorb treatment. Year fixed effects $\gamma_{yr(i)}$ absorb aggregate trends, and route fixed effects $\delta_{r(i)}$ control for time-invariant route features, vessel-type and flag fixed effects $\eta_{\text{type}(i)}$ and $\kappa_{\text{flag}(i)}$ account for vessel class and registry differences. With the treatment variation over time, standard errors are clustered by year-month.

[Insert Table 2 here.]

Table 2 reports estimates of equation 1 with voyage-specific vessel draft as the outcome. Columns 1 and 2 (3 and 4) cover voyages entering (clearing) U.S. ports. Columns 1 and 3 use the contemporaneous *Rainfall Anomaly*, while columns 2 and 4 use the cumulative anomaly over the current and preceding two months. The interaction of *Rainfall Anomaly* and *Panama Canal* is negative and statistically significant in three of four columns. The point estimate in column 1 implies that a one-standard-deviation change in rainfall is associated with a one-inch decrease in draft.[9] The immediate effect is more pronounced and attenuates over three months. The uninter-

as the PCA imposes draft restrictions when water is scarce. Triggering minimum water levels differ between the two types of locks. For instance, the PCA can cut allowable drafts in the larger Neopanamax locks while leaving the original Panamax chambers unchanged [Panama Canal Authority, 2023].

[9] As anecdotal evidence, Hapag-Lloyd expected a cargo deadweight reduction of around 5 to 6 percent on vessels conditional on service [Dupin, 2019].

acted *Rainfall Anomaly* coefficients are small and insignificant, indicating no comparable effect on non-Panama Canal voyages. Panel (b) repeats the exercise with the log of gross registered tonnage as the outcome. The interaction term is negative and significant in all four columns. Because gross registered tonnage is a fixed vessel characteristic rather than a loading decision, these estimates indicate a change in the composition of canal traffic. Panel (c) points in the same direction. Using an indicator for whether the transiting vessel is Neopanamax, the interaction is negative and significant at the 1% level in all four columns. Column 1 implies that a one-standard-deviation change in the rainfall anomaly shifts the probability that a canal-routed voyage is made by a Neopanamax vessel by 7.3 percentage points, or 17% relative to the sample mean of 0.431.[10]

[Insert Table 3 here.]

Supporting that rainfall captures frictions in shipping, the results show adjustments in draft and more substantial shifts in vessel composition, either due to re-routing or if shipping companies substitute toward smaller vessels. Both adjustments are costly to execute. Table 3 estimates whether rain affects voyage duration and uses the number of days between voyages as a proxy.[11] Estimations are separated for container vessels, tankers, and dry bulk carriers. Container vessels and tankers both show longer intervals between voyages on canal routes when water is scarce. For containers, a one-standard-deviation increase in water scarcity raises the interval by roughly one day relative to other routes, and the estimate is larger and more precise under the cumulative measure (columns 1 and 2). For tankers, the cumulative measure implies a differential of around four days (column 4). Panel (b) shows that vessels also spend slightly more time in ports.

Tables A.2 and A.3 replace *Rainfall Anomaly* with alternative measures of water scarcity: rainfall anomalies and dry-day counts from ERA5 and CHIRPS, log potential evaporation, log precipitation, the standardized SPI, SPEI, and SRI indices, the log water balance, and the minimum level of Lake Gatun. Higher values denote drier conditions for the first five measures and wetter conditions for the rest, so the expected sign flips from column 6 onward. Although the measures capture the same economic constraint, they share less variation than their common interpretation

[10] Because Neopanamax vessels are the largest class the canal accepts, substitution runs downward to Panamax vessels. Substituting the Neopanamax with a Panamax indicator yields the matching opposite effects.

[11] The interval between consecutive entries of the same vessel at the same U.S. port absorbs port time, intermediate calls, and idle time. Therefore, the measure is noisy and likely to attenuate θ toward zero.

might suggest. With signs aligned, their median pairwise correlation is 0.55 but 29 of the 66 pairs correlate below 0.5. Hence, finding consistent estimates despite the limited common variation limits the concern that the documented effects occur by chance.

For vessel draft and size, the interaction carries the expected sign in all fourteen columns and is significant in ten in both panels, with the same four exceptions: potential evaporation, log precipitation from either source, and the water balance. For shipping times, the three standardized indices are significant with the expected sign in both panels, as are the ERA5 anomaly for time between port entries and dry days and the lake level for time in port. The remaining coefficients are insignificant.

3.3 Inventory Buffers

Firms can cushion delayed deliveries by drawing on inventories. However, under just-in-time stocking or when inputs are specialized [Barrot and Sauvagnat, 2016, Sanz, 2026], delays that exhaust buffers can halt production and cause non-linear output declines. If changes in vessel size, draft, and voyage duration delay deliveries and reduce throughput, inventories could decline. Alternatively, precautionary stocking or a contraction in downstream demand would instead cause inventories to accumulate. To test which channel empirically dominates, I estimate firm-level regressions. Again, I rely on variation in precipitation over the watershed conditional on season. In addition, I use cross-sectional variation in firms' import and export exposure to the canal. Firm-level exposure is not randomly assigned, and three features affect its interpretation. First, firms select into canal use on characteristics related to outcomes. Table A.1 compares firms across the exposure distribution and shows that firms with zero exposure differ significantly from exposed firms, while differences are attenuated around the mean. Second, firms' responses to constraints are themselves endogenous: more sophisticated or more profitable firms might, e.g., negotiate different shipping terms. To limit confounding effects from endogenous responses, the main specifications use a fixed exposure measure using all available data.[12] Third, firms with similar measured exposure may ship inputs of differing economic importance, so identical measured exposure implies heterogeneous sensitivity to disruption. Taken together, tests of whether outcomes vary with import and export exposure are better described as cross-sectional comparisons than as a clean dose-response design.

[12] See the discussion in Section 2.

With these limitations in mind, I test whether drought-driven constraints deplete inventories, and whether the observed effects increase with firms' reliance on the canal:

$$\begin{aligned} y_{jq} = {} & \beta \, \textit{Rainfall Anomaly}_q^{(0:2)} \\ & + \theta^{\text{imp}} \left(\textit{Rainfall Anomaly}_q^{(0:2)} \times \textit{Import Exposure}_j \right) \\ & + \theta^{\text{exp}} \left(\textit{Rainfall Anomaly}_q^{(0:2)} \times \textit{Export Exposure}_j \right) \\ & + \mu_{j\,s(q)} + \gamma_{g(j)\,\tau(q)} + \delta_{h(j)\,\tau(q)} + \kappa^{\text{size}}_{p(j)\,\tau(q)} + \kappa^{\text{age}}_{a(j)\,\tau(q)} + \kappa^{\text{prof}}_{r(j)\,\tau(q)} + \varepsilon_{jq}. \end{aligned} \tag{2}$$

where y_{jq} measures inventories for firm j in fiscal quarter q. Related works on weather and firms show that effects can set in with delay of length that is unknown ex-ante [Addoum et al., 2023, Barrot and Sauvagnat, 2016, Pankratz and Schiller, 2024, Ponticelli et al., 2023]. $\textit{Rainfall Anomaly}_q^{(0:2)}$ is the rainfall anomaly accumulated over quarter q and the two preceding quarters, and I present alternative windows for robustness. $\textit{Import Exposure}_j$ and $\textit{Export Exposure}_j$ proxy firm j's reliance on the canal. Export exposure is set to zero for firms without observed exports.[13] In the threshold specifications, I sort firms into three mutually exclusive groups, above the cut-off in imports, exports, or both. Firms below the cut-off on both sides form the comparison group. The specification absorbs several sources of confounding variation. Firm-by-season fixed effects $\mu_{j\,s(q)}$ with $s(q)$ as the quarter of the fiscal year ensure that seasonality in firm operations is not attributed to the seasonality of rainfall in Panama. Industry-by-year fixed effects $\gamma_{g(j)\,\tau(q)}$ (three-digit NAICS) absorb industry trends, and region-by-year fixed effects $\delta_{h(j)\,\tau(q)}$ absorb geographically specific macroeconomic shocks though Figure 4 shows that exposure is not concentrated in particular regions. As Table A.1 documents differences in firm characteristics across the exposure distribution, size, age, and profitability tercile-by-year fixed effects $\kappa^{\text{size}}_{p(j)\,\tau(q)}$, $\kappa^{\text{age}}_{a(j)\,\tau(q)}$, and $\kappa^{\text{prof}}_{r(j)\,\tau(q)}$ absorb variation common to firms with similar 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. Alternative specifications are presented in robustness tests.

[Insert Table 4 here.]

[13] The confidentiality regime is independent for imports and exports. Under U.S. Customs and Border Protection [2024], a U.S. importer (exporter) can request to suppress identities. Because the two filings are distinct, a redacted import record does not imply a redacted export record. Not setting missing exports to zero would discard all non-exporters, and a large part of the sample. The chosen alternative introduces measurement error and attenuates estimates toward zero.

Table 4 reports estimates of equation 2 with inventories over lagged assets as the outcome in columns 1–4 and the quarterly change in inventories in columns 5–8. Within each group, the first column interacts *Rainfall Anomaly* with continuous exposure and the remaining columns replace it with indicators for exposure above the mean, the median, and the 75^{th} percentile. Exposed firms hold and accumulate less inventory when water is scarce. The indicators for exposure above the mean and the 75th percentile are significant for both outcomes, whereas continuous exposure and the median split are not significant in the level regressions (columns 1 and 3). The largest threshold estimate is the above-mean export-only interaction in column 6, at -0.1507: a one-standard-deviation increase in accumulated water scarcity is associated with a 1.5 million U.S. dollars lower quarterly change in inventories for these firms relative to firms below both cut-offs, or roughly 4.4% of the outcome's standard deviation. Comparable export-only estimates in columns 7 and 8 correspond to 3.8 to 4.1%, and the import-only estimates in columns 6 to 8 to 1.3 to 1.9% of a standard deviation. Including the uninteracted anomaly, which is negative and significant in columns 5, 6, and 8, the total decline in column 6 is 2.3 million U.S. dollars, or 6.5% of a standard deviation, for export-only firms, 1.2 million U.S. dollars (3.4%) for import-only firms, and 1.0 million U.S. dollars (3.0%) for firms above the mean on both sides, compared with 0.7 million U.S. dollars (2.1%) for firms below both cut-offs. At the median and the 75th percentile (columns 7 and 8), the total declines correspond to 5.5 to 6.0% of a standard deviation for export-only firms, 3.3 to 3.6% for import-only firms, and 3.6 and 2.2% for firms above the cut-off on both sides, the latter not statistically significant.

The appendix includes a series of five robustness tests. First, Table A.4 again replaces *Rainfall Anomaly* with alternative measures of water scarcity. The interaction for firms above the mean on the import side carries the expected sign in all twelve columns and is significant in eleven, the exception being the lake level in column 12. The export-only interaction is correctly signed in eleven columns and significant in ten of them. For firms above the mean on both sides, the interaction is likewise correctly signed throughout and significant in eleven columns, the exception being the ERA5 dry-day count in column 2. Second, I find that the results are also robust to when firms' exposure is measured. Instead of measuring exposure over the full sample, it is fixed based on shipments from 2010 to 2012 in Table A.5. Import exposure continues to predict lower inventory levels and export exposure lower inventory changes. Third, because shares computed from few

shipments are noisy, I shrink exposure shares using an empirical Bayes approach in the main tests. Table A.6 compares raw shares for firms with more than 50 shipments to the main estimates on all firms with shipment records, and the estimates are similar under both. However, standard errors narrow using the EB estimator. Fourth, because shipment value may overweight goods that are not constrained by draft limits, Table A.7 measures exposure by volume and weight. The export-only and two-sided interactions with the change in inventories remain negative and significant under all three measures. Finally, because global El Niño cycles could affect firms through channels other than the canal, Table A.8 removes the variation in the rainfall anomaly explained by the Oceanic Niño Index, and the interaction remains negative, significant, and statistically indistinguishable from the baseline.

3.4 Revenues and Operating Income

Following the conceptual framework, I first test whether shipping responds to water scarcity, and whether disruptions in logistics accumulate into measurable effects on inventories. Building on both, I next examine whether drought-driven constraints affect firm performance in reduced form. A null result would be informative in its own right: For instance, firms might hedge the price component of the shock financially through freight derivatives or contracts that fix rates in advance. In addition, firms could absorb pressure operationally, by holding buffer stocks, staggering shipments, or sourcing from suppliers on alternative routes. Where these margins are available and inexpensive, disruptions might not affect revenues or profitability. To test the extent to which adverse effects persist net of firms' hedging, I estimate equation 2, substituting revenues and operating income scaled by lagged assets for inventories.

[Insert Table 5 here.]

Columns 1 to 3 in Table 5 show the effects on revenues over lagged assets, and columns 4 to 6 and 7 to 9 repeat the tests for the year-over-year log change in revenues and for revenues standardized within firm. Within each outcome, the first column interacts *Rainfall Anomaly* with continuous canal exposure, and the remaining two replace it with indicators for exposure above the mean and the 75th percentile, separately for firms that import only, export only, or are exposed through both. Effects on revenues appear at higher levels of exposure. Continuous exposure (column 1) does not

yield a significant differential. With indicators, the export-only and joint interactions turn negative and significant, whereas the import-only interactions are small and insignificant. In column 2, a one-standard-deviation increase in accumulated water scarcity lowers revenues by 0.24 percentage points of lagged assets among firms below both cut-offs, as the uninteracted anomaly is negative and significant in all columns. For firms with above-mean export exposure only, the decline is 0.32 percentage points larger, for a total of 0.56 percentage points, and for firms above the mean on both sides it is 0.19 percentage points larger, for a total of 0.44 percentage points, a 2.2% and 1.7% decline relative to the sample median of 25.5. Revenue intensity is right-skewed, and the effects correspond to 1.8% and 1.4% at the mean.

Estimates at the 75th percentile (column 3) are of similar magnitude, with differentials of 0.32 and 0.21 percentage points and total declines of 0.57 and 0.45 percentage points, or 2.2% and 1.8% of the median, for export-only firms and firms above the cut-off on both sides. The alternative outcomes show the same pattern for exporting firms: the interaction is negative and significant for the log change in revenues (columns 4 to 6) and for standardized revenues (columns 8 and 9). For firms above the cut-off on both sides, the alternative outcomes do not show a significant decline, and the 75th-percentile estimate for standardized revenues is positive (column 9).

For robustness, Table A.9 re-estimates the revenue specification with above-mean import and export indicators, replacing *Rainfall Anomaly* with the eleven alternative measures of water scarcity in the Panama Canal watershed. Across the measures, the estimated magnitude is in a tight band. For a firm above the mean on both exposure margins, a one-standard-deviation increase in water scarcity implies a decline in revenues ranging from 1.2 to 3.9% of median revenue intensity across the twelve measures, with nine of twelve falling between 1.7 and 2.5%.

[Insert Table 6 here.]

Table 6 shows the effects on operating income over assets (columns 1 to 3), the year-over-year log change in operating income (columns 4 to 6) and operating income standardized within firm (columns 7 to 9) as alternative outcomes. The conceptual framework points toward simultaneous effects of drought-driven bottlenecks on revenues and operating income. The null hypothesis, however, could predict no effects on income despite decreases in revenues, i.e., if firms are able to adjust expenses in the short-run or insure against losses.

Yet, the results are stronger and more uniform than for revenues. Both exposure margins are negative and significant under continuous exposure (column 1), as is every import and export interaction in the threshold specifications. In column 2, a one-standard-deviation increase in accumulated water scarcity lowers operating income by 0.13, 0.10, and 0.12 percentage points of lagged assets for firms above the mean on the import side only, on the export side only, and on both sides, or 4.1%, 3.3%, and 3.8% relative to the sample median of 3.1. These totals include the uninteracted anomaly, which is small and insignificant at 0.02 percentage points, so that the differentials relative to firms below both cut-offs are 0.11, 0.08, and 0.10 percentage points. At the 75th percentile (column 3), the corresponding total effects are 5.0%, 3.4%, and 3.8% of the median. The alternative outcomes show similar declines for export-only firms, which are significant for the log change in operating income in columns 4 to 6 and for standardized operating income in columns 8 and 9. For import-only firms and firms above the cut-off on both sides, the alternative outcomes are mostly insignificant, and the 75th-percentile estimate for firms above the cut-off on both sides is positive for standardized operating income (column 9).

The contrast with the revenue estimates is interesting. Relative to their medians, revenues of firms above the mean on both sides fall by 1.7%, while operating income falls by 3.8%, more than twice as much. For import-only firms, operating income declines while revenues do not change significantly. Whereas margins cannot be cleanly isolated, this relation is consistent with what the conceptual framework implies. If higher freight costs and delay penalties raise costs, margins decrease by more than sales.

The operating income results are stable throughout a series of further tests. Table A.10 replaces *Rainfall Anomaly* with the eleven alternative measures of water scarcity. Twenty-two of the twenty-four interactions carry the expected sign and are significant. The exceptions are the import-side interactions with the two dry-day counts. Table A.11 compares using the raw shares of value shipped through the Panama Canal with the shrunk exposure used in the main tests. In levels, the import-only and export-only interactions are negative and significant under both, and the joint interaction is significant only for the raw share. For the alternative outcomes, the export-only interaction is significant under both. Measuring exposure by weight rather than value (Table A.12) documents significant declines for all three groups in levels. By volume, the import-only and joint interactions are significant and the export-only interaction is not. For the alternative

outcomes, only the weight-based export-only interaction is significant. Exposure measured on estimated routes over 2010 to 2012 (Table A.13) gives weaker estimates in levels, where only the above-mean import-only interaction is significant. It still shows significant declines for import-side exposure in standardized operating income and for joint exposure in the log change. Purging the anomaly of ENSO-related variation (Table A.14) moves the interaction from -0.014 to between -0.009 and -0.011, a difference that is not significant (p-values of 0.12 to 0.39). The import-only and export-only interactions remain significant under all six alternative clusterings of standard errors (Table A.15). When quarterly anomalies are estimated separately to understand the dynamics of the effect over time (Table A.16), the effects materialize with a delay of one to two quarters on $q-2$ and $q-1$, and for q with the exposure indicator. However, the effect becomes insignificant in $q-3$ and does not reverse. Also, a lead of a quarter $q+1$ does not show a significant effect. Finally, the interaction is stable when quarters in 2020, 2020–2021, 2008–2009, or the years defined as a recession by NBER are dropped. The coefficient is similar in significance and increases in size when only quarters after the expanded locks opened in 2016 are kept (Table A.17).

3.5 Heterogeneity in the Cross-Section

Tables A.18 to A.20 split the interaction of drought and canal exposure in the operating income specification by firm characteristics. Each variable is interacted as an above-median indicator or as a standardized variable. Across financial characteristics (Table A.18), the decline is concentrated among smaller and financially constrained firms. For firms above the median in total assets or market capitalization, the triple interaction offsets the baseline interaction almost completely. The standardized versions confirm that the effect weakens with size. Conversely, for firms with high SA, WW, or KZ index values and for firms that never pay dividends, the triple interaction is negative and significant, while the interaction for the remaining firms is small and insignificant. The standardized characteristics give the same result, except for the KZ index. This pattern is consistent with two channels in the conceptual framework. Larger firms likely have more bargaining power over carriers and suppliers and therefore bear a smaller share of higher trade costs, and constrained firms are less able to finance buffer stocks or expedited shipping, as a financial accelerator would predict. Among shipment characteristics (Table A.19), the decline is smaller for firms that ship goods of higher value per kilogram, whether measured over all shipments or over canal shipments only, and

for firms with an above-median share of shipments on Neopanamax vessels. Because freight charges scale with weight rather than value, a given increase in transport costs is a smaller share of the value of high-value goods. The decline does not vary significantly with the number of shipments or the Panamax share. Across industries and regions (Table A.20), the decline is concentrated in manufacturing, where imported intermediates affect production. It is absent for mining and utilities and shows no significant difference for wholesale or retail. Among headquarters regions, it is larger for firms in the South, whereas for firms in the Northeast the triple interaction more than offsets the baseline, with no significant difference for the Midwest, the West, or the West Coast.

3.6 Costs and Incidence

The results thus far indicate that earnings of U.S. firms are sensitive to the water supply of the Panama Canal. The conceptual framework predicts that the declines in operating income could in part be driven by effects of drought-driven constraints on costs. These costs arise from two sources: direct costs of transportation and indirect costs beyond the shipment itself.

Direct costs increase if freight rates rise and carriers pass on auction fees and congestion surcharges. Rerouting adds the cost of longer voyages or of shipping to the opposite coast and trucking. On the import side, these costs raise the effective price of imported inputs p_M, which compresses margins at any given level of output, lowers optimal input usage, and thereby output (see Section 3.1). On the export side, freight charges and delay penalties borne by the firm act as an iceberg cost τ on shipped output [Hummels and Schaur, 2013], raising expenses relative to revenues even when production is unaffected.

How much of these costs firms bear depends on who pays for shipping. Bargaining and contracts also decide who covers additional fees to obtain priority. Under long-term fixed-rate charters, firms are insulated from auctions and pay only the scheduled tolls. However, this insulation gives rise to an agency conflict. Carriers make bidding decisions while firms bear the cost of delays. Hence, carriers are unlikely to bid aggressively even when a faster passage is worth more to the firm than the auction fees. Under spot-linked or auction-clause contracts, incentives can be more closely aligned. Carriers bid for slots and pass surcharges straight through to the firm, or cap their maximum auction exposure with any excess absorbed by the receiving firm.[14]

[14]The stakes in that decision can be substantial. In November 2023, an operator paid $4 million for a single

In addition to direct costs, indirect costs come from multiple layers beyond the shipment. First, uncertain and longer transit times tie up goods in transit and require larger buffers, which raises inventory-holding and working-capital costs. Second, reduced canal throughput lowers the supply of goods. If buyers compete for available quantities and substitutes, input prices p_M rise even for firms who do not use the canal. Third, when inputs are unavailable, constraints on input quantities q_M force firms to switch to costlier alternatives. Fourth, delays and missing capital goods lower efficiency A. Because labor and capital adjust slowly, wL and rK are spread over less output, and average costs rise even if input prices are unchanged.

Transportation costs are the most immediate component of the cost increase, but not the only one. The following analyses first test whether transportation costs rise with water scarcity, and then whether firms' overall costs increase. Historical data on fees paid for canal passages are not publicly available, and route-level freight rates are costly to obtain. I therefore use aggregate series from FRED, the producer price index for deep sea freight transportation and the Cass Index of implied freight rates across all modes, including sea, air, and land to estimate the following OLS regressions:

$$y_t = \beta \, \textit{Rainfall Anomaly}_t + \mu_{m(t)} + \gamma_{yr(t)} + \varepsilon_t, \tag{3}$$

where t indexes year-months and y_t is alternatively the producer price index for deep sea freight transportation or the Cass Index of implied freight rates. $\textit{Rainfall Anomaly}_t$ is the rainfall anomaly over the Panama Canal watershed. Calendar-month fixed effects $\mu_{m(t)}$, where $m(t) \in \{1, \ldots, 12\}$, absorb seasonality in freight rates, and year fixed effects $\gamma_{yr(t)}$ absorb aggregate trends.[15]

[Insert Table 7 here.]

In Panel (a) of Table 7, the outcome is the producer price index for deep sea freight in columns 1 and 2 and the Cass Freight Index in columns 3 and 4. Deep sea freight prices rise with water scarcity. The contemporaneous coefficient is positive and significant in both specifications, and adding lags

Neopanamax slot, raising total transit costs to approximately $4.5 million. Despite the bid, the vessel faced a one-week wait before passage. For comparison, auction slots trade around $135,000 to $140,000 under normal conditions, and the peak represents roughly a thirtyfold premium [Bloomberg, 2023].

[15] Because $\textit{Rainfall Anomaly}_t$ varies across years within a calendar month, these fixed effects do not absorb the treatment.

leaves it unchanged. Responses appear concentrated in the month of the shock. For the Cass Index, which pools rates across modes and therefore dilutes any ocean-specific component, the effect appears with a one-month lag (column 4). Panel (b) repeats the exercise for truck tonnage and internal water transportation. However, neither responds at any lag. Because these modes share the same seasonal and macroeconomic environment as ocean freight but not the constraint, the absence of a response supports a canal-specific interpretation of the deep sea results despite the limited power and time series.[16]

To examine whether there are broader negative effects on operating expenses, I continue with the firm-level analyses. To test if bargaining matters, 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 five firms, and the market share per firm. Table 8 first tests whether firms' overall costs rise with water scarcity, using the log of operating expenses over revenues as the outcome. Panel (a) studies whether the increase is confined to firms that are themselves exposed to the canal. The uninteracted anomaly is positive and significant in all three columns: a one-standard-deviation increase in accumulated water scarcity raises the expense ratio by 0.3 to 0.4%. None of the interactions with canal exposure is significant, whether exposure enters continuously (column 1) or as indicators for firms above the mean (column 2) or the 75th percentile (column 3) on the import side only, the export side only, or both sides. The point estimates are small and of mixed sign, and none suggests a larger increase for exposed firms. This is consistent with the indirect costs discussed above: when reduced canal throughput raises prices in input markets, costs rise for exposed and unexposed firms. It also contrasts with operating income, where the decline is concentrated among exposed firms.

If costs rise across all firms in the economy, the question becomes who absorbs them. Panel (b) estimates the effect on the full sample and interacts the anomaly with three measures of market power. In column 1, the uninteracted estimate implies that a one-standard-deviation increase in accumulated scarcity raises the expense ratio by 0.5%, and the effect is significant at the 1% level

[16] For robustness, Table A.21 applies the alternative measures of drought to the freight-rate indicators of equation 3. For deep sea freight prices in Panel (a), the coefficient is correctly signed in eleven of twelve columns and significant in eight: the four anomaly and dry-day measures, potential evaporation, both log precipitation series, and the water balance. Panel (b) is weaker throughout as expected of an index that pools sea, air, and land rates. Ten of twelve coefficients carry the expected sign, but among these only SPI-1 (column 8) is significant. The endogenous minimum lake level is wrongly signed in both panels.

in every column. In columns 3 and 4, firms in more concentrated industries, and firms with larger shares of their own market, absorb less of the increase. In column 3, the effect declines linearly in industry concentration, from 0.7% where the five largest firms hold a negligible share to 0.5% where they hold half the market. Column 4 shows the same pattern in the firm's own market share, with the effect fully offset at a share of roughly 60%. The interaction with the industry HHI (column 2) has the same sign but is not significant. Consistent with evidence on tariffs [Amiti et al., 2019, Grossman et al., 2024], the cost increases arising from canal constraints therefore appear to not be borne uniformly but depend on firms' bargaining power.

For robustness, Table A.22 re-estimates the specification in column 3 of Panel (b) with the eleven alternative measures of water scarcity. The main effect has the expected sign in all twelve columns and is significant in nine. Exceptions are the dry-day counts from ERA5 and CHIRPS and the arguably endogenous minimum lake level. The interaction with the top-five market share is opposite in sign to the main effect in every column and significant in ten. In the nine columns where both terms are significant, the interaction offsets between 71 and 110% of the main effect for an industry in which the five largest firms hold the entire market. The gradient in market power therefore matches column 3 of Panel (b) and does not depend on how water scarcity is measured.

The cost results suggest that the effects of canal constraints spill over to firms that are not themselves exposed. Table A.23 tests this by estimating the effect of drought on standardized revenues and operating income separately for firms without exposure data, firms with zero exposure, and firms with positive exposure. Operating income declines significantly among firms with zero exposure in all three panels, while their revenues decline significantly only in Panel C. In line with the exposure gradients estimated above, the effects tend to be larger among exposed firms, but not uniformly so. The difference relative to zero-exposure firms is significant for both outcomes with full-period exposure (Panel A) and for revenues with exposure estimated and fixed between 2012 and 2014 (Panel B), but not with trailing three-year exposure (Panel C). Supporting the external validity of the estimates, the decline in operating income also holds for firms without exposure data, which could have shipment records redacted but are overall less likely to import or export directly. For these firms, operating income also declines significantly in all three panels, whereas revenues do not.

The spillover to firms without direct exposure could reflect the broad increase in costs doc-

umented in Table 8, or a combination of higher costs and other distortions transmitted through indirect links. Figure A.5 shows that firms' supply-chain partners, suppliers, customers, and competitors carry canal exposures similar to those of the firms themselves, so that firms with zero direct exposure can still be connected to the canal through the firms they trade or compete with. Across the three panels, which measure exposure over the full sample, over 2012 to 2014, and over the trailing three years, the pattern is broadly stable and does not depend on the horizon over which exposure is measured. Taken together, the declines in operating income among firms with and without measured exposure suggest that canal constraints affect a broad set of firms rather than only those routing shipments through the canal. Because the baseline specifications identify only differences between exposed and less exposed firms, this common component is absent from the cross-sectional estimates, which consequently understate the reach of the shock and point to effects that are systemic rather than confined to the exposed firms.

4 Awareness of Financial Market Participants

The results so far show that water scarcity shifts vessel composition on the canal toward smaller classes and lengthens intervals between voyages. These disruptions affect firm operations and exposed firms accumulate less or draw down more inventory. Revenues and operating income both decline in exposure. Freight prices rise and cost margins increase, likely economy-wide. An evident open question might be how these risks differ from those studied in the production network literature. Two possibilities stand out: First, the effects could be common from the start rather than idiosyncratic. A disruption to a trade route hits a large set of supply-chain links that is evenly distributed across industries and firms at once. It does not originate at a firm or a sector as in the canonical case [Acemoglu et al., 2012, Gabaix, 2011]. Second, exposure may be particularly opaque and hard to observe outside the firm. Firms disclose a subset of their portfolio of suppliers, but no framework requires them to report dependence on a particular transport mode or passage. The setting of the Panama Canal is an exception: customs reveal route usage because records include ports and vessel names. Hence, the setting is uniquely suited to tracking logistics. In the context of climate change and drought, inland waterways are often most severely affected while firms' risk exposures are largely unknown and challenging to recover. Beyond the context of climate risk,

possible infrastructure risks from bottlenecks in rail and road networks are similarly obscure.

In the next sections, I examine whether risks related to drought-driven constraints are indeed opaque to firms and financial market participants. My analyses proceed in three steps. First, I examine whether firms and analysts discuss drought-driven infrastructure risks in earnings calls. Second, I analyze short interest to better understand whether sophisticated investors respond to materializing risk. Third, I test if earnings surprises are affected by realized drought. If the risk is not recognized in advance, water scarcity should predict negative surprises among exposed firms.

4.1 Earnings Calls

To better understand if firms are aware of their own exposure to drought-driven infrastructure constraints, I use the transcripts of quarterly earnings conference calls from the Capital IQ Transcripts database. For every earnings call from 2008 to 2024, I obtain the full component texts from the most recent version. I keep records of firms that match to exactly one gvkey, and merge the sample with the data on import and export exposure as well as drought intensity over time. I measure topic mentions related to (1) the Panama Canal, (2) drought and shipping, supply chain pressures, and concerns related to inventories using custom dictionaries.[17] I then sum component-level counts at three levels of aggregation: the entire call, the call by component type (e.g., presentations vs. Q&A), and the call by speaker type (executives vs. analysts). At each level and for each theme, I construct three measures: the raw count, an indicator equal to one if the theme is mentioned at all, and mentions per thousand words. The median call runs 6,527 words.

[Insert Table 9 here.]

Related to the question of whether firms are aware of their risk exposures, it is interesting to see that the canal itself is barely mentioned. I.e., despite over 75% of firms with non-zero exposures, the canal is mentioned in less than 0.2% of calls and Panama appears 0.001 times per 1,000 words, on average. This contrasts with direct weather shocks: after hurricanes make landfall near firms'

[17] I measure mentions with four phrase dictionaries: drought and shipping (drought, water level, Gatun, low water, dry conditions, rainfall, El Niño, draft restriction, water shortage, transit restriction), Panama (Panama Canal, canal transit, canal restriction, canal congestion, Panama passage), supply chain (supply chain, disruption, bottleneck, congestion, shipping and freight delay, logistics, reroute, divert, diversion, transit time, ocean freight, freight rate, lead time), and inventory (inventor-, destock, restock, inventory build, safety stock, stockpil-, working capital). I lowercase each transcript component and count occurrences. In the next iteration, I will cleanly separate mentions of the Panama Canal, and discussions of drought separate of and in the context of shipping.

establishments, discussions of hurricane impacts on earnings calls jump and remain elevated for several months [Kruttli et al., 2025].

Next, I test if occurrences increase in times of scarcity, and whether awareness of the topic increases with firms' exposure in the cross-section. Table 9 reports the effect on mentions of the four topics. Panel (a) covers executives to examine if firms proactively discuss the topic. Panel (b) separates mentions by analysts. Odd columns use the contemporaneous anomaly and even columns add the two preceding months. When it comes to executives, no coefficient in the Panama Canal columns is significant (columns 1–2). For drought, the only significant coefficient is economically small and marginally significant (column 3). Exposed firms do not appear to discuss the passage their goods depend on, even when water is scarce. In contrast, materializing risk surfaces a bit more in general language on supply chains (columns 5–6). Executives at import-exposed firms talk more about supply chains when water is scarce. At the mean import exposure, a one-standard-deviation anomaly raises supply chain mentions by 1.3% of their average frequency (column 5). Despite the pronounced estimated effect of infrastructure constraints on inventories, specific discussions related to the topic do not seem to increase with adverse exposure over time or in the cross-section.

Compared to firms' executives, analysts' speech appears slightly more responsive to drought exposure. Explicit questions related to the canal are similarly rare, and the only significant exposure interactions conflict in sign (column 2). However, questions related to drought and transportation infrastructure increase for firms with more import exposure, and mentions of supply chains and inventories also rise with water scarcity for firms generally, by 3 to 5% of their means (columns 5–6). Yet, this response does not vary with exposure. In unreported tests using probit regressions with an indicator of any mention of any of the topics as the dependent variable, the estimated effects are consistently indistinguishable from zero. Overall, the observed patterns are weak, consistent with the impression that drought-driven infrastructure risk is challenging to observe.

4.2 Interest in Shorting Firms' Stock

If firms' and analysts' awareness is limited, I next test whether investors recognize the risk stemming from drought-driven bottlenecks. Short interest provides a revealed-preference test of whether a subset of sophisticated market participants acquires information. On the one hand, analyst and executive speech lets firm exposures seem opaque. On the other hand, water levels at

the canal are published daily by the Panama Canal Authority. Hence, their economic relevance itself is known and data becomes public in real time. Further, short sellers are among the best-informed traders and are documented to build positions ahead of negative fundamental news [Boehmer et al., 2008, Dechow et al., 2001, Engelberg et al., 2012]. Hedge funds in particular are also known to use satellite imagery for trades [Katona et al., 2025].

I measure short-selling activity using two monthly security-level series obtained from FactSet from 2000 to 2024. The first is Markit's short score, an integer between 0 and 5 that increases in shorting activity and is populated from 2006 onward. The second variable is short interest as a percentage of the free float from FactSet's Ownership database. The two measures show a correlation of 0.75. Mean short interest rises monotonically from 1.3% of float for securities scored zero to 25.5% for securities scored five. I set implausible float values above 100% to missing, and reshape both series to the firm-month level. I drop firm-months for which a gvkey cannot be uniquely identified. I then merge the records with firms' Panama route exposure and the data on water scarcity over time.

[Insert Table 10 here.]

The tests again follow equation 2. Columns 1 to 3 assign canal routing using estimated routes to compare to columns 4 to 6 using confirmed routes. Across tests, short interest rises with import exposure when water is scarce. The import interaction is positive and significant in all six columns and consistent across both routing definitions. Export exposure enters negatively but only significantly in columns 4 and 6. This pattern suggests that a subset of investors does engage in costly and specific information collection. However, the economic magnitudes of responses are small, potentially consistent with the idea that the effect is driven by a niche group of investors. A one-standard-deviation anomaly raises the short score of a firm at mean import exposure by less than 1%. The threshold specifications imply 1.0 to 1.6%.

For robustness, Table A.24 holds the baseline confirmed-route, above-median exposure specification fixed and varies the water-scarcity measure across the same twelve columns as Table A.3, so that column 1 reproduces column 5 of Table 10. The interaction with import exposure is correctly signed in all twelve columns of both panels and significant in ten, at the 1% level throughout Panel (a) and in eight of the ten significant columns of Panel (b). The exceptions are the same in

both panels: ERA5 dry days (column 2), a count that discards the intensity of the shortfall, and the log water balance (column 11), which is unnormalized and estimated on roughly 28% fewer observations.

4.3 Analyst Forecast Errors

The previous sections indicate that exposed firms and their analysts do not name the canal, and that short sellers do position on the same exposure. However, the magnitude of their activity is modest. The tests aim to measure attention, but do not speak to whether exposure could be priced into expectations. To get closer to this question, I next examine analyst forecasts. If analysts underestimate risk related to supply-chain infrastructure or climate, surprises could become more negative when drought conditions intensify. Related evidence suggests that investors underreact to public information on extreme weather: options markets underestimate the uncertainty hurricanes create for firms, and the bias only diminishes after a highly salient event [Hong et al., 2019, Kruttli et al., 2025, Wilson, 2019]. Yet, assuming efficient markets, the null hypothesis is that analysts should update forecasts based on publicly observable information about water scarcity and firms' reliance on the canal. To address these hypotheses, I collect data from IBES on analyst forecasts. I compare analysts' expectations for revenues, pre-tax income, and earnings per share to their realizations. I scale earnings surprises by assets and trim all variables above (below) the 99^{th} (1^{st}) percentile. Further, I construct a setting in which information is publicly available and could be incorporated into forecasts. Figure A.6 illustrates the setup. During any given financial quarter, the Panama Canal is subject to a realized level of rainfall anomalies. Firm performance is subsequently revealed on the announcement date, which occurs after the close of the fiscal quarter with a reporting lag. I limit the sample to summaries of forecasts after the close of the financial quarter. Enforcing this gap between realized drought exposure and the revelation of earnings 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.

[Insert Table 11 here.]

I align the tests with previous analyses, and follow equation 2, with the sales, pre-tax income, and earnings per share surprise scaled by assets replacing the firm-level outcomes. Table 11 shows

the results. Columns 1 to 3 use surprises in sales, columns 4 to 6 in pre-tax income, and columns 7 to 9 in earnings per share. Pre-tax income surprises become more negative, with the continuous measure significant at the 5% level. Sales surprises load primarily on both the exposure measures and the uninteracted anomaly, consistent with the tests on how drought-driven infrastructure constraints affect revenues in the baseline. These effects could be consistent with a component common to firms in the sample rather than one specific to exposure. However, pre-tax income and earnings per share surprises are significant for a subset of tests.

5 Conclusion

This study analyzes how capacity constraints at a major trade route shape U.S. firm performance and financial responses. Using quasi-exogenous variation in water scarcity, I document that rainfall anomalies affect shipping patterns and contribute to bottlenecks in supply chains with adverse financial effects. Inventories are drawn down and both revenues and operating income decline. Aggregate freight rates as well as operational expenses increase, although less so when markets are more concentrated and when firms have more market power. Three sets of tests suggest that the effects are financially material yet opaque: Executives and analysts rarely mention the canal but appear to discuss the disruptions it produces. Short sellers act on exposure, though the magnitudes are modest. Forecasts miss in the direction canal exposure predicts. In sum, the risk seems large enough to move earnings, and obscure enough that it is not anticipated by professionals.

The literature in economics and finance studies how idiosyncratic shocks propagate through production networks and under which conditions idiosyncratic disturbances aggregate. Yet, much of this work focuses on shocks to firms and does not consider infrastructure-based vulnerabilities such as canals, straits, ports, inland waterways, rail and road networks, bridges, and border crossings. The stylized facts in this paper highlight why this omission matters: the shared use of specific infrastructure assets can be highly concentrated. Moreover, 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, Krueger et al., 2020], while this paper connects to other works documenting possible limits to attention or heterogeneous beliefs.

Whether the documented constraints become more frequent remains an open question. Using 27 climate models, Muñoz et al. [2025] project that disruptive low-water conditions in Gatun Lake become increasingly common under moderate and high emissions scenarios but not under low-emissions pathways. Other assessments argue that El Niño and rising water demand rather than a detectable climate trend explain the shortfall [World Weather Attribution, 2024], and that the region's position within the Intertropical Convergence Zone makes precipitation projections uncertain with median projections close to historical norms [Mitchell and Menzies Pluer, 2024]. This uncertainty complicates adaptation. Firms can respond to canal constraints but adaptation investments are often costly and only justified if the canal becomes persistently less reliable.

Constraints also have environmental side effects. According to the PCA, the route avoided more than 13 million tons of CO_2-equivalent emissions in 2020 relative to the most likely alternatives. Between Asia and the U.S. East Coast, the canal saves roughly 12% of container emissions relative to the Suez route and 18% relative to the Cape of Good Hope [Panama Canal Authority, 2021]. Rerouting, smaller vessels, and longer wait times all raise emissions per unit of cargo. This creates a feedback loop: physical climate risk at the canal increases shipping emissions, which in turn add to the warming as well as transition risk faced not only by firms that rely on maritime trade.

The economy-wide reach of these effects connects to a growing concern among regulators and institutional investors that climate change creates systemic risk. Large asset owners describe climate change as a risk that cannot be mitigated through diversification, because universal owners hold portfolios that span the entire economy [AP7, 2025]. The results in this paper illustrate one driving channel: More than 75% of sample firms rely on the canal, across industries and states. Operating costs rise for firms with and without direct exposure, and supply-chain partners and competitors show exposures similar to those of the firms themselves. Because the cross-sectional estimates difference out this common component, they understate the aggregate effect, and diversified investors bear the part of the shock that firm-level comparisons do not capture. At the same time, short sellers respond only modestly, and analyst forecasts do not fully anticipate the effects. This suggests that a transportation chokepoint could be a source of correlated, under-recognized risk in diversified portfolios.

References

Acemoglu, D. and P. D. Azar (2020). Endogenous production networks. *Econometrica 88*(1), 33–82.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica 80*(5), 1977–2016.

Acharya, V. V., T. C. Johnson, S. M. Sundaresan, and T. Tomunen (2022). Is physical climate risk priced? evidence from regional variation in exposure to heat stress. NBER Working Paper 30445, National Bureau of Economic Research.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2020). Temperature shocks and establishment sales. *The Review of Financial Studies 33*(3), 1331–1366.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2023). Temperature shocks and industry earnings news. *Journal of Financial Economics 150*(1), 1–45.

Alessandria, G., S. Y. Khan, A. Khederlarian, C. Mix, and K. J. Ruhl (2023, dec). The aggregate effects of global and local supply chain disruptions: 2020–2022. *Journal of International Economics 146*, 103788.

Amiti, M., S. J. Redding, and D. E. Weinstein (2019). The impact of the 2018 tariffs on prices and welfare. *Journal of Economic perspectives 33*(4), 187–210.

Andonov, A., R. Kräussl, and J. Rauh (2021). Institutional investors and infrastructure investing. *The Review of Financial Studies 34*(8), 3880–3934.

Antràs, P., T. C. Fort, and F. Tintelnot (2017). The margins of global sourcing: Theory and evidence from US firms. *American Economic Review 107*(9), 2514–2564.

AP7 (2025). Universal ownership: Systems thinking for asset owners. Technical report, AP7 (Swedish National Pension Fund).

Associated Press (2022a, October). Barges grounded by low water halt Mississippi river traffic. Associated Press, via WTTW. Accessed October 13, 2026.

Associated Press (2022b, August). Yangtze shrinks as China's drought disrupts industry. Associated Press, via NY1. Accessed October 13, 2026.

Ayyagari, M., J. Gao, and P. Ma (2024). Partisan friendshoring. Working Paper 5024127, SSRN.

Bai, X., J. Fernández-Villaverde, Y. Li, R. Marto, and F. Zanetti (2026). Shipping to America. NBER Working Paper 35808, National Bureau of Economic Research.

Balboni, C., J. Boehm, and M. Waseem (2026). Firm adaptation in production networks: Evidence from extreme weather events in Pakistan. *American Economic Review*. Forthcoming.

Bansal, R., D. Kiku, and M. Ochoa (2016). Price of long-run temperature shifts in capital markets. NBER Working Paper 22529, National Bureau of Economic Research.

Baqaee, D. R. and E. Farhi (2019). The macroeconomic impact of microeconomic shocks: Beyond hulten's theorem. *Econometrica 87*(4), 1155–1203.

Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics 131*(3), 1543–1592.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999). The financial accelerator in a quantitative business cycle framework. In J. B. Taylor and M. Woodford (Eds.), *Handbook of Macroeconomics*, Volume 1, pp. 1341–1393. Elsevier.

Bloomberg (2023, November). LPG tanker pays record $4 million for Panama Canal slot. Republished by gCaptain. Reporting by Ruth Liao and Anna Shiryaevskaya. Accessed: 2026-08-07.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *The Review of Economics and Statistics 101*(1), 60–75.

Boehmer, E., C. M. Jones, and X. Zhang (2008). Which shorts are informed? *The Journal of Finance 63*(2), 491–527.

Bolton, P. and M. Kacperczyk (2021). Do investors care about carbon risk? *Journal of financial economics 142*(2), 517–549.

Brancaccio, G., M. Kalouptsidi, and T. Papageorgiou (2020). Geography, transportation, and endogenous trade costs. *Econometrica 88*(2), 657–691.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Climate and conflict. *Annual Review of Economics 7*(1), 577–617.

Carreras-Valle, M.-J. (Forthcoming). Increasing inventories: The role of delivery times. *American Economic Journal: Macroeconomics*.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2021). Supply chain disruptions: Evidence from the Great East Japan Earthquake. *The Quarterly Journal of Economics 136*(2), 1255–1321.

CNBC (2023). Drought threatens major european river trade route, with ripples across the continent. Accessed: 2025-02-25.

Cohen, L. and A. Frazzini (2008). Economic links and predictable returns. *Journal of Finance 63*(4), 1977–2011.

Cuculiza, C., A. Kumar, W. Xin, and C. Zhang (2026). Temperature sensitivity, mispricing, and predictable returns. *Management Science 72*(3), 1918–1958.

Custodio, C., M. A. Ferreira, E. Garcia-Appendini, and A. Lam (2022). Economic impact of climate change. Nova SBE Working Paper 645, Nova School of Business and Economics.

Dechow, P. M., A. P. Hutton, L. K. Meulbroek, and R. G. Sloan (2001). Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics 61*(1), 77–106.

Donaldson, D. and R. Hornbeck (2016). Railroads and american economic growth: A "market access" approach. *Quarterly Journal of Economics 131*(2), 799–858.

Downey, M., N. Lind, and J. G. Shrader (2023). Adjusting to rain before it falls. *Management science 69*(12), 7399–7422.

Dupin, C. (2019, May). Panama Canal plans another draft restriction. FreightWaves / American Shipper. Accessed October 13, 2026.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg (2012). How are shorts informed? short sellers, news, and information processing. *Journal of Financial Economics 105*(2), 260–278.

European Space Agency (2022). Drought causes yangtze to shrink. Accessed: 26 February 2025.

Federal Maritime Commission. Licensed freight forwarders - trade names. Accessed 2026-01-31.

Federal Maritime Commission. Licensed nvoccs. Accessed 2026-01-31.

Flaaen, A., F. Haberkorn, L. Lewis, A. Monken, J. Pierce, R. Rhodes, and M. Yi (2023). Bill of lading data in international trade research with an application to the covid-19 pandemic. *Review of International Economics 31*(3), 1146–1172.

Funk, C., P. Peterson, M. Landsfeld, D. Pedreros, J. Verdin, S. Shukla, G. Husak, J. Rowland, L. Harrison, A. Hoell, and J. Michaelsen (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data 2*, 150066.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica 79*(3), 733–772.

Ganapati, S., W. F. Wong, and O. Ziv (2024). Entrepôt: Hubs, scale, and trade costs. *American Economic Journal: Macroeconomics 16*(4), 239–278.

Giglio, S., M. Maggiori, K. Rao, J. Stroebel, and A. Weber (2021). Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies 34*(8), 3527–3571.

Global Fishing Watch (2026). Global fishing watch ais-based vessel presence data. https://globalfishingwatch.org. Licensed under CC BY-NC 4.0. Accessed: 2026-08-07.

Grossman, G. M., E. Helpman, and S. J. Redding (2024). When tariffs disrupt global supply chains. *American Economic Review 114*(4), 988–1029.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2022). Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? *American Economic Review 112*(5), 1437–1474.

Halili, G. (2022). searoute-py: A python package to calculate the shortest sea route between two points on earth. https://github.com/genthalili/searoute-py. Accessed: 2025-02-26.

Heiland, I., A. Moxnes, K. H. Ulltveit-Moe, and Y. Zi (2025). Trade from space: Shipping networks and the global implications of local shocks. *Review of Economics and Statistics*.

Hersbach, H., B. Bell, P. Berrisford, S. Hirahara, A. Horányi, J. Muñoz-Sabater, J. Nicolas, C. Peubey, R. Radu, D. Schepers, et al. (2020). The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society 146*(730), 1999–2049.

Herskovic, B. (2018). Networks in production: Asset pricing implications. *The Journal of Finance 73*(4), 1785–1818.

Hirtzer, M. (2023, September). Low water levels on Mississippi river delaying barge cargo. Bloomberg, via Transport Topics. Accessed October 13, 2026.

Hong, H., F. W. Li, and J. Xu (2019). Climate risks and market efficiency. *Journal of Econometrics 208*(1), 265–281. Special Issue on Financial Engineering and Risk Management.

Howell, S. T., Y. Jang, H. Kim, and M. S. Weisbach (2026). All clear for takeoff: Evidence from airports on the effects of infrastructure privatization. *The Review of Financial Studies*. Advance article, hhag023.

Hulten, C. R. (1978). Growth accounting with intermediate inputs. *The Review of Economic Studies 45*(3), 511–518.

Hummels, D. L. and G. Schaur (2013). Time as a trade barrier. *American Economic Review 103*(7), 2935–2959.

Ilhan, E., Z. Sautner, and G. Vilkov (2021). Carbon tail risk. *The Review of Financial Studies 34*(3), 1540–1571.

Jung, P. H., K. Kim, A.-H. Jo, and J. S.-H. Cho (2025). Panama canal drought and supply chain disruptions in Asia–United States trade: Evidence from micro-level trade shipments and vessel trajectory data. ADB Economics Working Paper 822, Asian Development Bank.

Katona, Z., M. O. Painter, P. N. Patatoukas, and J. Zeng (2025). On the capital market consequences of big data: Evidence from outer space. *Journal of Financial and Quantitative Analysis 60*(2), 551–579.

Komaromi, A., D. A. Cerdeiro, and Y. Liu (2022). Supply chains and port congestion around the world. IMF Working Paper 22/59, International Monetary Fund.

Krueger, P., Z. Sautner, and L. T. Starks (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies 33*(3), 1067–1111.

Kruttli, M. S., B. R. Tran, and S. W. Watugala (2025). Pricing poseidon: Extreme weather uncertainty and firm return dynamics. *The Journal of Finance 80*(2), 783–832.

Lim, K. (2018). Endogenous production networks and the business cycle. Working Paper.

Liu, E., Y. Liu, V. Smirnyagin, and A. Tsyvinski (2025). Supply chain disruptions, supplier capital, and financial constraints. Cowles Foundation Discussion Paper 2402r1, Cowles Foundation for Research in Economics, Yale University.

Mishra, A. K. and V. P. Singh (2010). A review of drought concepts. *Journal of Hydrology 391*(1-2), 202–216.

Mitchell, P. and E. Menzies Pluer (2024, July). No, the Panama Canal is not running dry. New Security Beat, Wilson Center Environmental Change and Security Program. 17 July 2024. Accessed: 2026-10-13.

Muñoz, S. E., L. Lawrence, and S. Wang (2025). Drying of the Panama Canal in a warming climate. *Geophysical Research Letters 52*(18), e2025GL117038.

NASA Earth Observatory (2023). The mississippi is mighty parched. Accessed: 2025-02-25.

Oberfield, E. (2018). A theory of input–output architecture. *Econometrica 86*(2), 559–589.

Panama Canal Authority (2021, July). Celebrating the legacy and future of the panama canal's green connection environmental program. Press release, 21 July 2021. Accessed: 2026-10-13.

Panama Canal Authority (2023, March 24). Advisory to shipping no. a-14-2023: Draft adjustment to 14.48 m (47.5 feet) tfw in the neopanamax locks. Technical report, Panama Canal Authority. Accessed: 2025-06-27.

Panama Canal Authority (2025). Panama canal water reports. Accessed: 2025-02-26.

Pankratz, N., R. Bauer, and J. Derwall (2023). Climate change, firm performance, and investor surprises. *Management Science 69*(12), 7352–7398.

Pankratz, N. M. and C. M. Schiller (2024). Climate change and adaptation in global supply-chain networks. *The Review of Financial Studies 37*(6), 1729–1777.

Ponticelli, J., Q. Xu, and S. Zeume (2023). Temperature, adaptation, and local industry concentration. NBER Working Paper 31533, National Bureau of Economic Research.

Reuters (2026, July). Record low Danube water levels in Serbia, Croatia leave boats beached, reveal decades-old shipwrecks. Reuters, via WSAU. Accessed October 13, 2026.

Sanz, L. (2026). Building corporate resilience to supply chain disruptions. Working paper, Fisher College of Business WP 2023-03-025 / Charles A. Dice Center WP 2023-25. Available at SSRN 4635488.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023). Pricing climate change exposure. *Management Science 69*(12), 7540–7561.

Schafhäutle, S. G. and G. Sran (2025). Redacted identities in shipment records: Evidence from forced labor scrutiny in supply chains. Working paper. Available at SSRN 5140247.

Schlenker, W. and C. A. Taylor (2021). Market expectations of a warming climate. *Journal of Financial Economics 142*(2), 627–640.

Smithsonian Tropical Research Institute (2025). STRI GIS portal. Accessed: 2025-02-25.

Tran, N. K., H. Haralambides, T. Notteboom, and K. Cullinane (2025, January). The costs of maritime supply chain disruptions: The case of the Suez Canal blockage by the 'Ever Given' megaship. *International Journal of Production Economics 279*, 109464.

U.S. Customs and Border Protection (2024). Information on vessel manifests and summary statistical reports. 19 C.F.R. § 103.31. Confidentiality certification provisions: § 103.31(d)(1) (inward manifests) and § 103.31(d)(2) (outward manifests); each certification valid two years.

U.S. Energy Information Administration (2023). Drought at the panama canal delays energy shipments, increasing shipping costs. Today in Energy, October 31, 2023. Accessed: 2026-08-07.

Veetil, V. P. and F. S. Vemmarath (2026). Macroeconomic risks from maritime trade disruptions. arXiv preprint arXiv:2607.09951.

Walters, C. R. (2024). Empirical Bayes methods in labor economics. In C. Dustmann and T. Lemieux (Eds.), *Handbook of Labor Economics*, Volume 5, pp. 183–260. Elsevier.

Wilson, D. J. (2019). Clearing the fog: The predictive power of weather for employment reports and their asset price responses. *American Economic Review: Insights 1*(3), 373–388.

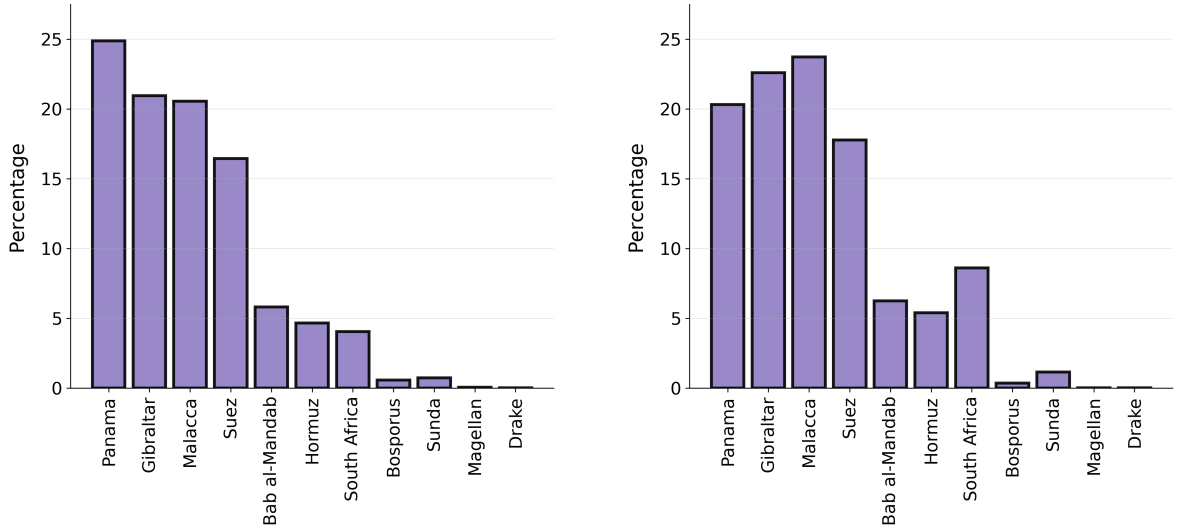
World Meteorological Organization (2022). Developing the climate science information for climate action. Wmo-no. 1287, World Meteorological Organization.

World Weather Attribution (2024, May). Low water levels in Panama Canal due to increasing demand exacerbated by El Niño event. Technical report, Imperial College London.

Zhang, P., O. Deschênes, K. Meng, and J. Zhang (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *Journal of Environmental Economics and Management 88*, 1–17.

Tables and Figures

Figure 1: Economic Reliance on Trade Routes of US Firms

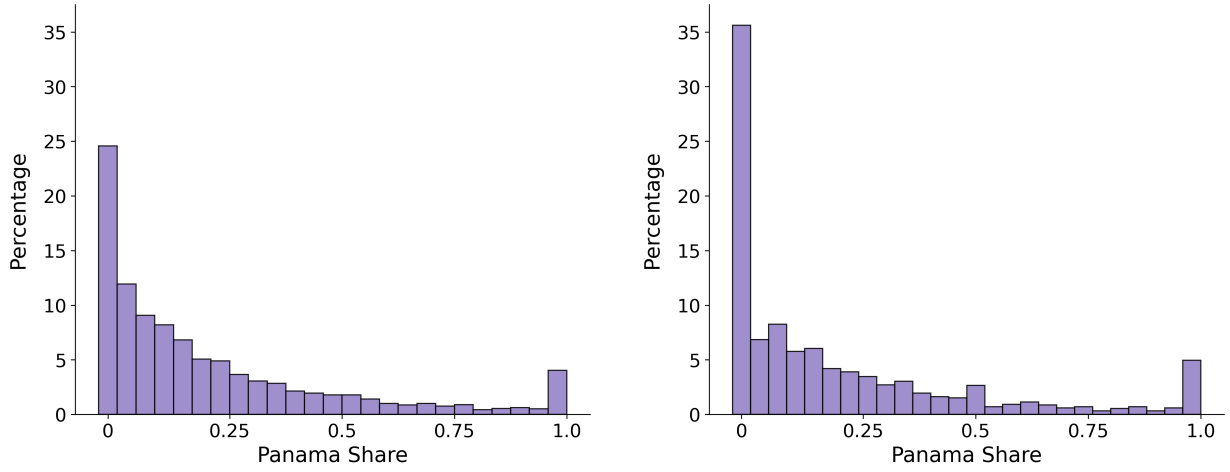


(a) Passages Traversed for Incoming Shipments

(b) Passages Traversed for Outgoing Shipments

Notes: This figure shows the share of shipping volume traversing each major maritime passage. In this graph, shares use confirmed routing within a 60-day window before arrival in the U.S, computed on the volumes of all S&P Panjiva shipments summed over 2012 to 2025. Figure (a) covers imports and Figure (b) exports.

Figure 2: Firm-Level Exposure to the Panama Canal

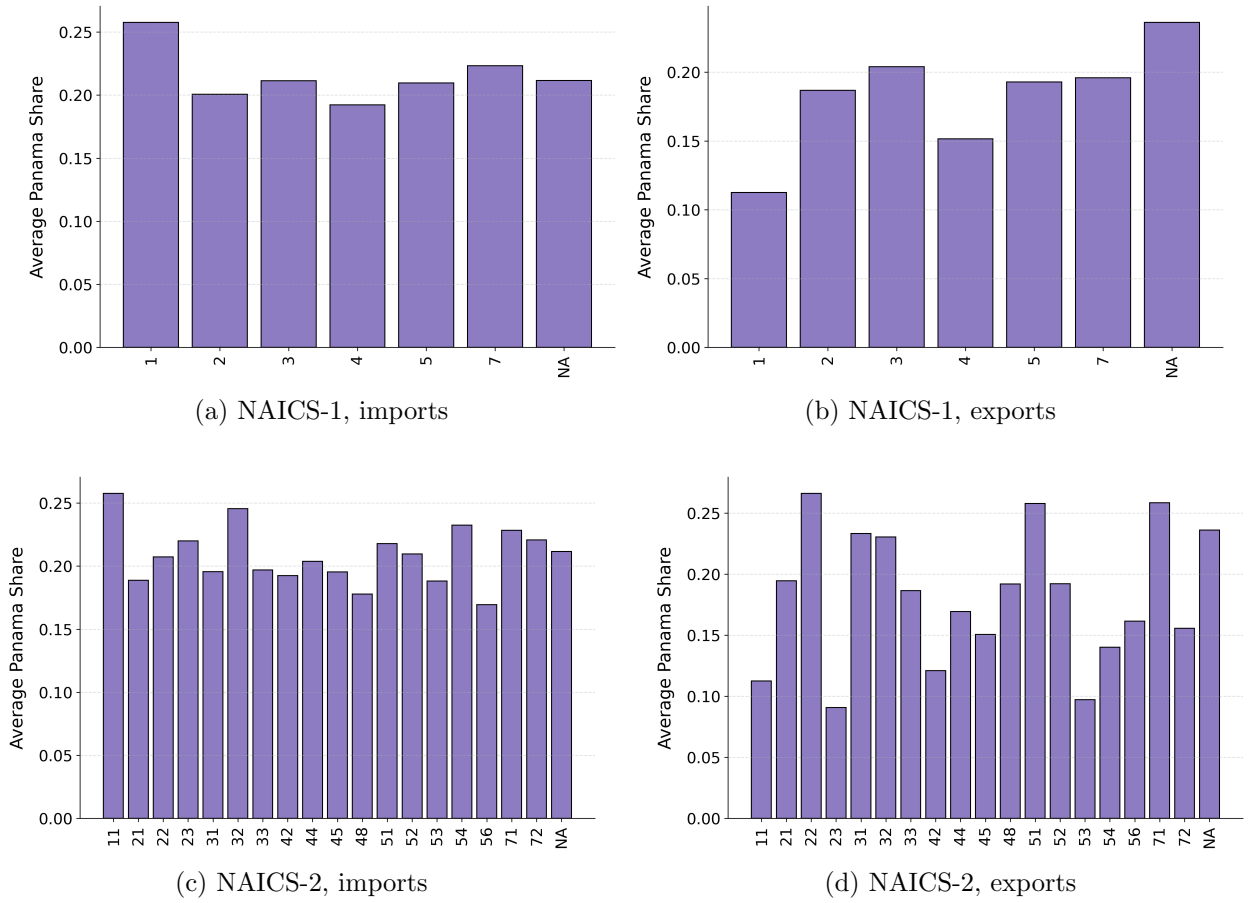


(a) Share of Incoming Shipments by Volume

(b) Share of Outgoing Shipments by Volume

Notes: This figure shows the distribution of import and export shares relying on the Panama Canal at the firm level. Shares are aggregated for listed firms covered by Compustat. Reliance on the canal is defined as the share of shipping volume routed through the Panama Canal, measured within a 60-day window using vessel names in S&P Panjiva and AIS data from Global Fishing Watch. Firms with no volume routed through the Panama Canal appear as the leftmost bar, a share of exactly zero. Figure (a) shows incoming shipments (imports) and Figure (b) outgoing shipments (exports).

Figure 3: Route Exposure of Listed Firms by Industry



(a) NAICS-1, imports

(b) NAICS-1, exports

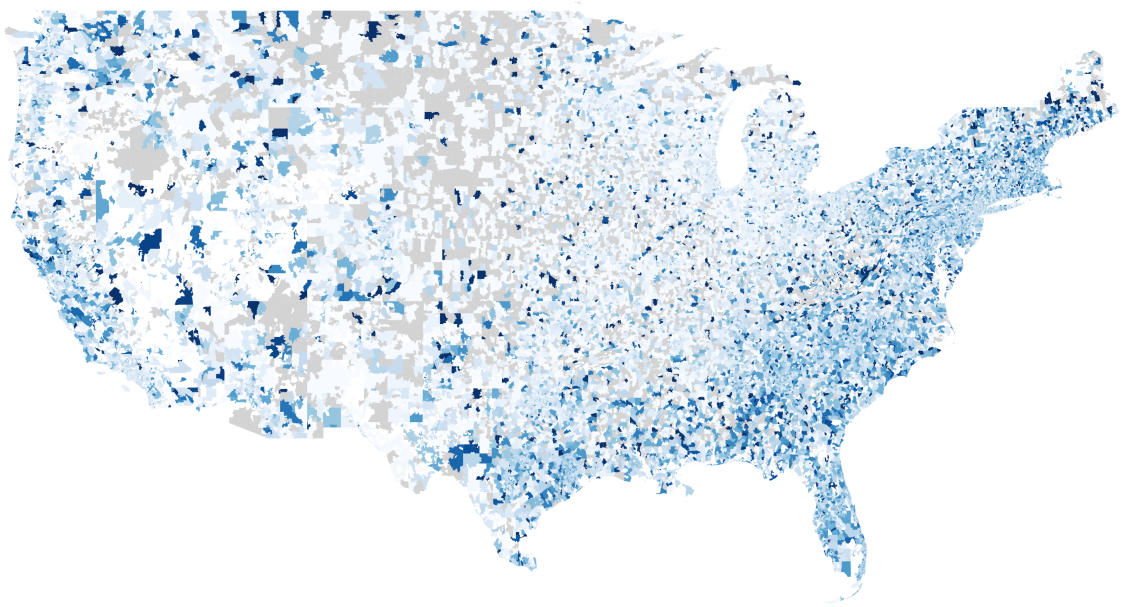
(c) NAICS-2, imports

(d) NAICS-2, exports

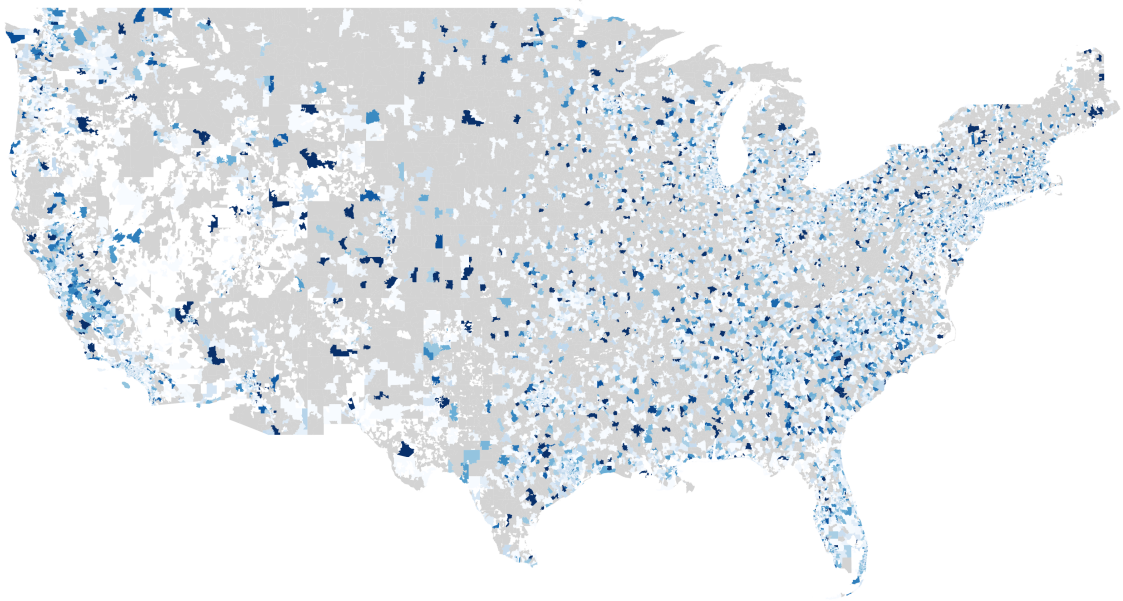
Notes: This figure shows the mean Panama Canal share of shipment volume by industry. Each firm's Panama share is measured from confirmed routing linking AIS data with vessel names in S&P Panjiva. Industries come from the firm's NAICS code in Compustat. The top row uses one-digit NAICS and the bottom row two-digit NAICS. Left panels show incoming shipments (imports), right panels outgoing shipments (exports). Firms without NAICS codes available and nonclassifiable codes beginning with '999' are shown as NA. Financial firms and logistics companies operating in the maritime sector, i.e., firms in NAICS sectors 6x, 49, and 81, are excluded.

Figure 4: Geographic Variation in Route Exposure

(a) Inbound Shipments

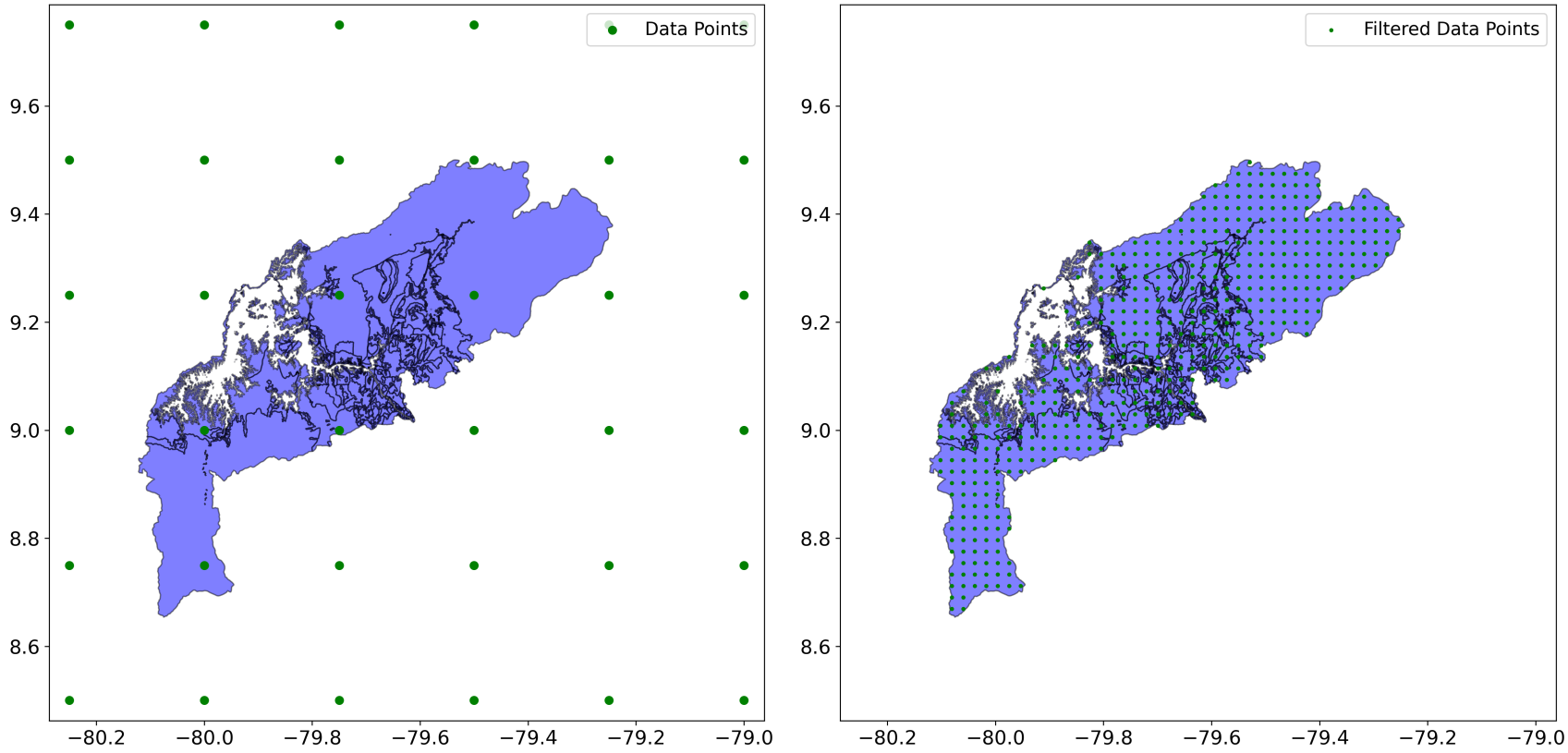


(b) Outbound Shipments



Notes: This figure shows the share of shipment volume AIS-confirmed to have traversed the Panama Canal within a 60-day window, aggregated to the zip code level of shipment destinations in Panjiva and computed from volumes summed over 2012 to 2024. Observations listing ocean transportation intermediaries, freight forwarders, or non-vessel operating common carriers as the receiving firm are excluded. Figure (a) covers inbound shipments and Figure (b) outbound shipments.

Figure 5: Aggregation of Precipitation Data over the Watershed of the Panama Canal

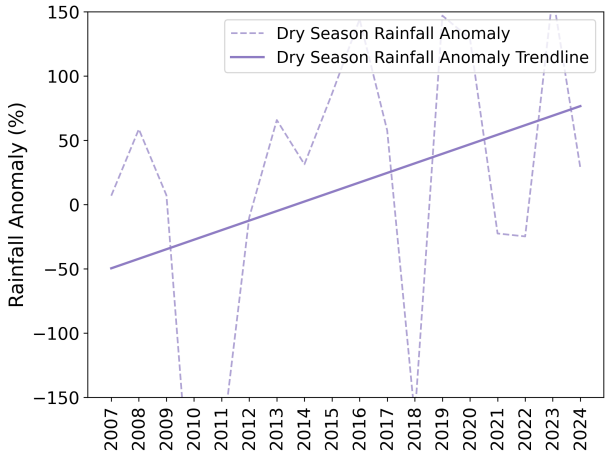


(a) Gatun Lake watershed and ERA5 grid nodes

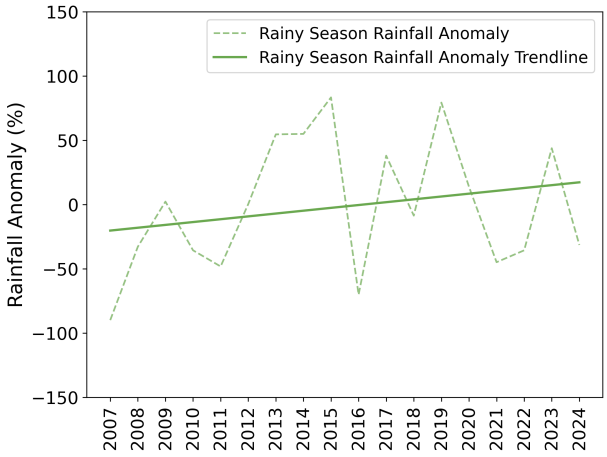
(b) Aggregation of ERA5 data points

Notes: This figure shows how ERA5 precipitation and evaporation are aggregated to the Gatun Lake watershed by area-weighted averaging across grid cells. In Figure (a), the shapefile marks the watershed boundary and green dots are ERA5 grid nodes. Figure (b) shows the points of a grid ten times finer than the ERA5 grid that fall within the watershed, onto which the ERA5 data are interpolated before averaging.

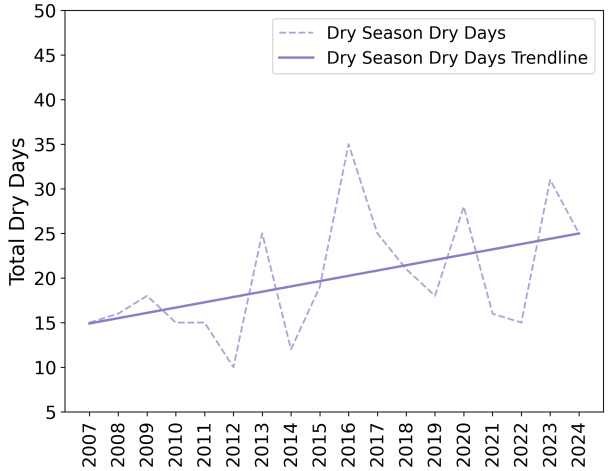
Figure 6: Drought Trends by Season over Time



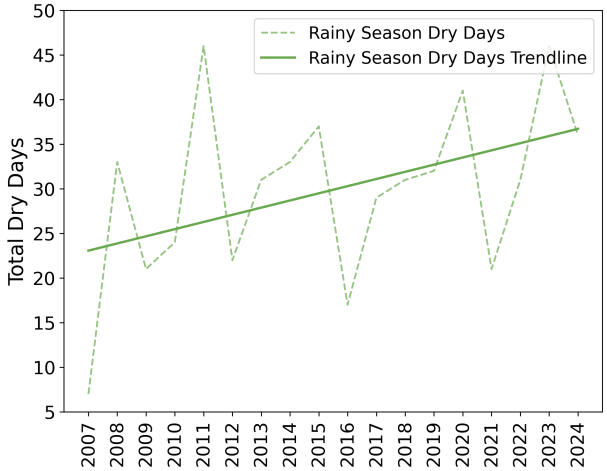
(a) Anomaly in the Dry Season



(b) Anomaly in the Rainy Season



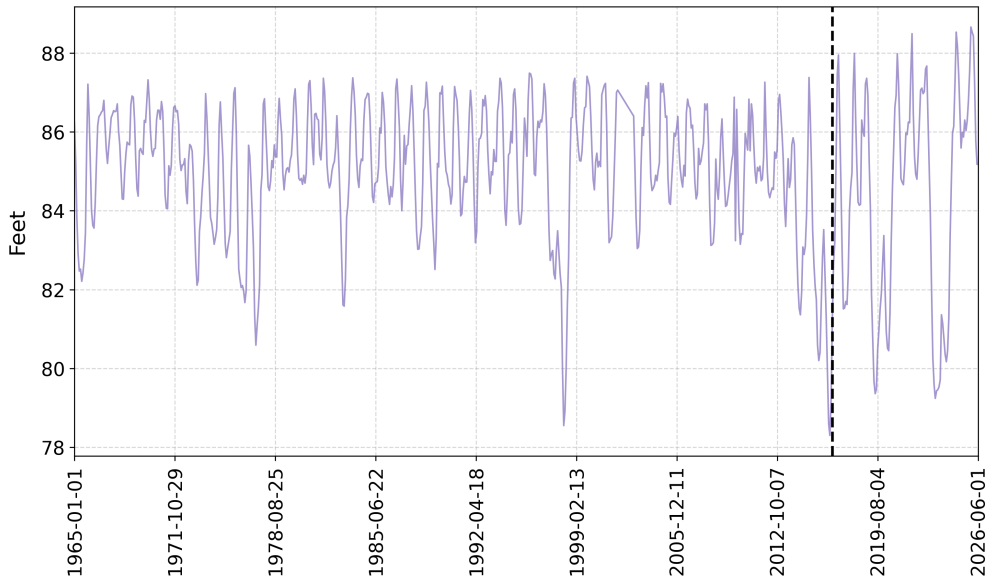
(c) Dry Days in the Dry Season



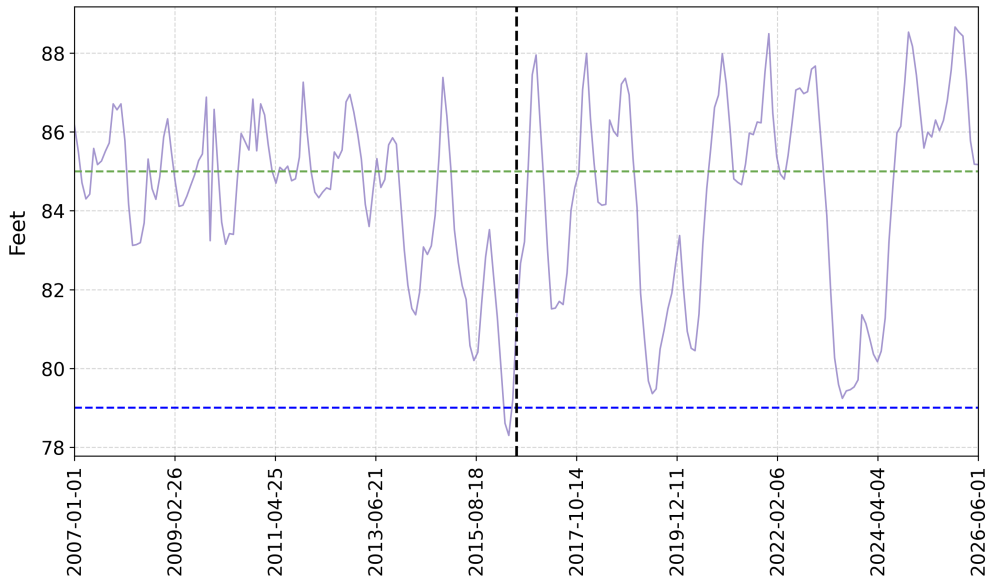
(d) Dry Days in the Rainy Season

Notes: This figure shows precipitation trends over the Gatun Lake watershed. Aggregation follows the illustration in Figure 5. Figures (a) and (b) plot the rainfall anomaly and Figures (c) and (d) the number of dry days, each summed over the months of the season, for 2007 to 2024, with a linear trend line. The left column covers the dry season (December to April) and the right column the rainy season (May to November). Anomalies are inverted, so higher values mean drier conditions.

Figure 7: 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. A June 2016 expansion added a new traffic lane (Neopanamax), marked by the dashed vertical line. Figure (a) shows all available records; Figure (b) starts in 2007, when Panjiva data begin. When levels fall below the green (blue) line, the Panama Canal Authority (PCA) must impose draft restrictions for the Neopanamax (Panamax) locks. The number of passages can be capped before these restrictions bind.

Table 1: **Summary Statistics**

Notes: This table shows summary statistics. Panel (a) covers container vessel movements at U.S. ports from the U.S. Army Corps of Engineers, including indicators for an AIS-confirmed Panama Canal transit. Panel (b) covers the firm financial and accounting performance. Panel (c) covers topics raised on earnings calls, measured as mentions per 1,000 words in statements by executives. Panels (d) and (e) cover short selling and analyst forecast surprises. Anomalies are inverted, so higher values mean drier conditions. Exposure is the share of shipment value routed through the canal in Panels (b), (d), and (e), and of shipment volume in Panel (c). In Panel (b) it is reported both raw and shrunk with an empirical Bayes beta-binomial estimator. Financial and accounting measures are in million U.S. dollars; ratios to lagged assets are in percent, and exposure shares are fractions.

(a) Vessel Movements

	N	Mean	StDev	p25	Median	p75
Draft (inches)	365421	391.492	84.778	348.000	408.000	454.000
Gross Registered Tonnage	369990	54662.844	35152.776	25803.000	51931.000	76199.000
Neo-Panamax Vessel	369990	0.431	0.495	0.000	0.000	1.000
Days Between Voyages	156939	61.966	103.391	21.000	43.000	70.000
Days in U.S. Port	179888	0.644	1.908	0.000	0.000	1.000
Panama Canal Transit (45 days)	353849	0.299	0.458	0.000	0.000	1.000
Panama Canal Transit (60 days)	353849	0.315	0.464	0.000	0.000	1.000
$\sum$ Rainfall Anomaly, Monthly (%)	369990	5.274	31.912	-3.209	8.312	20.680
$\sum$ Rainfall Anomaly over three Months (%)	369990	4.735	18.215	-3.918	6.432	14.448

(b) Firm Performance and Canal Exposure

	N	Mean	StDev	p25	Median	p75
Rainfall Anomaly, Quarterly (%)	202607	0.754	20.654	-7.197	1.256	12.743
Rainfall Anomaly within Quarter (%)	202607	0.000	20.261	-7.634	0.686	13.155
Rainfall Anomaly over three Quarters (%)	202607	-0.093	10.290	-6.428	1.005	7.098
Rainfall Anomaly within three Quarters (%)	202607	-0.000	10.210	-5.905	0.897	7.877
Precipitation (m cubicm)	202607	5547.465	2591.888	3336.226	6195.309	7668.513
Precipitation within Quarter (m cubicm)	202607	-0.000	840.116	-498.536	-58.231	419.697
Drought Days	202607	11.952	5.816	8.000	11.000	16.000
Drought Days within Quarter	202607	0.000	5.771	-4.028	-1.099	3.972
Minimum Water Level of Gatun Lake	196282	84.255	3.330	83.147	84.967	85.947
Maximum Water Level of Gatun Lake	197682	84.941	5.436	83.943	86.033	86.953
Revenues over Lagged Assets	195663	28.382	21.939	13.149	23.164	37.120
Revenues	197370	794.273	1656.180	37.120	197.027	715.000
Operating Income after Depr. over Lagged Assets	201340	-0.451	12.943	-0.066	1.665	3.266
Operating Income before Depr. over Lagged Assets	202607	0.722	12.890	0.938	2.694	4.449
Operating Income	201497	95.533	242.393	-0.047	12.683	73.302
Assets	202291	4846.180	11871.826	157.895	853.924	3681.961
Cost of Goods Sold	200759	497.254	1093.018	17.698	108.457	425.073
Sales, General, Administrative Expenses	177511	134.476	292.012	8.370	34.736	116.903
Inventories over Lagged Assets	195039	12.807	13.785	1.378	8.881	19.545
Inventories	197232	297.108	688.903	3.479	46.805	242.000
Change in Inventories	188940	3.075	29.348	-1.080	0.000	3.888
Depreciation	201645	40.752	91.477	1.230	7.933	33.300
Accounts Payable	201529	358.826	1241.339	7.408	44.900	202.621
Accounts Receivable	200784	450.041	1318.479	14.118	86.957	344.987
>0 % Value Imported	202607	0.803	0.397	1.000	1.000	1.000
% Value Imported	202607	0.174	0.238	0.006	0.078	0.226
% Value Imported	202607	0.171	0.179	0.043	0.108	0.224
>0 % Value Exported	202607	0.315	0.464	0.000	0.000	1.000
% Value Exported	112063	0.120	0.219	0.000	0.010	0.132
% Value Exported	202607	0.070	0.129	0.000	0.011	0.089

(c) Earnings Calls

	N	Mean	StDev	p25	Median	p75
Panama Mentions per 1,000 Words	59585	0.001	0.019	0.000	0.000	0.000
Drought Mentions per 1,000 Words	59585	0.014	0.097	0.000	0.000	0.000
Supply Chain Mentions per 1,000 Words	59585	0.542	0.859	0.000	0.226	0.703
Inventory Mentions per 1,000 Words	59585	0.985	1.209	0.138	0.567	1.410
% Exposed Volume of Incoming Shipments	59585	0.206	0.167	0.082	0.167	0.282
% Exposed Volume of Outgoing Shipments	59585	0.193	0.254	0.000	0.090	0.275
$\sum$ Rainfall Anomaly, Monthly (%)	58076	1.220	29.479	-11.015	5.664	16.885
$\sum$ Rainfall Anomaly over three Months (%)	58076	0.450	23.784	-7.286	1.168	13.025

(d) Short Interest

	N	Mean	StDev	p25	Median	p75
Markit Short Score	196591	0.955	1.125	0.000	1.000	1.000
Short Interest (% of Float)	196728	5.594	6.899	1.606	3.215	6.795
% Exposed Value of Incoming Shipments	204608	0.200	0.193	0.056	0.141	0.286
% Exposed Value of Outgoing Shipments	204608	0.140	0.245	0.000	0.003	0.176
$\sum$ Rainfall Anomaly, Monthly (%)	204608	3.506	30.741	-7.098	5.571	19.960
$\sum$ Rainfall Anomaly over three Months (%)	204608	1.967	22.988	-5.673	4.362	13.392

(e) Analyst Forecasts

	N	Mean	StDev	p25	Median	p75
Mean Revenue Surprise (% of Assets)	64848	0.07981	1.49099	-0.43980	0.10380	0.73383
Mean Pre-Tax Income Surprise (% of Assets)	61074	0.04841	0.88273	-0.20450	0.07406	0.38678
Mean EPS Surprise (% of Assets)	65680	0.00012	0.02929	-0.00086	0.00047	0.00447
% Exposed Value of Incoming Shipments	73854	0.20246	0.18973	0.05944	0.14476	0.28604
% Exposed Value of Outgoing Shipments	73854	0.14968	0.25100	0.00000	0.01308	0.19232
$\sum$ Rainfall Anomaly, Monthly (%)	73854	3.38404	28.98352	-11.70664	2.14606	20.07924
$\sum$ Rainfall Anomaly over three Months (%)	73854	2.71974	19.75711	-5.66924	4.78915	13.10964

Table 2: **Infrastructure Constraints and Vessel Composition**

Notes. This table shows how drought in the Lake Gatun watershed changes vessel movements at U.S. ports, using U.S. Army Corps of Engineers entrances and clearances for container vessels from 2013 to 2022. Dependent variables are vessel draft in inches in Panel (a) and log gross registered tonnage in Panel (b), both by OLS, and an indicator of Neo-Panamax vessels in Panel (c), by Poisson. Columns (1) and (2) cover entering vessels and columns (3) and (4) clearing vessels. Anomalies are inverted, so higher values mean drier conditions. *Panama Canal* equals one when the vessel has an AIS-confirmed Panama Canal transit within 45 days of the port call. Fixed effects are listed in the table. Standard errors clustered by year-month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Vessel Draft

	Draft (Inches)			
	(1)	(2)	(3)	(4)
	Entering US Ports		Clearing US Ports	
Rainfall Anomaly × Panama Canal	-0.0211**		-0.0144*	
	(0.01)		(0.01)	
Rainfall Anomaly (m to m-2) × Panama Canal		-0.0146**		-0.0097
		(0.01)		(0.01)
Rainfall Anomaly	0.0099		0.0056	
	(0.01)		(0.01)	
Rainfall Anomaly (m to m-2)		0.0012		-0.0009
		(0.00)		(0.00)
Month x Passage FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes
Observations	173311	173311	173976	173976
R^2	.678	.678	.665	.665

(b) Vessel Size

	Ln(Gross Registered Tonnage)			
	(1)	(2)	(3)	(4)
	Entering US Ports		Clearing US Ports	
Rainfall Anomaly × Panama Canal	-0.0004**		-0.0002*	
	(0.00)		(0.00)	
Rainfall Anomaly (m to m-2) × Panama Canal		-0.0004***		-0.0002***
		(0.00)		(0.00)
Rainfall Anomaly	0.0001*		0.0000	
	(0.00)		(0.00)	
Rainfall Anomaly (m to m-2)		0.0001**		0.0000
		(0.00)		(0.00)
Month x Passage FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes
Observations	175634	175634	174826	174826
R^2	.791	.791	.8	.8

(c) Vessel Types

	Neo-Panamax			
	(1)	(2)	(3)	(4)
	Entering US Ports		Clearing US Ports	
Rainfall Anomaly × Panama Canal	-0.0023***		-0.0022***	
	(0.00)		(0.00)	
Rainfall Anomaly (m to m-2) × Panama Canal		-0.0020***		-0.0019***
		(0.00)		(0.00)
Rainfall Anomaly	0.0003*		0.0001	
	(0.00)		(0.00)	
Rainfall Anomaly (m to m-2)		0.0003***		0.0001
		(0.00)		(0.00)
Month x Passage FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes
Observations	143622	143622	144900	144900
R^2				

Table 3: **Infrastructure Constraints and Shipping Time**

Notes. This table shows OLS regressions of vessel movement at U.S. ports on drought in the Lake Gatun watershed, using U.S. Army Corps of Engineers entrances and clearances from 2013 to 2022. The dependent variable is days between voyages in Panel (a) and days spent in U.S. ports in Panel (b). Columns (1) and (2) cover container vessels, (3) and (4) tankers, and (5) and (6) dry bulk carriers. Anomalies are inverted, so higher values mean drier conditions. *Panama Canal* equals one when the vessel has an AIS-confirmed Panama Canal transit within 60 days of the port call. Fixed effects are listed in the table. Standard errors, clustered by vessel and year-month in Panel (a) and by year-month in Panel (b), are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Time Between Port Entries

	Days Between Voyages					
	(1)	(2)	(3)	(4)	(5)	(6)
	Containers		Tankers		Dry Bulk	
Rainfall Anomaly × Panama Canal	0.0331**		0.0860		-0.2152	
	(0.01)		(0.09)		(0.22)	
Rainfall Anomaly (m to m-2) × Panama Canal		0.0683**		0.2188*		-0.0097
		(0.03)		(0.12)		(0.37)
Rainfall Anomaly	-0.0173		-0.0498*		-0.0725	
	(0.02)		(0.03)		(0.06)	
Rainfall Anomaly (m to m-2)		-0.0379		-0.0476		-0.4791***
		(0.03)		(0.07)		(0.11)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	149949	149949	84237	84237	23308	23308
R^2	.107	.107	.29	.29	.376	.377

(b) Time in Ports

	Days in U.S. Port					
	(1)	(2)	(3)	(4)	(5)	(6)
	Containers		Tankers		Dry Bulk	
Rainfall Anomaly × Panama Canal	0.0004		-0.0002		0.0057***	
	(0.00)		(0.00)		(0.00)	
Rainfall Anomaly (m to m-2) × Panama Canal		0.0026***		0.0001		0.0110***
		(0.00)		(0.00)		(0.00)
Rainfall Anomaly	-0.0006		0.0004		-0.0015	
	(0.00)		(0.00)		(0.00)	
Rainfall Anomaly (m to m-2)		-0.0029**		-0.0002		-0.0039**
		(0.00)		(0.00)		(0.00)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171307	171307	135134	135134	63475	63475
R^2	.334	.334	.263	.263	.39	.39

Table 4: **Infrastructure Constraints and Inventories**

Notes. This table shows OLS regressions of firm inventories on drought in the Lake Gatun watershed. The dependent variable is inventories over lagged assets in columns (1) to (4), and the quarterly change in inventories in columns (5) to (8). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Within each group, the first column uses continuous canal exposure, the share of shipment value routed through the canal on AIS-confirmed routes within a 45-day window, shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. The remaining columns replace it with indicators for exposure above the mean, median, and 75th percentile. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms, and requires firms to have more than 50 shipments. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Inventories/Assets				Change in Inventories			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Anomaly (q-2,q)	-0.0051	-0.0016	-0.0081	-0.0037	-0.0764**	-0.0733*	-0.0494	-0.0770**
	(-0.95)	(-0.28)	(-1.31)	(-0.70)	(-2.09)	(-1.97)	(-1.44)	(-2.07)
Rainfall Anomaly (q-2,q) × % Value Imported	-0.0150				-0.0668			
	(-1.58)				(-1.36)			
Rainfall Anomaly (q-2,q) × % Value Exported	-0.0050				-0.1792***			
	(-0.55)				(-3.22)			
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only		-0.0139***				-0.0433**		
		(-4.13)				(-2.31)		
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only		-0.0110**				-0.1507***		
		(-2.61)				(-5.31)		
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported		-0.0160***				-0.0293		
		(-3.30)				(-1.08)		
Rainfall Anomaly (q-2,q) × > Median % Value Imported only			0.0009				-0.0652***	
			(0.21)				(-2.98)	
Rainfall Anomaly (q-2,q) × > Median % Value Exported only			-0.0016				-0.1403***	
			(-0.32)				(-5.60)	
Rainfall Anomaly (q-2,q) × > Median % Value Imported & Exported			0.0004				-0.0731***	
			(0.09)				(-2.66)	
Rainfall Anomaly (q-2,q) × > P75 % Value Imported only				-0.0094**				-0.0474**
				(-2.44)				(-2.32)
Rainfall Anomaly (q-2,q) × > P75 % Value Exported only				-0.0110***				-0.1298***
				(-3.22)				(-4.90)
Rainfall Anomaly (q-2,q) × > P75 % Value Imported & Exported				-0.0134**				0.0030
				(-2.25)				(0.09)
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	128068	128068	128068	128068	127302	127302	127302	127302
Firms	1948	1948	1948	1948	1936	1936	1936	1936
R^2	.841	.841	.841	.841	.386	.386	.386	.386

Table 5: **Infrastructure Constraints and Firm Revenues**

Notes. This table shows OLS regressions of firm revenues on drought in the Lake Gatun watershed. The dependent variable is revenues over lagged assets in percent in columns (1) to (3); the year-over-year log change in revenues in percent in columns (4) to (6); and revenues standardized by the firm's mean and standard deviation in columns (7) to (9). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Within each group, the first column uses continuous canal exposure, the share of shipment value routed through the canal on AIS-confirmed routes within a 45-day window, shrunk toward the average across firms with an empirical Bayes (beta-binomial) estimator. The remaining columns replace it with indicators for exposure above the mean and the 75th percentile on the import side only, the export side only, and both sides. Firms below the cut-off on both sides are the comparison group. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Revenues/Assets			Log Change in Revenues (YoY)			Standardized Revenues		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rainfall Anomaly (q-2,q)	-0.0239**	-0.0237**	-0.0237**	-0.1072**	-0.1028**	-0.1034**	-0.0017**	-0.0013*	-0.0013*
	(-2.30)	(-2.22)	(-2.24)	(-2.52)	(-2.38)	(-2.41)	(-2.27)	(-1.77)	(-1.87)
Rainfall Anomaly (q-2,q) × % Value Imported	-0.0166			0.0562			0.0016		
	(-0.83)			(0.93)			(1.46)		
Rainfall Anomaly (q-2,q) × % Value Exported	-0.0300			-0.1895**			-0.0020		
	(-1.31)			(-2.58)			(-1.31)		
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only		-0.0017			-0.0165			-0.0006	
		(-0.22)			(-0.79)			(-1.42)	
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only		-0.0311***			-0.0874***			-0.0017***	
		(-2.94)			(-3.38)			(-2.83)	
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported		-0.0188***			0.0084			0.0005	
		(-2.99)			(0.42)			(0.63)	
Rainfall Anomaly (q-2,q) × > P75 % Value Imported only			-0.0010			-0.0205			-0.0006
			(-0.12)			(-0.80)			(-1.47)
Rainfall Anomaly (q-2,q) × > P75 % Value Exported only			-0.0314***			-0.0613**			-0.0020***
			(-3.48)			(-2.44)			(-3.75)
Rainfall Anomaly (q-2,q) × > P75 % Value Imported & Exported			-0.0204**			-0.0061			0.0023**
			(-2.18)			(-0.21)			(2.30)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130502	130502	130502	133132	133132	133132	142009	142009	142009
Firms	1945	1945	1945	1939	1939	1939	1961	1961	1961
R^2	.749	.749	.749	.191	.191	.191	.472	.472	.472

Table 6: **Infrastructure Constraints and Operating Income**

Notes. This table shows OLS regressions of firm operating income on drought in the Lake Gatun watershed. The dependent variable is operating income before depreciation and amortization over lagged assets, in percent in columns (1) to (3), the year-over-year log change in operating income in percent in columns (4) to (6), defined only when operating income is positive in both quarters, and operating income standardized by the firm's mean and standard deviation in columns (7) to (9). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Within each group, the first column uses continuous canal exposure, the share of shipment value routed through the canal on AIS-confirmed routes within a 45-day window, shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. The remaining columns replace it with indicators for exposure above the mean and the 75th percentile on the import side only, the export side only, and both sides. Firms below the cut-off on both sides are the comparison group. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms, and requires firms to have more than 50 shipments. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Op. Income/Assets			Log Change in Op. Income (YoY)			Standardized Op. Income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rainfall Anomaly (q-2,q)	-0.0008	-0.0019	-0.0021	-0.0712	-0.0934	-0.0806	-0.0026***	-0.0020**	-0.0019**
	(-0.25)	(-0.59)	(-0.70)	(-0.93)	(-1.23)	(-1.05)	(-3.19)	(-2.60)	(-2.53)
Rainfall Anomaly (q-2,q) × % Value Imported	-0.0259**			-0.0734			0.0023		
	(-2.49)			(-0.59)			(1.64)		
Rainfall Anomaly (q-2,q) × % Value Exported	-0.0145**			-0.2837**			-0.0017		
	(-2.21)			(-2.14)			(-1.09)		
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only		-0.0104***			-0.0051			-0.0004	
		(-2.64)			(-0.10)			(-0.94)	
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only		-0.0079***			-0.1950***			-0.0024***	
		(-2.63)			(-3.62)			(-4.11)	
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported		-0.0093***			0.0789			0.0008	
		(-2.73)			(1.26)			(1.10)	
Rainfall Anomaly (q-2,q) × > P75 % Value Imported only			-0.0127***			-0.0524			-0.0009**
			(-2.98)			(-0.77)			(-2.07)
Rainfall Anomaly (q-2,q) × > P75 % Value Exported only			-0.0081***			-0.1486***			-0.0024***
			(-3.00)			(-2.92)			(-4.01)
Rainfall Anomaly (q-2,q) × > P75 % Value Imported & Exported			-0.0092**			0.0300			0.0020**
			(-2.61)			(0.40)			(2.22)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	127675	127675	127675	108266	108266	108266	138093	138093	138093
Firms	1957	1957	1957	1823	1823	1823	1973	1973	1973
R^2	.546	.546	.546	.13	.13	.13	.38	.38	.38

Table 7: **Infrastructure Constraints and Transportation Costs**

Notes. This table shows OLS regressions of monthly transportation costs on drought in the Lake Gatun watershed. Panel (a) uses the FRED producer price index for deep sea freight transportation and the Cass Freight Index of implied freight rates. Panel (b) uses truck tonnage and internal water transportation. Even-numbered columns add the first and second monthly lags of the rainfall anomaly. Anomalies are inverted, so higher values mean drier conditions. The sample is monthly and covers 2007 to 2024. Fixed effects are listed in the table. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Transportation Costs

	PPI Deep Sea		Cass Rates	
	(1)	(2)	(3)	(4)
Rainfall Anomaly	0.0619*	0.0591*	0.0003	0.0003
	(0.03)	(0.03)	(0.00)	(0.00)
Rainfall Anomaly (m-1)		0.0049		0.0006**
		(0.03)		(0.00)
Rainfall Anomaly (m-2)		-0.0251		0.0001
		(0.03)		(0.00)
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	216	216	216	216
R^2	.957	.957	.969	.97

(b) Other Modes of Transportation

	Truck Tonnage		Internal Water	
	(1)	(2)	(3)	(4)
Rainfall Anomaly	0.0031	0.0032	-0.0005	-0.0006
	(0.00)	(0.00)	(0.00)	(0.00)
Rainfall Anomaly (m-1)		0.0022		0.0009
		(0.00)		(0.00)
Rainfall Anomaly (m-2)		0.0033		-0.0002
		(0.00)		(0.00)
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	216	216	216	216
R^2	.986	.986	.85	.85

Table 8: **Infrastructure Constraints, Operating Expenses, and Market Power**

Notes. This table shows OLS regressions of the log of firm operating expenses over revenues on drought in the Lake Gatun watershed. Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Columns (2) to (4) add interactions with three market power measures: NAICS4 HHI, the Herfindahl-Hirschman index of the firm's 4-digit NAICS industry, averaged over the firm's quarters, Top 5 Market Share, the combined market share of the five largest firms in the industry, averaged over the firm's quarters; and Firm Market Share, the firm's own market share in the quarter. The sample excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by quarter are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Expense Ratios and Constraint Exposure

	Ln(Op. Expenses/Revenues)		
	(1)	(2)	(3)
Rainfall Anomaly (q-2,q)	0.0004*	0.0004**	0.0003*
	(1.93)	(2.06)	(1.93)
Rainfall Anomaly (q-2,q) × % Value Imported	-0.0005		
	(-1.11)		
Rainfall Anomaly (q-2,q) × % Value Exported	0.0002		
	(0.56)		
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only		-0.0002	
		(-1.49)	
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only		0.0001	
		(0.40)	
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported		-0.0001	
		(-0.49)	
Rainfall Anomaly (q-2,q) × > P75 % Value Imported only			-0.0002
			(-1.21)
Rainfall Anomaly (q-2,q) × > P75 % Value Exported only			0.0001
			(0.66)
Rainfall Anomaly (q-2,q) × > P75 % Value Imported & Exported			-0.0002
			(-1.14)
Firm-Season FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes
Observations	89205	89205	89205
Firms	1937	1937	1937
R^2	.709	.709	.709

(b) Market Power and Concentration

	(1)	(2)	(3)	(4)
Rainfall Anomaly (q-2,q)	0.0005***	0.0007***	0.0007***	0.0006***
	(2.77)	(2.61)	(3.02)	(2.97)
Rainfall Anomaly (q-2,q) × NAICS4 HHI		-0.0009		
		(-1.27)		
Rainfall Anomaly (q-2,q) × Top 5 Market Share			-0.0005***	
			(-2.80)	
Rainfall Anomaly (q-2,q) × Firm Market Share				-0.0010**
				(-2.50)
Firm-Season FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Observations	156061	156061	156061	155338
Firms	5088	5088	5088	5052
R^2	.789	.789	.789	.788

Table 9: **Infrastructure Constraints and Earnings Call Discussions**

Notes. This table shows OLS regressions of earnings-call topic mentions on drought in the Lake Gatun watershed. The dependent variable is the mention rate per 1,000 words for the Panama Canal, drought, supply chains, and inventories. Panel (a) covers executives, Panel (b) analysts. Each topic has two columns: the first uses the contemporaneous anomaly, the second the anomaly accumulated over the current and two preceding months. Anomalies are inverted, so higher values mean drier conditions. Canal exposure is the share of shipment volume routed through the canal on AIS-confirmed routes. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by firm, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Executives

	Panama		Drought		Supply Chain		Inventory	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Anomaly	0.00000		0.00000		0.00020		-0.00004	
	(0.39)		(0.05)		(1.31)		(-0.17)	
Rainfall Anomaly × % Volume Imported	-0.00004		0.00013*		0.00119**		0.00086	
	(-1.04)		(1.73)		(2.35)		(1.08)	
Rainfall Anomaly × % Volume Exported	0.00001		-0.00003		0.00023		-0.00024	
	(1.31)		(-0.86)		(0.58)		(-0.43)	
Rainfall Anomaly (m, m-2)		0.00000		0.00003		0.00061***		-0.00018
		(0.12)		(1.07)		(3.57)		(-0.61)
Rainfall Anomaly (m, m-2) × % Volume Imported		-0.00001		0.00007		0.00036		0.00130
		(-0.45)		(0.96)		(0.61)		(1.20)
Rainfall Anomaly (m, m-2) × % Volume Exported		0.00000		0.00004		-0.00001		-0.00036
		(0.47)		(0.74)		(-0.03)		(-0.53)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56738	56738	56738	56738	56738	56738	56738	56738
Firms	1084	1084	1084	1084	1084	1084	1084	1084
R^2	.289	.289	.314	.314	.556	.556	.58	.58

(b) Analysts

	Panama		Drought		Supply Chain		Inventory	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Anomaly	0.00001		0.00000		0.00052**		0.00092**	
	(0.99)		(0.02)		(2.17)		(2.11)	
Rainfall Anomaly × % Volume Imported	-0.00005		0.00027**		0.00044		-0.00058	
	(-0.85)		(2.15)		(0.48)		(-0.37)	
Rainfall Anomaly × % Volume Exported	0.00000		-0.00001		0.00019		-0.00070	
	(0.12)		(-0.15)		(0.32)		(-0.64)	
Rainfall Anomaly (m, m-2)		0.00003*		0.00004		0.00102***		0.00085
		(1.85)		(1.00)		(3.36)		(1.45)
Rainfall Anomaly (m, m-2) × % Volume Imported		-0.00003		0.00043***		-0.00007		0.00057
		(-0.82)		(3.11)		(-0.07)		(0.26)
Rainfall Anomaly (m, m-2) × % Volume Exported		-0.00006***		-0.00005		0.00023		-0.00142
		(-2.64)		(-0.61)		(0.33)		(-1.14)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55541	55541	55541	55541	55541	55541	55541	55541
Firms	1077	1077	1077	1077	1077	1077	1077	1077
R^2	.156	.156	.21	.21	.326	.326	.374	.374

Table 10: **Infrastructure Constraints and Short Interest**

Notes. This table shows OLS regressions of short selling on drought in the Lake Gatun watershed. The dependent variable is the Markit short-selling score in Panel (a) and short interest as a percentage of float in Panel (b). Anomalies are inverted and higher values mean drier conditions. Canal exposure is the share of shipment value routed through the canal from estimated routes in columns (1) to (3) and AIS-confirmed routes within a 60-day window in (4) to (6). In each group, the first column uses the continuous measure, the next two indicators for exposure above the median and the 75th percentile. Fixed effects are listed in the table. t-statistics based on standard errors clustered by month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Markit Score

	Estimated Routes			Confirmed Routes		
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Anomaly	0.0001	0.0002	0.0002*	0.0002	0.0002	0.0003**
	(0.84)	(1.19)	(1.85)	(1.22)	(1.15)	(2.41)
Rainfall Anomaly × % Value Imported	0.0014***			0.0013***		
	(2.90)			(2.64)		
Rainfall Anomaly × % Value Exported	0.0001			-0.0004**		
	(0.39)			(-2.18)		
Rainfall Anomaly × > Median % Value Imported		0.0003***			0.0004***	
		(2.70)			(4.65)	
Rainfall Anomaly × > Median % Value Exported		-0.0003			-0.0002	
		(-1.36)			(-1.51)	
Rainfall Anomaly × > P75 % Value Imported			0.0005***			0.0004*
			(2.87)			(1.96)
Rainfall Anomaly × > P75 % Value Exported			-0.0000			-0.0002*
			(-0.25)			(-1.78)
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
Observations	179254	179254	179254	179328	179328	179328
Firms	1447	1447	1447	1438	1438	1438
R^2	.526	.526	.526	.525	.525	.525

(b) Short Interest as % of Float

	Estimated Routes			Confirmed Routes		
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Anomaly	-0.0004	-0.0005	0.0003	-0.0003	-0.0010	0.0004
	(-0.59)	(-0.48)	(0.50)	(-0.40)	(-1.23)	(0.67)
Rainfall Anomaly × % Value Imported	0.0060***			0.0062**		
	(3.30)			(2.51)		
Rainfall Anomaly × % Value Exported	0.0010			-0.0002		
	(1.15)			(-0.10)		
Rainfall Anomaly × > Median % Value Imported		0.0019*			0.0027***	
		(1.84)			(4.26)	
Rainfall Anomaly × > Median % Value Exported		0.0003			0.0018***	
		(0.29)			(2.75)	
Rainfall Anomaly × > P75 % Value Imported			0.0020***			0.0022*
			(3.26)			(1.90)
Rainfall Anomaly × > P75 % Value Exported			-0.0002			-0.0002
			(-0.28)			(-0.30)
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
Observations	179071	179071	179071	179970	179970	179970
Firms	1418	1418	1418	1420	1420	1420
R^2	.588	.588	.588	.587	.587	.587

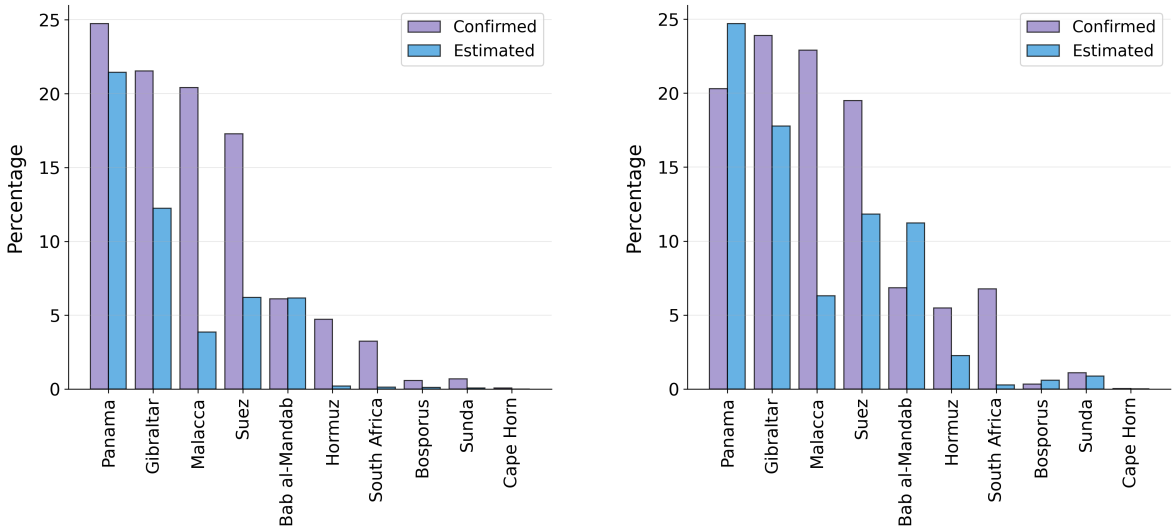
Table 11: **Infrastructure Constraints and Analyst Forecast Surprises**

Notes. This table shows OLS regressions of analyst forecast surprises on drought in the Lake Gatun watershed. Surprises are realized performance minus the mean consensus forecast, scaled by the firm's average total assets and expressed in percent, and cover revenues, pre-tax income, and earnings per share. The consensus is the one formed after the fiscal period ends. Anomalies are inverted, so higher values mean drier conditions. Drought is the rainfall anomaly accumulated over the three months of the fiscal quarter. Canal exposure is the share of shipment value routed through the canal on AIS-confirmed routes within a 60-day window. In each group of three columns, the first uses the continuous measure, the next two use indicators for exposure above the median and the 75th percentile on the import side only, the export side only, and both sides. Firms below the cut-off on both sides as the comparison group. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-month, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Mean SAL Surprise			Mean PRE Surprise			Mean EPS Surprise		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rainfall Anomaly (q)	-0.00186*	-0.00142	-0.00231**	-0.00031	-0.00055	-0.00052	-0.00000	0.00000	0.00000
	(-1.84)	(-1.45)	(-2.26)	(-0.44)	(-0.77)	(-0.79)	(-0.12)	(0.08)	(0.22)
Rainfall Anomaly (q) × % Value Imported	-0.00214			-0.00210**			-0.00002		
	(-1.49)			(-2.14)			(-0.54)		
Rainfall Anomaly (q) × % Value Exported	-0.00208*			0.00010			-0.00000		
	(-1.85)			(0.15)			(-0.13)		
Rainfall Anomaly (q) × > Median % Value Imported only		-0.00046			-0.00008			-0.00000	
		(-0.60)			(-0.17)			(-0.23)	
Rainfall Anomaly (q) × > Median % Value Exported only		-0.00213**			0.00026			-0.00002	
		(-2.03)			(0.39)			(-0.83)	
Rainfall Anomaly (q) × > Median % Value Imported & Exported		-0.00235**			-0.00048			-0.00001	
		(-2.48)			(-0.87)			(-1.08)	
Rainfall Anomaly (q) × > P75 % Value Imported only			-0.00120			-0.00097**			-0.00004**
			(-1.53)			(-2.44)			(-2.38)
Rainfall Anomaly (q) × > P75 % Value Exported only			-0.00039			0.00011			-0.00002*
			(-0.56)			(0.25)			(-1.81)
Rainfall Anomaly (q) × > P75 % Value Imported & Exported			-0.00058			-0.00048			0.00002
			(-0.60)			(-0.78)			(0.75)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64549	64549	64549	60742	60742	60742	65365	65365	65365
Firms	1640	1640	1640	1629	1629	1629	1619	1619	1619
R^2	.266	.266	.266	.286	.286	.286	.295	.295	.295

Appendix

Figure A.1: Economic Reliance on Trade Routes — Confirmed vs. Estimated Routing

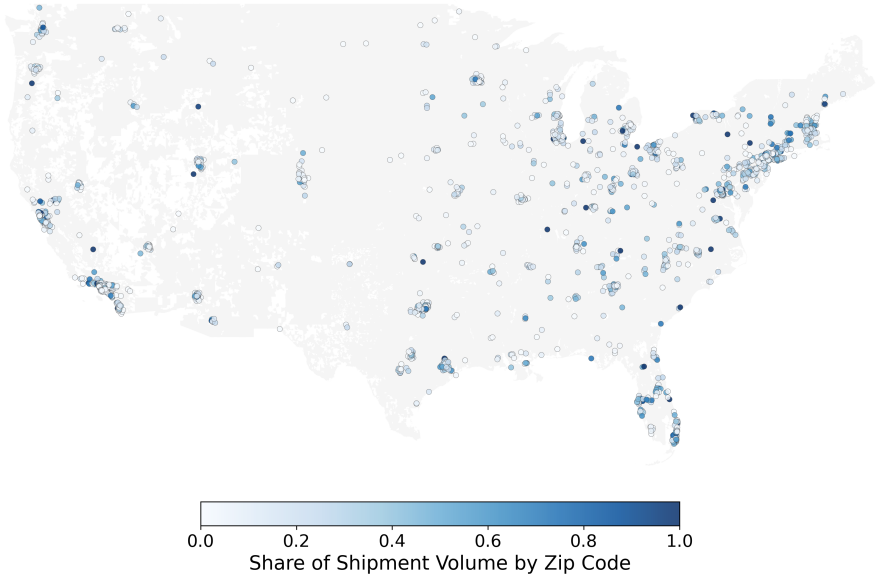


(a) Passages Traversed for Incoming Shipments

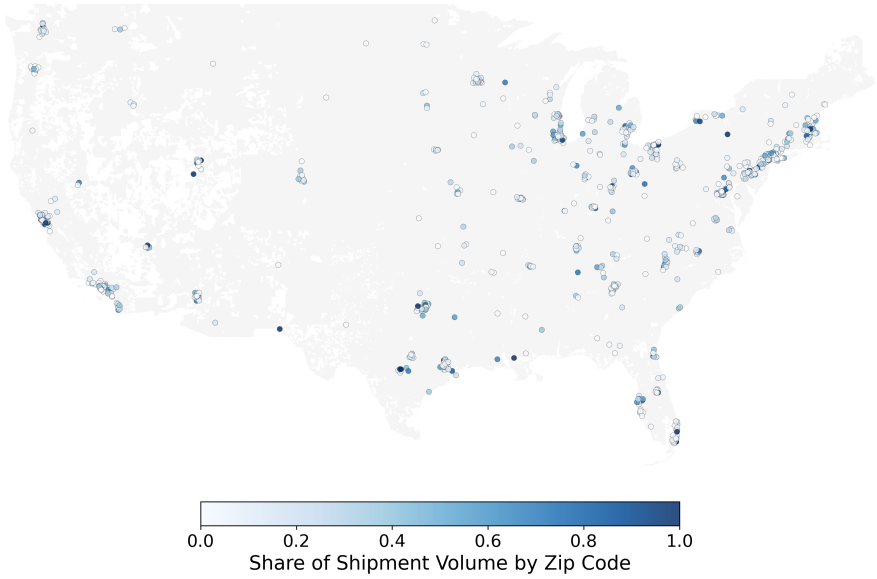
(b) Passages Traversed for Outgoing Shipments

Notes: This figure shows the share of shipment volume through each of ten major maritime routes under two routing definitions. Confirmed routing counts a shipment only if the carrying vessel is AIS-confirmed to have transited the passage before the date when the shipment is unloading and clears customs in the U.S. port. Estimated routing infers the passage from the S&P Panjiva ports of origin and destination, taking the most efficient route between them, estimated using the Python package searoute.py. Shares use volumes summed over 2012 to 2024. Figure (a) shows imports, Figure (b) exports.

Figure A.2: Geographic Distribution of Panama Canal Exposure by Firm Headquarters



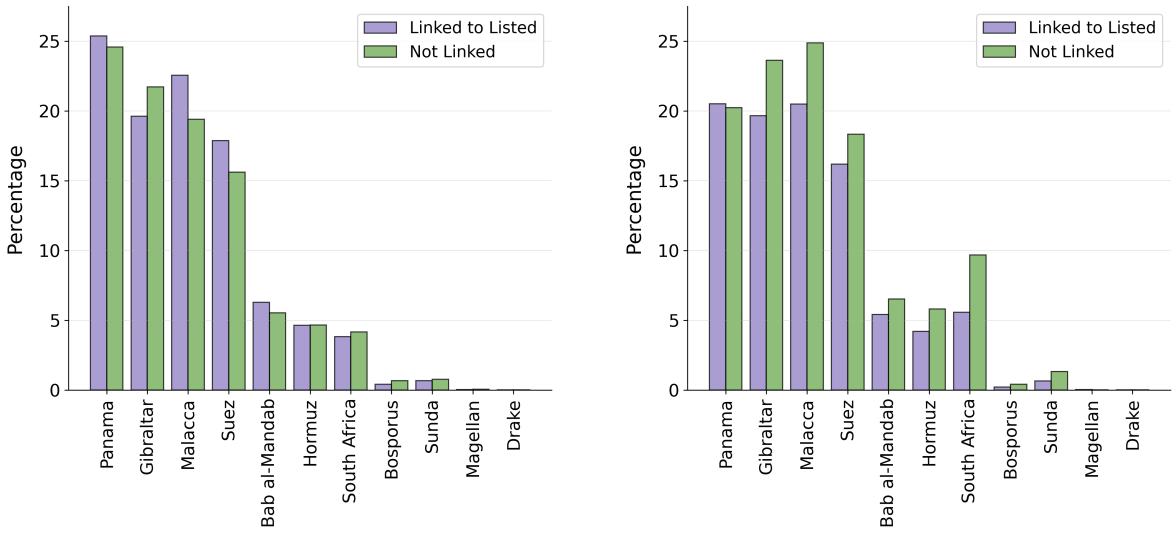
(a) Inbound Shipments



(b) Outbound Shipments

Notes: This figure shows the average Panama Canal share of shipment volume for listed firms, mapped by the zip code of the firm's headquarters. Each firm's Panama share is measured from confirmed routing within a 60-day window, then averaged equal-weighted within each HQ zip code. Because data on headquarters is sparse, zip-code centroids are plotted as markers colored by Panama share. Figure (a) shows imports, Figure (b) exports.

Figure A.3: Economic Reliance on Trade Routes by Listed Status

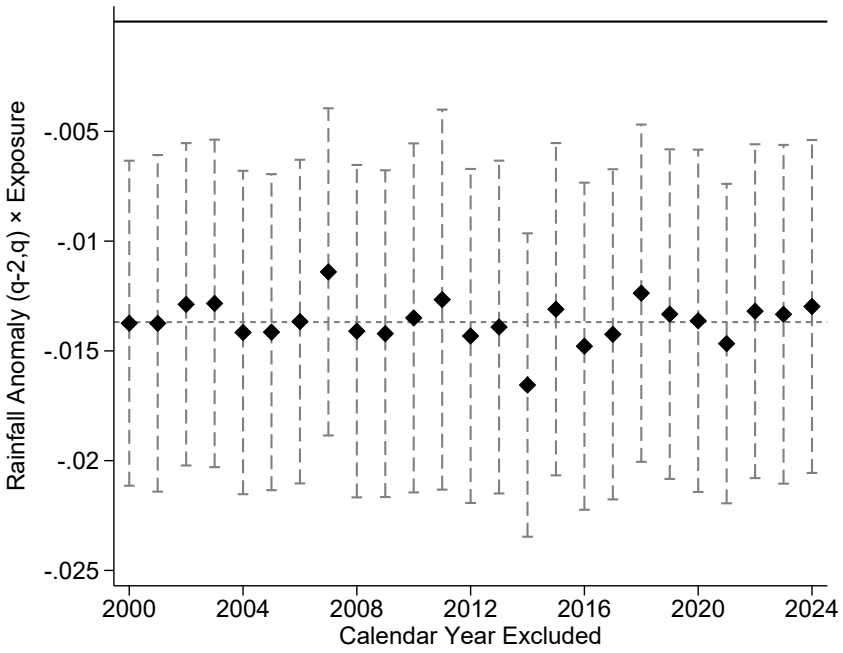


(a) Passages Traversed for Incoming Shipments

(b) Passages Traversed for Outgoing Shipments

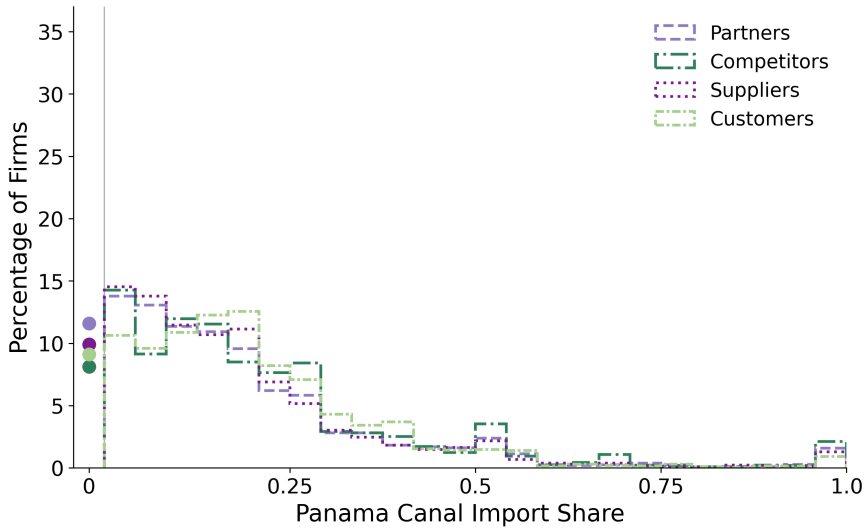
Notes: This figure shows the share of shipment volume through each of eleven maritime chokepoints, split by whether the shipper is linked to a publicly listed parent firm or not. Shipments are S&P Panjiva records and a shipment counts toward a passage only if the carrying vessel is AIS-confirmed to have transited that passage within a 60-day window prior to the arrival date of the shipment in a U.S. port. Shares are computed on volumes summed over 2012 to 2025 within each group, so each pair of bars is the share of that group's total shipment volume. Figure (a) shows imports, Figure (b) exports.

Figure A.4: Leave-One-Year-Out Stability of the Operating Income Coefficient

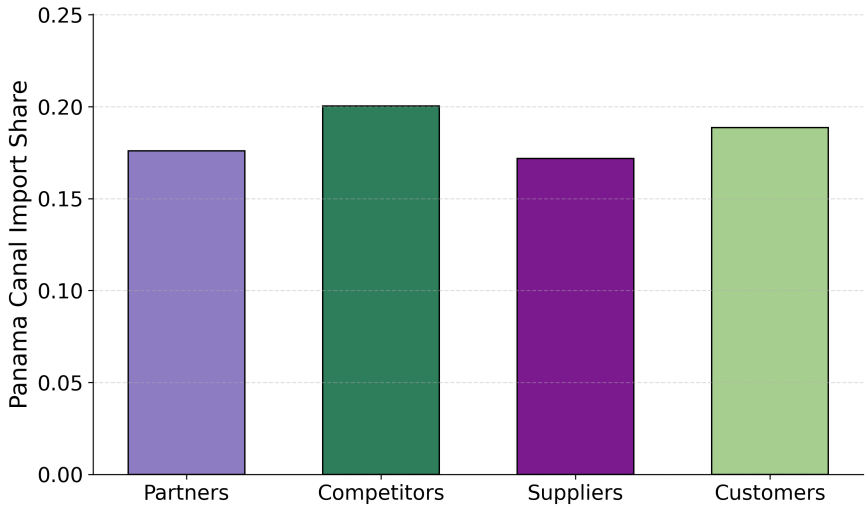


Notes: This figure shows the coefficient on the interaction between drought and canal exposure from the operating income specification in Table 6, re-estimated excluding one calendar year from 2000 to 2024. The dependent variable is operating income before depreciation and amortization over lagged assets in percent. Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the combined share of import and export shipment value, shrunk toward the average across firms with an empirical Bayes beta-binomial estimator, and entered as an indicator for above-mean exposure. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms, and includes all firms with shipment records. Each marker shows the estimate with the year on the horizontal axis excluded, and the bars show 95% confidence intervals based on standard errors clustered by year-quarter. The dashed horizontal line marks the full-sample estimate, and the solid line marks zero.

Figure A.5: Indirect Exposure Share by Firm



(a) Distribution of Exposures Across Linked Entities



(b) Mean Panama Import Share by Entity Type

Notes: This figure shows firms' indirect exposures through entities such as supply-chain partners, competitors, suppliers, and customers (FactSet Revere). The data is aggregated by obtaining a list of linked entities by firm, merging these firms with their import exposure shares (the share of import value AIS-confirmed to have transited the Panama Canal within a 60-day window) where available, and averaging by entity type at the level of the focal firm. Figure (a) shows the distribution as a percentage of firms. The dots on the left-hand side show the share of firms with precise zero exposures. Figure (b) shows the averaged import share by entity type.

Figure A.6: **Construction of the Tests on Earnings Surprises**

Notes: This figure shows the timeline behind the tests on forecast errors, which is built so that information on realized drought conditions is public before earnings are announced. *Drought* (t) measures rainfall anomalies over a quarterly fiscal period t, marked $Affected\ Fiscal\ Period\ (t)$ and drawn here as the shaded quarter from 30-Jun to 30-Sep. Earnings for that period are announced with a lag, at *Announcement* (t). In principle, analysts can make use of this lag to update their forecasts between the end of the fiscal period and the announcement date ($Window\ for\ Adjustment\ (a)$) even if drought conditions are realized in the very end of the quarter. If there are lagged effects by one quarter [two quarters], the window extends to the announcement of $t+1$ $[t+2]$, shown as $Window\ for\ Adjustment\ (b)$ $[(c)]$.

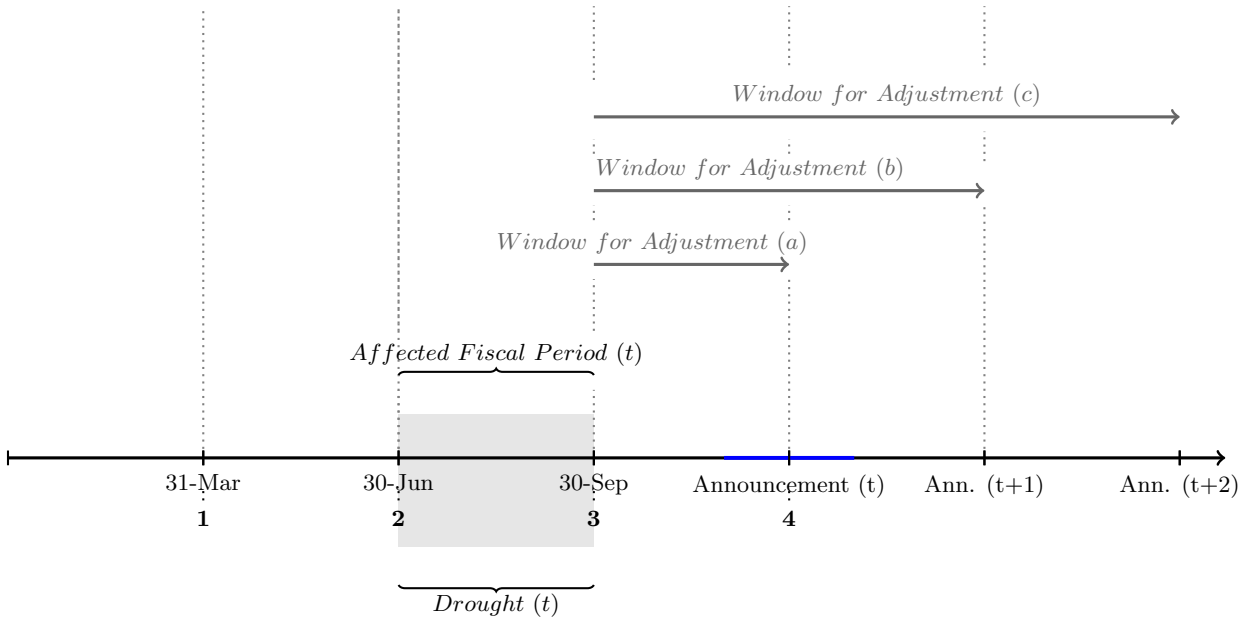


Table A.1: **Firm Characteristics and Chokepoint Exposure**

Notes. This table shows firm characteristics by canal exposure, the share of the value of a firm's shipments AIS-confirmed to have transited the canal within a 45-day window. The sample covers fiscal years 2000 to 2024 and keeps the firm-quarters in the estimation sample of the operating income regressions. Panel (a) splits firms by whether the raw exposure share is zero. Panel (b) keeps exposed firms and splits them at the mean of the exposure share shrunk with an empirical Bayes estimator. Within each panel, Panel A splits on import exposure, Panel B on export exposure, and Panel C on both. Financial measures are in million U.S. dollar and averaged within firm; exposure and age are firm-level maxima. Columns 5 and 6 report the difference in means, the low-exposure group minus the high-exposure group, and a Welch t-statistic allowing for unequal variances.

(a) Zero vs. Non-Zero Exposure

	N (Exp. = Zero)	Mean (Exp. = Zero)	N (Exp. > Zero)	Mean (Exp. > Zero)	Diff (0–1)	t-stat
Panel A: Imports						
Revenues	886	183.32	2,624	910.22	-726.90	-18.24
Assets	914	1,232.10	2,638	5,276.79	-4,044.69	-15.50
Operating Income/Assets	914	-0.08	2,637	-0.01	-0.07	-11.51
Operating Income/Assets (Alt)	831	-0.02	2,577	0.01	-0.03	-13.13
Revenues/Assets	885	23.87	2,621	28.56	-4.69	-6.35
Cash Holdings	912	112.46	2,627	356.95	-244.49	-12.25
Firm Age	914	22.02	2,638	30.35	-8.33	-14.52
% Value Imported	914	0.00	2,638	0.23	-0.23	-44.53
% Value Imported	914	0.08	2,638	0.20	-0.12	-29.54
% Value Exported	111	0.08	1,536	0.12	-0.04	-1.95
% Value Exported	914	0.01	2,638	0.07	-0.06	-19.62
Upstreamness	860	2.06	2,527	1.98	0.08	3.92
Market Share in NAICS4 Industry	875	0.03	2,608	0.09	-0.05	-11.10
HHI in NAICS 4 Industry	914	0.17	2,638	0.20	-0.03	-5.74
Panel B: Exports						
Revenues	2,619	418.34	891	1,633.25	-1,214.91	-13.77
Assets	2,657	2,645.87	895	8,956.69	-6,310.82	-10.79
Operating Income/Assets	2,657	-0.05	894	0.02	-0.07	-20.36
Operating Income/Assets (Alt)	2,517	-0.00	891	0.02	-0.03	-21.22
Revenues/Assets	2,615	26.15	891	30.97	-4.82	-6.62
Cash Holdings	2,654	198.38	885	580.52	-382.14	-10.46
Firm Age	2,657	25.65	895	35.80	-10.15	-15.38
% Value Imported	2,657	0.18	895	0.16	0.02	2.05
% Value Imported	2,657	0.17	895	0.16	0.01	1.89
% Value Exported	752	0.00	895	0.22	-0.22	-24.95
% Value Exported	2,657	0.02	895	0.18	-0.16	-26.64
Upstreamness	2,509	1.99	878	2.02	-0.02	-1.09
Market Share in NAICS4 Industry	2,595	0.05	888	0.14	-0.09	-12.55
HHI in NAICS 4 Industry	2,657	0.18	895	0.23	-0.05	-7.41
Panel C: Imports & Exports						
Revenues	2,649	416.93	861	1,679.89	-1,262.96	-13.93
Assets	2,687	2,645.12	865	9,177.89	-6,532.78	-10.86
Operating Income/Assets	2,687	-0.05	864	0.02	-0.07	-20.61
Operating Income/Assets (Alt)	2,547	-0.00	861	0.02	-0.03	-21.97
Revenues/Assets	2,645	26.14	861	31.17	-5.03	-6.81
Cash Holdings	2,683	197.56	856	596.03	-398.47	-10.62
Firm Age	2,687	25.64	865	36.18	-10.54	-15.81
% Value Imported	2,687	0.18	865	0.17	0.01	1.06
% Value Imported	2,687	0.17	865	0.17	0.01	1.09
% Value Exported	782	0.01	865	0.21	-0.20	-21.92
% Value Exported	2,687	0.02	865	0.18	-0.16	-25.56
Upstreamness	2,539	2.00	848	2.01	-0.01	-0.56
Market Share in NAICS4 Industry	2,624	0.05	859	0.14	-0.09	-12.64
HHI in NAICS 4 Industry	2,687	0.18	865	0.23	-0.05	-7.58

(b) Below vs. Above-Mean Exposure

	N (Exp. < Mean)	Mean (Exp. < Mean)	N (Exp. > Mean)	Mean (Exp. > Mean)	Diff (0–1)	t-stat
Panel A: Imports						
Revenues	1,514	1,001.74	1,110	785.39	216.35	2.98
Assets	1,520	5,651.93	1,118	4,766.75	885.18	1.83
Operating Income/Assets	1,520	-0.00	1,117	-0.03	0.03	5.21
Operating Income/Assets (Alt)	1,499	0.01	1,078	0.01	0.01	4.43
Revenues/Assets	1,512	29.73	1,109	26.97	2.75	3.67
Cash Holdings	1,514	387.43	1,113	315.49	71.93	2.33
Firm Age	1,520	30.88	1,118	29.63	1.25	1.85
% Value Imported	1,520	0.06	1,118	0.47	-0.41	-50.24
% Value Imported	1,520	0.07	1,118	0.39	-0.32	-60.24
% Value Exported	959	0.11	577	0.13	-0.02	-1.39
% Value Exported	1,520	0.08	1,118	0.07	0.01	1.51
Upstreamness	1,460	1.98	1,067	1.98	-0.00	-0.17
Market Share in NAICS4 Industry	1,508	0.09	1,100	0.08	0.01	1.96
HHI in NAICS 4 Industry	1,520	0.21	1,118	0.20	0.01	0.93
Panel B: Exports						
Revenues	479	1,674.07	412	1,585.79	88.28	0.51
Assets	481	8,675.36	414	9,283.55	-608.19	-0.53
Operating Income/Assets	481	0.02	413	0.02	0.01	2.33
Operating Income/Assets (Alt)	479	0.02	412	0.02	0.00	2.37
Revenues/Assets	479	31.96	412	29.83	2.13	1.72
Cash Holdings	478	626.12	407	526.96	99.16	1.44
Firm Age	481	36.65	414	34.81	1.84	1.57
% Value Imported	481	0.15	414	0.18	-0.03	-2.68
% Value Imported	481	0.15	414	0.18	-0.03	-3.10
% Value Exported	481	0.05	414	0.41	-0.36	-27.10
% Value Exported	481	0.05	414	0.33	-0.28	-32.69
Upstreamness	473	2.03	405	2.00	0.03	0.74
Market Share in NAICS4 Industry	477	0.14	411	0.14	0.00	0.08
HHI in NAICS 4 Industry	481	0.22	414	0.24	-0.01	-1.21
Panel C: Imports & Exports						
Revenues	695	1,696.98	166	1,608.35	88.63	0.40
Assets	698	8,948.58	167	10,136.37	-1,187.79	-0.70
Operating Income/Assets	698	0.02	166	0.02	0.01	1.38
Operating Income/Assets (Alt)	695	0.02	166	0.02	0.00	0.59
Revenues/Assets	695	31.48	166	29.88	1.60	1.02
Cash Holdings	692	600.31	164	577.96	22.35	0.25
Firm Age	698	36.13	167	36.37	-0.23	-0.15
% Value Imported	698	0.13	167	0.34	-0.21	-15.17
% Value Imported	698	0.12	167	0.34	-0.21	-15.74
% Value Exported	698	0.17	167	0.41	-0.24	-10.31
% Value Exported	698	0.15	167	0.32	-0.18	-12.03
Upstreamness	686	2.02	162	1.96	0.06	1.28
Market Share in NAICS4 Industry	693	0.14	166	0.14	0.00	0.03
HHI in NAICS 4 Industry	698	0.23	167	0.25	-0.02	-1.39

Table A.2: **Robustness – Alternative Measures of Water Scarcity: Vessel Draft and Size**

Notes. This table shows the specification in Table 2 re-estimated with a different measure of water scarcity in the Lake Gatun watershed in each column, in place of the baseline rainfall anomaly, and reports only the interaction with *Panama Canal*. The dependent variable is vessel draft in inches in Panel (a) and the log of gross registered tonnage in Panel (b), both estimated by OLS. Columns use, in order, the ERA5 rainfall anomaly, dry days (rainfall below the 10th percentile of the daily distribution), the CHIRPS anomaly, CHIRPS dry days, log potential evaporation, log ERA5 and CHIRPS precipitation, the standardized precipitation and precipitation-evaporation indices at three and nine months, the standardized runoff index at three months, the log water balance (precipitation less potential evaporation), and the minimum Lake Gatun level. Apart from the standardized indices, which are their native three- and nine-month versions, each measure is accumulated over the current and two preceding months. *Panama Canal* marks voyages AIS-confirmed to have transited the canal within a 45-day window. The sample covers container vessels entering and clearing U.S. ports between 2013 and 2022, pooled across directions. Anomalies are inverted, so higher values mean drier conditions. Fixed effects are listed in the table. Standard errors, clustered by year-month, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Vessel Draft

	Draft (Inches)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Containers, Entering and Clearing US Ports													
	Higher value = drier					Higher value = wetter								
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-3	SPI-9	SPEI-3	SPEI-9	SRI-3	LnBalnce	LakeLvl
Drought × Panama Canal	-0.0390*	-0.1800**	-0.0248*	-0.2118***	-3.1103	0.1646	0.4288	0.6357**	1.5188***	0.5804**	1.1353***	0.6977*	0.0413	0.8995***
	(0.02)	(0.08)	(0.01)	(0.06)	(2.35)	(0.60)	(0.52)	(0.28)	(0.32)	(0.22)	(0.32)	(0.39)	(0.47)	(0.14)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	347914	347914	347914	347914	347914	347914	347914	347914	347914	347914	347914	347914	278864	347914
R^2	.648	.648	.648	.648	.648	.648	.648	.648	.648	.648	.648	.648	.648	.648

(b) Vessel Size

	Ln(Gross Registered Tonnage)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Containers, Entering and Clearing US Ports													
	Higher value = drier					Higher value = wetter								
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-3	SPI-9	SPEI-3	SPEI-9	SRI-3	LnBalnce	LakeLvl
Drought × Panama Canal	-0.0011***	-0.0031**	-0.0007***	-0.0038***	-0.0586	0.0081	0.0111	0.0151***	0.0360***	0.0143***	0.0256***	0.0206***	0.0044	0.0146***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	351086	351086	351086	351086	351086	351086	351086	351086	351086	351086	351086	351086	281412	351086
R^2	.774	.774	.774	.774	.774	.774	.774	.774	.775	.774	.774	.774	.774	.774

Table A.3: **Robustness – Alternative Measures of Water Scarcity: Shipping Time**

Notes. This table shows the specification in Table 3 re-estimated with a different contemporaneous measure of water scarcity in the Lake Gatun watershed in each column. The dependent variable is days between the previous clearance from the same port and the current entrance in Panel (a) and days in the U.S. port between an entrance and the following clearance in Panel (b). Columns use the ERA5 rainfall anomaly, dry days, the CHIRPS anomaly, CHIRPS dry days, log potential evaporation, log ERA5 and CHIRPS precipitation, the standardized precipitation, precipitation-evaporation, the log water balance precipitation less potential evaporation, and the minimum Lake Gatun level, each measured in the month of the observation. *Panama Canal* marks voyages AIS-confirmed to have transited the canal within a 60-day window. The sample covers container vessels calling at U.S. ports between 2013 and 2022. Panel (a) also excludes gaps shorter than three days. Anomalies are inverted, so higher values mean drier conditions. Fixed effects are listed in the table. Standard errors clustered by year-month are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Time Between Port Entries

	Days Between Voyages											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Containers											
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-1	SPEI-1	SRI-1	LnBalnce	LakeLvl
Drought × Panama Canal	0.0331**	0.1882	0.0200	0.2943	-1.1635	0.1054	-0.0062	-0.9278*	-1.2755**	-1.6135***	0.0775	-0.5289
	(0.01)	(0.24)	(0.01)	(0.20)	(3.45)	(0.91)	(0.68)	(0.51)	(0.49)	(0.57)	(1.39)	(0.32)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	149949	149949	149949	149949	149949	149949	149949	149949	149949	149949	109714	149949
R^2	.107	.107	.107	.107	.107	.107	.107	.107	.107	.107	.107	.107

(b) Time in Ports

	Days in U.S. Port											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Containers											
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-1	SPEI-1	SRI-1	LnBalnce	LakeLvl
Drought × Panama Canal	0.0004	0.0106*	0.0000	0.0069	-0.1290	0.0490*	0.0345	-0.0246**	-0.0282**	-0.0369***	-0.0057	-0.0291***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.10)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Month x Passage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Route FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rig FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171307	171307	171307	171307	171307	171307	171307	171307	171307	171307	123433	171307
R^2	.334	.334	.334	.334	.334	.334	.334	.334	.334	.334	.349	.335

Table A.4: **Robustness – Alternative Measures of Water Scarcity: Inventories**

Notes. This table shows the inventory specification in Table 4 re-estimated with a different measure of water scarcity in the Lake Gatun watershed in each column. The dependent variable is inventories over lagged assets in percent. Columns use, in order, the ERA5 rainfall anomaly, dry days (rainfall below the 10th percentile of the daily distribution), the CHIRPS anomaly, CHIRPS dry days, log potential evaporation, log ERA5 and CHIRPS precipitation, the standardized precipitation, precipitation-evaporation and runoff indices at the nine-month scale, the log water balance (precipitation less potential evaporation), and the minimum Lake Gatun level. Apart from the standardized indices, which are their native nine-month versions, each measure is accumulated over the fiscal quarter and the two before it $(q-2, q)$, with the lake level taken as the minimum over this window. Higher values mean drier conditions in columns (1) to (5) and wetter conditions in columns (6) to (12). The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Inventories/Assets											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-9	SPEI-9	SRI-9	LnBalnce	LakeLvl
Drought Measure	-0.0016	-0.0044	-0.0060	-0.0048	-2.0290	0.1767	0.6303	0.0197	0.0232	0.0421	0.0328	0.0000
	(-0.28)	(-0.88)	(-1.42)	(-1.00)	(-1.22)	(0.31)	(1.46)	(0.38)	(0.46)	(0.84)	(0.11)	(0.00)
Drought × > Mean % Value Imported only	-0.0139***	-0.0155***	-0.0114***	-0.0143***	-5.9833***	1.4333***	1.1517***	0.1313***	0.1474***	0.1152***	0.8688***	0.0034
	(-4.13)	(-3.93)	(-4.87)	(-4.43)	(-5.54)	(4.14)	(4.94)	(4.16)	(4.88)	(3.33)	(4.56)	(1.36)
Drought × > Mean % Value Exported only	-0.0110**	-0.0085**	-0.0053*	-0.0030	-3.2809***	1.1253**	0.5061*	0.1056***	0.1076***	0.1164***	0.6155**	-0.0059***
	(-2.61)	(-2.17)	(-1.93)	(-0.95)	(-2.90)	(2.61)	(1.85)	(2.70)	(2.94)	(2.84)	(2.62)	(-5.36)
Drought × > Mean % Value Imported & Exported	-0.0160***	-0.0069	-0.0144***	-0.0131***	-4.9311***	1.6349***	1.4515***	0.1437***	0.1503***	0.1004*	0.9124***	0.0049***
	(-3.30)	(-1.41)	(-4.55)	(-3.34)	(-3.41)	(3.30)	(4.69)	(3.07)	(3.31)	(1.86)	(3.34)	(3.13)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	128068	128068	128068	128068	128068	128068	128068	128068	128068	128068	128068	128068
Firms	1948	1948	1948	1948	1948	1948	1948	1948	1948	1948	1948	1948
R^2	.841	.841	.841	.841	.841	.841	.841	.841	.841	.841	.841	.841

Table A.5: **Robustness – Pre-Period Exposure on Estimated Routes: Inventories**

Notes. This table shows the inventory specification in Table 4 re-estimated with canal exposure measured before most of the sample period. The dependent variable is inventories over lagged assets in columns (1) to (4), and the quarterly change in inventories in columns (5) to (8). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the share of shipment value whose shortest sea route between origin and destination port passes through the canal, measured over 2010 to 2012 and shrunk toward the average across firms with an empirical Bayes estimator. Within each group, the first column uses continuous canal exposure, and the remaining columns replace it with indicators for exposure above the mean, median, and 75th percentile. The sample excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Inventories/Assets				Change in Inventories			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Anomaly (q-2,q)	-0.0100	-0.0084	-0.0097	-0.0106*	-0.1354***	-0.1337***	-0.1057**	-0.1378***
	(-1.57)	(-1.34)	(-1.48)	(-1.72)	(-3.12)	(-3.09)	(-2.55)	(-3.23)
Rainfall Anomaly (q-2,q) × % Value Imported (2010-12/EB)	-0.0156**				0.0174			
	(-2.12)				(0.39)			
Rainfall Anomaly (q-2,q) × % Value Exported (2010-12/EB)	-0.0029				-0.2678***			
	(-0.42)				(-4.09)			
Rainfall Anomaly (q-2,q) × > Mean % Value Imported (2010-12/EB)		-0.0132***				0.0051		
		(-3.49)				(0.22)		
Rainfall Anomaly (q-2,q) × > Mean % Value Exported (2010-12/EB)		-0.0023				-0.1680***		
		(-0.69)				(-4.20)		
Rainfall Anomaly (q-2,q) × > Median % Value Imported (2010-12/EB)			-0.0105**				-0.0262	
			(-2.42)				(-1.12)	
Rainfall Anomaly (q-2,q) × > Median % Value Exported (2010-12/EB)			0.0065**				-0.1525***	
			(2.20)				(-4.76)	
Rainfall Anomaly (q-2,q) × > P75 % Value Imported (2010-12/EB)				-0.0072*				0.0187
				(-1.86)				(0.78)
Rainfall Anomaly (q-2,q) × > P75 % Value Exported (2010-12/EB)				-0.0021				-0.1638***
				(-0.62)				(-4.11)
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	75318	75318	75318	75318	71876	71876	71876	71876
Firms	1559	1559	1559	1559	1547	1547	1547	1547
R^2	.876	.876	.876	.876	.423	.423	.423	.423

Table A.6: **Robustness – Raw vs. Shrunk Exposure: Inventories**

Notes. This table shows the inventory specification in Table 4 estimated with raw and empirical Bayes measures of canal exposure. The dependent variable is inventories over lagged assets in columns (1) and (2), the quarterly change in inventories in columns (3) and (4), and the year-over-year log change in inventories in percent in columns (5) and (6). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the share of shipment value routed through the canal on AIS-confirmed routes. Odd columns use the raw share and require firms to have more than 50 shipments. Even columns shrink the share toward the average across firms with an empirical Bayes estimator and drop the shipment requirement. The sample covers fiscal years 2000 to 2024 and excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Inventories/Assets		Change in Inventories		Log Change in Inventories (YoY)	
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Anomaly (q-2,q)	-0.0021	0.0017	-0.0682*	-0.0491**	-0.1149**	-0.1075**
	(-0.37)	(0.43)	(-1.86)	(-2.06)	(-2.54)	(-2.58)
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only	-0.0125***		-0.0472**		-0.0287	
	(-3.73)		(-2.60)		(-1.38)	
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only	-0.0091**		-0.1708***		-0.0821***	
	(-2.28)		(-5.83)		(-3.30)	
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported	-0.0159***		-0.0373		-0.0493*	
	(-3.34)		(-1.37)		(-1.73)	
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only (EB)		-0.0125***		-0.0120		-0.0023
		(-4.60)		(-0.97)		(-0.09)
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only (EB)		-0.0196***		-0.1562***		-0.0731***
		(-4.83)		(-5.76)		(-2.90)
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported (EB)		-0.0179***		-0.0652**		-0.0397
		(-3.73)		(-2.31)		(-1.64)
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	128068	204731	127302	208307	117024	171403
Firms	1948	3553	1936	3531	1822	3022
R^2	.841	.836	.386	.387	.186	.179

Table A.7: **Robustness – Value, Volume, and Weight Exposure: Inventories**

Notes. This table shows the inventory specification in Table 4 re-estimated with canal exposure measured by shipment value, volume, and weight. The dependent variable is inventories over lagged assets in columns (1) to (3), the quarterly change in inventories in columns (4) to (6), and the year-over-year log change in inventories in percent in columns (7) to (9). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Within each group, canal exposure is the share of shipment value (US dollars), volume (TEU), or weight (tons) routed through the canal on AIS-confirmed routes within a 45-day window, shrunk toward the average across firms with an empirical Bayes estimator. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Inventories/Assets			Change in Inventories			Log Change in Inventories (YoY)		
	(1) Value	(2) Volume	(3) Weight	(4) Value	(5) Volume	(6) Weight	(7) Value	(8) Volume	(9) Weight
Rainfall Anomaly (q-2,q)	0.0017	-0.0024	-0.0001	-0.0491**	-0.0569**	-0.0478**	-0.1075**	-0.1174***	-0.0990**
	(0.43)	(-0.62)	(-0.02)	(-2.06)	(-2.47)	(-2.07)	(-2.58)	(-2.83)	(-2.40)
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only	-0.0125***			-0.0120			-0.0023		
	(-4.60)			(-0.97)			(-0.09)		
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only	-0.0196***			-0.1562***			-0.0731***		
	(-4.83)			(-5.76)			(-2.90)		
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported	-0.0179***			-0.0652**			-0.0397		
	(-3.73)			(-2.31)			(-1.64)		
Rainfall Anomaly (q-2,q) × > Mean % Volume Imported only		-0.0063**			0.0040			0.0004	
		(-2.62)			(0.37)			(0.02)	
Rainfall Anomaly (q-2,q) × > Mean % Volume Exported only		0.0018			-0.1207***			-0.0001	
		(0.51)			(-4.06)			(-0.00)	
Rainfall Anomaly (q-2,q) × > Mean % Volume Imported & Exported		-0.0087**			-0.0731**			-0.0013	
		(-2.08)			(-2.14)			(-0.04)	
Rainfall Anomaly (q-2,q) × > Mean % Weight Imported only			-0.0081***			-0.0130			-0.0265
			(-3.05)			(-1.16)			(-1.19)
Rainfall Anomaly (q-2,q) × > Mean % Weight Exported only			-0.0091**			-0.1557***			-0.0571**
			(-2.25)			(-4.78)			(-2.23)
Rainfall Anomaly (q-2,q) × > Mean % Weight Imported & Exported			-0.0214***			-0.0687**			-0.0659***
			(-5.28)			(-2.53)			(-2.70)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204731	203709	204830	208307	207307	208421	171403	170957	171531
Firms	3553	3526	3556	3531	3507	3535	3022	3009	3025
R^2	.836	.836	.836	.387	.386	.387	.179	.179	.179

Table A.8: **Robustness – Water Scarcity Net of El Niño: Inventories**

Notes. This table shows the inventory specification in Table 4 re-estimated with the rainfall anomaly orthogonalized to variation associated with the El Niño–Southern Oscillation (ENSO). The dependent variable is inventories over lagged assets in percent. Column (1) uses the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Columns (2) to (4) replace it with the residual from a regression of this anomaly on the Oceanic Niño Index (ONI): its average over $(q-2, q)$ in column (2), its values in each quarter from $q-2$ to q in column (3), and its values in each quarter from $q-4$ to q in column (4). Higher values mean drier conditions. The p-value tests whether the interaction coefficient equals the one in column (1), from a stacked regression with fixed effects interacted with the specification and standard errors clustered by year-quarter. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firm. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
Rainfall Anomaly (q-2,q)	-0.0010			
	(-0.24)			
Rainfall Anomaly (q-2,q) × > Mean % Value Imported/Exported	-0.0100***			
	(-3.79)			
Rainfall Anomaly, ENSO-adj. (avg. ONI q-2,q)		0.0024		
		(0.54)		
Rainfall Anomaly, ENSO-adj. (avg. ONI q-2,q) × > Mean % Value Imported/Exported		-0.0079**		
		(-2.20)		
Rainfall Anomaly, ENSO-adj. (ONI q-2,q)			0.0023	
			(0.53)	
Rainfall Anomaly, ENSO-adj. (ONI q-2,q) × > Mean % Value Imported/Exported			-0.0079**	
			(-2.19)	
Rainfall Anomaly, ENSO-adj. (ONI q-4,q)				0.0007
				(0.14)
Rainfall Anomaly, ENSO-adj. (ONI q-4,q) × > Mean % Value Imported/Exported				-0.0105***
				(-2.83)
Firm-Season FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
p-value vs. (1)		0.279	0.291	0.829
Observations	204796	204796	204796	204796
Firms	3554	3554	3554	3554
R^2	.836	.836	.836	.836

Table A.9: **Robustness – Alternative Measures of Water Scarcity: Firm Revenues**

Notes. This table shows the revenue specification in Table 5 re-estimated with a different measure of water scarcity in the Lake Gatun watershed in each column. The dependent variable is revenues over lagged assets in percent. Columns use, in order, the ERA5 rainfall anomaly, dry days (rainfall below the 10th percentile of the daily distribution), the CHIRPS anomaly, CHIRPS dry days, log potential evaporation, log ERA5 and CHIRPS precipitation, the standardized precipitation, precipitation-evaporation and runoff indices at the nine-month scale, the log water balance (precipitation less potential evaporation), and the minimum Lake Gatun level. Apart from the standardized indices, which are their native nine-month versions, each measure is accumulated over the fiscal quarter and the two before it $(q-2, q)$. Canal exposure is the share of shipment value routed through the canal. The sample excludes transportation, financial, real estate, and unclassified firms. Anomalies are inverted, so higher values mean drier conditions. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by fiscal quarter-end date, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Revenues / Assets											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-9	SPEI-9	SRI-9	LnBalnce	LakeLvl
Drought Measure	-0.0105	-0.0139*	-0.0010	-0.0174***	-6.0511**	1.2647	0.0773	0.1075	0.1183	0.1050	0.9123	0.1032*
	(-0.94)	(-1.67)	(-0.19)	(-3.00)	(-2.45)	(1.09)	(0.15)	(1.11)	(1.32)	(1.12)	(1.45)	(1.93)
Drought × > Mean % Value Imported	-0.0121*	-0.0097	-0.0099***	-0.0099**	-5.1163***	1.1001	0.9663***	0.0847	0.0933*	0.0597	0.6364*	0.0964***
	(-1.81)	(-1.53)	(-2.63)	(-2.12)	(-2.96)	(1.63)	(2.66)	(1.44)	(1.68)	(1.00)	(1.81)	(3.47)
Drought × > Mean % Value Exported	-0.0264**	-0.0127	-0.0120**	-0.0165**	-6.2134***	2.7760***	1.2355**	0.2668***	0.2248***	0.3410***	1.4076***	0.1147***
	(-2.55)	(-1.56)	(-2.13)	(-2.10)	(-2.89)	(2.71)	(2.20)	(3.08)	(2.77)	(3.88)	(2.66)	(2.97)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80757	80757	80757	80757	80757	80757	80757	80757	80757	80757	80757	80757
Firms	1985	1985	1985	1985	1985	1985	1985	1985	1985	1985	1985	1985
R^2	.798	.798	.798	.798	.798	.798	.798	.798	.798	.798	.798	.798

Table A.10: **Robustness – Alternative Measures of Water Scarcity: Firm Operating Income**

Notes. This table shows the operating-income specification in Table 6 re-estimated with a different measure of water scarcity in each column. The dependent variable is operating income before depreciation and amortization over lagged assets in percent. The measures are the ERA5 rainfall anomaly, dry days (rainfall below the 10th percentile of its daily distribution), the CHIRPS anomaly, CHIRPS dry days, log potential evaporation, log ERA5 and log CHIRPS precipitation, the standardized precipitation, precipitation-evaporation, and runoff indices at nine months, the log water balance (precipitation less potential evaporation), and the minimum level of Lake Gatun. Measures are accumulated over the fiscal quarter and the two before it $(q-2, q)$. The standardized indices are their native nine-month versions. The sample covers fiscal years 2011 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by fiscal quarter-end date, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Operating Income / Assets											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-9	SPEI-9	SRI-9	LnBalnce	LakeLvl
Drought Measure	0.0022	-0.0007	0.0037**	-0.0007	0.0328	-0.1751	-0.3497**	-0.0148	-0.0178	-0.0026	-0.0670	-0.0070
	(0.69)	(-0.23)	(2.28)	(-0.32)	(0.05)	(-0.54)	(-2.14)	(-0.54)	(-0.67)	(-0.08)	(-0.40)	(-0.44)
Drought × > Mean % Value Imported	-0.0155***	0.0012	-0.0086***	-0.0023	-2.3683*	1.5656***	0.8143***	0.1348***	0.1274***	0.1084***	0.8329***	0.0437**
	(-4.50)	(0.26)	(-3.39)	(-0.64)	(-1.91)	(4.32)	(3.15)	(3.89)	(3.83)	(2.73)	(4.26)	(2.21)
Drought × > Mean % Value Exported	-0.0205***	-0.0130***	-0.0152***	-0.0160***	-5.7484***	2.1141***	1.5054***	0.1843***	0.1758***	0.1777***	1.1780***	0.0917***
	(-5.95)	(-3.18)	(-7.43)	(-5.62)	(-6.82)	(6.12)	(7.57)	(5.84)	(5.81)	(4.73)	(6.40)	(4.27)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82140	82140	82140	82140	82140	82140	82140	82140	82140	82140	82140	82140
Firms	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003
R^2	.603	.603	.603	.603	.603	.603	.603	.603	.603	.603	.603	.603

Table A.11: **Robustness – Raw vs. Shrunk Exposure: Operating Income**

Notes. This table shows the operating income specification in Table 6 estimated with raw and empirical Bayes measures of canal exposure. The dependent variable is operating income before depreciation and amortization over lagged assets in percent in columns (1) and (2), the year-over-year log change in operating income in percent in columns (3) and (4), and operating income standardized by the firm's mean and standard deviation in columns (5) and (6). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the share of shipment value routed through the canal. Odd columns use the raw share and require firms to have more than 50 shipments. Even columns shrink the share toward the average across firms with an empirical Bayes estimator and drop the shipment requirement. The sample covers fiscal years 2000 to 2024 and excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Op. Income/Assets		Log Change in Op. Income (YoY)		Standardized Op. Income	
	(1) Raw	(2) EB	(3) Raw	(4) EB	(5) Raw	(6) EB
Rainfall Anomaly (q-2,q)	-0.0017	-0.0013	-0.0936	-0.1310**	-0.0019**	-0.0018***
	(-0.53)	(-0.34)	(-1.22)	(-2.14)	(-2.44)	(-2.76)
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only	-0.0077*		-0.0036		-0.0007	
	(-1.98)		(-0.08)		(-1.53)	
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only	-0.0086***		-0.1822***		-0.0030***	
	(-2.85)		(-3.59)		(-4.54)	
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported	-0.0177***		0.0734		0.0009	
	(-3.41)		(1.14)		(1.16)	
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only (EB)		-0.0145***		-0.0050		-0.0007**
		(-3.39)		(-0.12)		(-2.11)
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only (EB)		-0.0115***		-0.1276**		-0.0027***
		(-3.00)		(-2.40)		(-4.56)
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported (EB)		-0.0070		0.0811		0.0008
		(-1.64)		(1.51)		(1.26)
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	127675	202607	108266	154284	138093	223587
Firms	1957	3552	1823	2904	1973	3631
R^2	.546	.576	.13	.127	.38	.332

Table A.12: **Robustness – Value, Volume, and Weight Exposure: Operating Income**

Notes. This table shows the operating income specification in Table 6 re-estimated with canal exposure measured by shipment value, weight, and volume. The dependent variable is operating income before depreciation and amortization over lagged assets in columns (1) to (3), the year-over-year log change in operating income in columns (4) to (6), and operating income standardized by the firm's mean and standard deviation in columns (7) to (9). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Within each group, canal exposure is the share of shipment value (US dollars), weight (tons), or volume (TEU) routed through the canal on AIS-confirmed routes within a 45-day window, shrunk toward the average across firms with an empirical Bayes estimator. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Op. Income/Assets			Log Change in Op. Income (YoY)			Standardized Op. Income		
	(1) Value	(2) Weight	(3) Volume	(4) Value	(5) Weight	(6) Volume	(7) Value	(8) Weight	(9) Volume
Rainfall Anomaly (q-2,q)	-0.0013	-0.0012	-0.0020	-0.1310**	-0.1247**	-0.1367**	-0.0018***	-0.0020***	-0.0021***
	(-0.34)	(-0.32)	(-0.52)	(-2.14)	(-2.02)	(-2.24)	(-2.76)	(-3.03)	(-3.20)
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only	-0.0145***			-0.0050			-0.0007**		
	(-3.39)			(-0.12)			(-2.11)		
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only	-0.0115***			-0.1276**			-0.0027***		
	(-3.00)			(-2.40)			(-4.56)		
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported	-0.0070			0.0811			0.0008		
	(-1.64)			(1.51)			(1.26)		
Rainfall Anomaly (q-2,q) × > Mean % Weight Imported only		-0.0128***			-0.0086			-0.0003	
		(-2.92)			(-0.22)			(-0.89)	
Rainfall Anomaly (q-2,q) × > Mean % Weight Exported only		-0.0078**			-0.0828*			-0.0016***	
		(-2.11)			(-1.73)			(-3.07)	
Rainfall Anomaly (q-2,q) × > Mean % Weight Imported & Exported		-0.0077*			-0.0911			0.0002	
		(-1.93)			(-1.43)			(0.30)	
Rainfall Anomaly (q-2,q) × > Mean % Volume Imported only			-0.0098**			0.0182			-0.0002
			(-2.49)			(0.50)			(-0.50)
Rainfall Anomaly (q-2,q) × > Mean % Volume Exported only			0.0005			-0.0669			-0.0010
			(0.14)			(-1.18)			(-1.45)
Rainfall Anomaly (q-2,q) × > Mean % Volume Imported & Exported			-0.0191***			-0.0301			0.0000
			(-3.00)			(-0.50)			(0.05)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	202607	202694	201558	154284	154513	153787	223587	223710	222348
Firms	3552	3555	3524	2904	2907	2887	3631	3636	3604
R^2	.576	.578	.576	.127	.127	.127	.332	.332	.333

Table A.13: **Robustness – Pre-Period Exposure to Routes: Operating Income**

Notes. This table shows the operating income specification in Table 6 re-estimated with canal exposure measured before most of the sample period. The dependent variable is operating income before depreciation and amortization over lagged assets in percent in columns (1) to (3), the year-over-year log change in operating income in percent in columns (4) to (6), and operating income standardized by the firm's mean and standard deviation in columns (7) to (9). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the share of shipment value that passes through the canal measured over 2010 to 2012 and shrunk toward the average across firms with an empirical Bayes estimator. Within each group, the first column uses continuous canal exposure. The remaining columns replace it with indicators for exposure above the mean and the 75th percentile on the import side only, the export side only, and both sides. Firms below the cut-off on both sides are the comparison group. The sample covers fiscal years 2010 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Op. Income/Assets			Log Change in Op. Income (YoY)			Standardized Op. Income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rainfall Anomaly (q-2,q)	-0.0059**	-0.0050*	-0.0062**	-0.0528	-0.0507	-0.0551	-0.0021**	-0.0020**	-0.0021**
	(-2.14)	(-1.74)	(-2.21)	(-0.65)	(-0.61)	(-0.66)	(-2.66)	(-2.30)	(-2.51)
Rainfall Anomaly (q-2,q) × % Value Imported (2010-12/EB)	-0.0109			-0.0912			-0.0038***		
	(-1.57)			(-0.81)			(-4.14)		
Rainfall Anomaly (q-2,q) × % Value Exported (2010-12/EB)	0.0076*			-0.1407			0.0003		
	(1.84)			(-1.14)			(0.25)		
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only (2010-12/EB)		-0.0075**			-0.0248			-0.0024***	
		(-2.42)			(-0.37)			(-3.95)	
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only (2010-12/EB)		0.0004			-0.1127*			-0.0016**	
		(0.14)			(-1.71)			(-2.07)	
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported (2010-12/EB)		-0.0008			-0.2285**			0.0013	
		(-0.14)			(-2.20)			(0.95)	
Rainfall Anomaly (q-2,q) × > P75 % Value Imported only (2010-12/EB)			-0.0042			-0.0114			-0.0022***
			(-1.26)			(-0.15)			(-4.08)
Rainfall Anomaly (q-2,q) × > P75 % Value Exported only (2010-12/EB)			0.0022			-0.1008			-0.0009
			(0.88)			(-1.67)			(-1.23)
Rainfall Anomaly (q-2,q) × > P75 % Value Imported & Exported (2010-12/EB)			-0.0014			-0.2721**			0.0003
			(-0.23)			(-2.46)			(0.20)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76162	76162	76162	65693	65693	65693	77921	77921	77921
Firms	1572	1572	1572	1510	1510	1510	1577	1577	1577
R^2	.597	.597	.597	.138	.138	.138	.405	.405	.405

Table A.14: **Robustness – Water Scarcity Net of El Niño: Operating Income**

Notes. This table shows the operating income specification in Table 6 re-estimated with the rainfall anomaly orthogonalized to variation associated with the El Niño–Southern Oscillation (ENSO). The dependent variable is operating income before depreciation and amortization over lagged assets, in percent. Column (1) uses the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Columns (2) to (4) replace it with the residual from a regression of this anomaly on the Oceanic Niño Index (ONI): its average over the same time period as the rainfall anomaly $(q-2, q)$ in column (2), its values in each quarter from $q-2$ to q in column (3), and its values in each quarter from $q-4$ to q in column (4). Higher values mean drier conditions. Canal exposure is the combined share of import and export shipment value routed through the canal shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. The p-value tests whether the interaction coefficient equals the one in column (1), from a stacked regression with fixed effects interacted with the specification and standard errors clustered by year-quarter. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
Rainfall Anomaly (q-2,q)	-0.0014			
	(-0.38)			
Rainfall Anomaly (q-2,q) × > Mean % Value Imported/Exported	-0.0137***			
	(-3.68)			
Rainfall Anomaly, ENSO-adj. (avg. ONI q-2,q)		-0.0017		
		(-0.38)		
Rainfall Anomaly, ENSO-adj. (avg. ONI q-2,q) × > Mean % Value Imported/Exported		-0.0098*		
		(-1.96)		
Rainfall Anomaly, ENSO-adj. (ONI q-2,q)			-0.0020	
			(-0.49)	
Rainfall Anomaly, ENSO-adj. (ONI q-2,q) × > Mean % Value Imported/Exported			-0.0094*	
			(-1.93)	
Rainfall Anomaly, ENSO-adj. (ONI q-4,q)				-0.0009
				(-0.21)
Rainfall Anomaly, ENSO-adj. (ONI q-4,q) × > Mean % Value Imported/Exported				-0.0109**
				(-2.18)
Firm-Season FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
p-value vs. (1)		0.130	0.115	0.394
Observations	202662	202662	202662	202662
Firms	3553	3553	3553	3553
R^2	.578	.578	.578	.578

Table A.15: **Robustness – Alternative Standard Errors: Operating Income**

Notes. This table shows the operating income specification in Table 6 re-estimated with alternative clustering of standard errors. The dependent variable is operating income before depreciation and amortization over lagged assets in percent. Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the share of shipment value routed through the canal shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. Standard errors are clustered by firm in column (1), by two-digit NAICS industry in column (2), by firm and year-quarter in column (3), by industry and year-quarter in column (4), by firm and year in column (5), and by industry and year in column (6). The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Firm	NAICS2	Firm+Quarter	NAICS2+Quarter	Firm+Year	NAICS2+Year
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Anomaly (q-2,q)	-0.0013	-0.0013	-0.0013	-0.0013	-0.0013	-0.0013
	(-0.34)	(-0.90)	(-0.33)	(-0.60)	(-0.32)	(-0.57)
Rainfall Anomaly (q-2,q) × > Mean % Value Imported only	-0.0145**	-0.0145*	-0.0145**	-0.0145*	-0.0145*	-0.0145**
	(-2.00)	(-2.03)	(-2.02)	(-2.07)	(-2.03)	(-2.12)
Rainfall Anomaly (q-2,q) × > Mean % Value Exported only	-0.0115*	-0.0115***	-0.0115*	-0.0115***	-0.0115*	-0.0115***
	(-1.80)	(-4.17)	(-1.83)	(-5.22)	(-1.88)	(-4.71)
Rainfall Anomaly (q-2,q) × > Mean % Value Imported & Exported	-0.0070	-0.0070	-0.0070	-0.0070	-0.0070	-0.0070
	(-1.20)	(-1.38)	(-1.18)	(-1.39)	(-1.15)	(-1.35)
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	202607	202607	202607	202607	202607	202607
Firms	3552	3552	3552	3552	3552	3552
R^2	.576	.576	.576	.576	.576	.576

Table A.16: **Robustness – Timing of Water Scarcity: Operating Income**

Notes. This table shows the operating income specification in Table 6 re-estimated with drought measured in individual fiscal quarters. The dependent variable is operating income before depreciation and amortization over lagged assets in percent. Columns (1) and (4) use the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Columns (2) and (5) replace it with the rainfall anomaly in each fiscal quarter from $q-3$ to q and columns (3) and (6) add the rainfall anomaly in the following quarter $q+1$. Higher values mean drier conditions. Canal exposure is the combined share of import and export shipment value routed through the canal shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	% Exposure			Exposure > Mean		
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Anomaly (q,q+1)			0.0017			0.0018
			(1.35)			(1.46)
Rainfall Anomaly (q,q+1) × % Value Imported/Exported			-0.0050			
			(-0.88)			
Rainfall Anomaly (q,q+1) × > Mean % Value Imported/Exported						-0.0027
						(-1.39)
Rainfall Anomaly (q)		-0.0005	-0.0006		0.0001	0.0000
		(-0.41)	(-0.46)		(0.11)	(0.02)
Rainfall Anomaly (q) × % Value Imported/Exported		-0.0043	-0.0033			
		(-0.75)	(-0.58)			
Rainfall Anomaly (q) × > Mean % Value Imported/Exported					-0.0040**	-0.0034**
					(-2.40)	(-2.08)
Rainfall Anomaly (q-1)		-0.0014	-0.0014		-0.0020	-0.0019
		(-1.04)	(-0.95)		(-1.56)	(-1.47)
Rainfall Anomaly (q-1) × % Value Imported/Exported		-0.0105*	-0.0102*			
		(-1.82)	(-1.75)			
Rainfall Anomaly (q-1) × > Mean % Value Imported/Exported					-0.0034*	-0.0032*
					(-1.98)	(-1.86)
Rainfall Anomaly (q-2)		0.0004	0.0005		-0.0002	-0.0001
		(0.22)	(0.27)		(-0.12)	(-0.08)
Rainfall Anomaly (q-2) × % Value Imported/Exported		-0.0121**	-0.0119**			
		(-2.21)	(-2.12)			
Rainfall Anomaly (q-2) × > Mean % Value Imported/Exported					-0.0041**	-0.0040**
					(-2.59)	(-2.42)
Rainfall Anomaly (q-3)		-0.0004	-0.0002		-0.0007	-0.0005
		(-0.29)	(-0.16)		(-0.49)	(-0.34)
Rainfall Anomaly (q-3) × % Value Imported/Exported		-0.0069	-0.0071			
		(-1.12)	(-1.14)			
Rainfall Anomaly (q-3) × > Mean % Value Imported/Exported					-0.0027	-0.0028
					(-1.42)	(-1.50)
Rainfall Anomaly (q-2,q)	0.0004			-0.0012		
	(0.11)			(-0.35)		
Rainfall Anomaly (q-2,q) × % Value Imported/Exported	-0.0386***					
	(-3.15)					
Rainfall Anomaly (q-2,q) × > Mean % Value Imported/Exported				-0.0140***		
				(-3.79)		
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	202654	202654	202654	202654	202654	202654
Firms	3553		3553	3553		3553
R^2	.578	.578	.578	.578	.578	.578

Table A.17: **Robustness – Crisis Periods: Operating Income**

Notes. This table shows the operating income specification in Table 6 re-estimated without crisis periods. The dependent variable is operating income before depreciation and amortization over lagged assets, in percent. Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the combined share of import and export shipment value routed through the canal on AIS-confirmed routes, shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. Column (1) uses the full sample. Columns (2) to (5) drop quarters ending in calendar year 2020, in 2020 and 2021, in 2008 and 2009, and in the NBER definition of the recession from 2007Q4 to 2009Q2. Column (6) keeps only quarters ending from July 2016 onward, after the expanded locks of the canal opened in June 2016. The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms, and includes all firms with shipment records. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Baseline	Excl. 2020	Excl. 2020–21	Excl. 2008–09	Excl. 2007Q4–2009Q2	Post-Expansion
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Anomaly (q-2,q) × % Value Imported/Exported	-0.0379***	-0.0380***	-0.0407***	-0.0416***	-0.0383***	-0.0539**
	(-3.06)	(-2.86)	(-3.14)	(-3.29)	(-3.01)	(-2.10)
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	202662	193841	185000	186087	188318	75749
Firms	3553	3545	3531	3552	3553	3028
R^2	.578	.579	.585	.583	.582	.667

Table A.18: **Heterogeneity – Financial Characteristics: Operating Income**

Notes. This table shows the operating income specification in Table 6 with the interaction of drought and canal exposure split by firm financial characteristics. The dependent variable is operating income before depreciation and amortization over lagged assets in percent. Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the combined share of import and export shipment value routed through the canal shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. Characteristics are firm averages of log total assets, log market capitalization, and the SA, WW, and KZ indices of financial constraints, and an indicator for firms that never pay a dividend. Within each pair, the first column uses an indicator for firms above the median (High), and the second the standardized characteristic (z). The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms, and includes all firms with shipment records. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Assets		Market Cap.		SA Index		WW Index		KZ Index		Non-Payer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rainfall Anomaly (q-2,q) × % Value Imported/Exported	-0.0763***	-0.0418***	-0.0774***	-0.0416***	-0.0084	-0.0602**	-0.0062	-0.0395***	-0.0131	-0.0423***	0.0008	-0.0395***
	(-3.44)	(-3.06)	(-2.98)	(-3.07)	(-1.05)	(-2.58)	(-0.76)	(-2.92)	(-1.00)	(-3.29)	(0.13)	(-3.04)
High=1 × Rainfall Anomaly (q-2,q)	-0.0089		-0.0085		0.0235**		0.0082		0.0118*		0.0169***	
	(-1.37)		(-1.50)		(2.02)		(1.32)		(1.74)		(2.91)	
High=1 × Rainfall Anomaly (q-2,q) × % Value Imported/Exported	0.0713***		0.0690**		-0.0888***		-0.0626***		-0.0631**		-0.0892***	
	(3.13)		(2.61)		(-2.72)		(-2.77)		(-2.08)		(-3.35)	
Rainfall Anomaly (q-2,q) × Characteristic (z)		-0.0135**		-0.0112**		0.0248**		0.0109**		0.0007		0.0026
		(-2.01)		(-2.34)		(2.15)		(2.17)		(0.09)		(1.26)
Rainfall Anomaly (q-2,q) × % Value Imported/Exported × Characteristic (z)		0.0530**		0.0481***		-0.0720*		-0.0450**		-0.0103		-0.0241**
		(2.48)		(2.66)		(-1.84)		(-2.26)		(-0.44)		(-2.57)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	202662	202662	193965	193965	202662	202662	201272	201272	193071	193071	202662	202662
Firms	3553	3553	3434	3434	3553	3553	3493	3493	3375	3375	3553	3553
R^2	.578	.578	.577	.577	.578	.578	.571	.571	.569	.569	.578	.578

Table A.19: **Heterogeneity – Shipment Characteristics: Operating Income**

Notes. This table shows the operating income specification in Table 6 with the interaction of drought and canal exposure split by firm shipment characteristics. The dependent variable is operating income before depreciation and amortization over lagged assets in percent. Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the combined share of import and export shipment value routed through the canal shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. Characteristics are measured over the full sample: log shipment value per kilogram across all shipments and across canal shipments, the log number of shipments, and the shares of shipments on vessels that fit the original (Panamax) locks and on vessels that fit only the expanded (Neopanamax) locks. Within each pair, the first column uses an indicator for firms above the median (High), and the second the standardized characteristic (z). The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Value/kg		Panama Value/kg		Shipments		Panamax Share		Neopanamax Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall Anomaly (q-2,q) × % Value Imported/Exported	-0.0636***	-0.0399***	-0.0376*	-0.0233*	-0.0394*	-0.0385***	-0.0201	-0.0384***	-0.0611***	-0.0386***
	(-3.39)	(-3.15)	(-1.72)	(-1.67)	(-1.81)	(-2.97)	(-1.09)	(-3.15)	(-4.19)	(-3.16)
High=1 × Rainfall Anomaly (q-2,q)	-0.0069		-0.0060		-0.0075		0.0087*		-0.0098**	
	(-1.48)		(-1.35)		(-1.26)		(1.68)		(-2.08)	
High=1 × Rainfall Anomaly (q-2,q) × % Value Imported/Exported	0.0454**		0.0338		0.0016		-0.0363		0.0461**	
	(2.16)		(1.49)		(0.07)		(-1.53)		(2.34)	
Rainfall Anomaly (q-2,q) × Characteristic (z)		-0.0007		-0.0028		-0.0030		0.0034		-0.0030
		(-0.30)		(-1.38)		(-0.89)		(0.97)		(-0.98)
Rainfall Anomaly (q-2,q) × % Value Imported/Exported × Characteristic (z)		0.0192**		0.0202***		0.0016		-0.0141		0.0207
		(2.26)		(2.66)		(0.14)		(-0.91)		(1.43)
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	202267	202267	164052	164052	202662	202662	202644	202644	202644	202644
Firms	3545	3545	2667	2667	3553	3553	3552	3552	3552	3552
R^2	.578	.578	.569	.569	.578	.578	.578	.578	.578	.578

Table A.20: **Heterogeneity – Industries and Regions: Operating Income**

Notes. This table shows the operating income specification in Table 6 with the interaction of drought and canal exposure split by industry and headquarters region. The dependent variable is operating income before depreciation and amortization over lagged assets in percent. Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the combined share of import and export shipment value routed through the canal shrunk toward the average across firms with an empirical Bayes beta-binomial estimator. High indicates manufacturing (NAICS 31–33), wholesale (42), retail (44–45), and mining and utilities (21–22) in columns (1) to (4), and headquarters in the Census region or on the West Coast (California, Oregon, and Washington) in columns (5) to (9). The sample covers fiscal years 2000 to 2024, excludes transportation, financial, real estate, and unclassified firms, and includes all firms with shipment records. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Mfg.	Wholesale	Retail	Mining/Util.	Northeast	Midwest	South	West	West Coast
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rainfall Anomaly (q-2,q) × % Value Imported/Exported	-0.0073	-0.0390***	-0.0390***	-0.0469***	-0.0679***	-0.0405***	-0.0126	-0.0274**	-0.0318**
	(-0.55)	(-3.08)	(-2.98)	(-3.64)	(-4.74)	(-2.85)	(-0.79)	(-2.47)	(-2.51)
High=1 × Rainfall Anomaly (q-2,q)	0.0061	0.0033	-0.0076	-0.0031	-0.0061	0.0012	0.0016	0.0018	-0.0061
	(0.75)	(0.30)	(-0.94)	(-0.33)	(-0.81)	(0.23)	(0.23)	(0.20)	(-0.73)
High=1 × Rainfall Anomaly (q-2,q) × % Value Imported/Exported	-0.0654***	0.0629	0.0198	0.0556***	0.1118***	0.0236	-0.0726***	-0.0399	-0.0379
	(-3.05)	(1.36)	(0.63)	(2.95)	(4.65)	(1.00)	(-2.69)	(-1.57)	(-1.22)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	202662	202662	202662	202662	202662	202662	202662	202662	202662
Firms	3553	3553	3553	3553	3553	3553	3553	3553	3553
R^2	.578	.578	.578	.578	.578	.578	.578	.578	.578

Table A.21: **Robustness – Alternative Measures of Drought: Transportation Costs**

Notes. This table shows the transportation-cost specification in Table 7 re-estimated with a different measure of water scarcity in each column. The dependent variable is the FRED producer price index for deep sea freight transportation in the first panel and the Cass Freight Index of implied freight rates in the second, both in index levels. The measures are the ERA5 rainfall anomaly, dry days (rainfall below the 10th percentile of its daily distribution), the CHIRPS anomaly, CHIRPS dry days, log potential evaporation, log ERA5 and log CHIRPS precipitation, the standardized precipitation, precipitation-evaporation, and runoff indices at one month, the log water balance (precipitation less potential evaporation), and the minimum level of Lake Gatun. Each is contemporaneous and monthly. Signs should flip at the midpoint, where the headings switch from drier to wetter measures. Anomalies are inverted, so higher values mean drier conditions. The sample covers 2007 to 2024 at the monthly frequency. Fixed effects are listed in the table. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Producer Price Index, Deep Sea Freight

	PPI Deep Sea											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-1	SPEI-1	SRI-1	LnBalnce	LakeLvl
Drought Measure	0.0619*	0.7469*	0.0630**	0.6627*	29.8965**	-8.4995**	-5.7578**	-1.3934	-1.2997	-0.3693	-3.5887**	1.3750*
	(0.03)	(0.40)	(0.02)	(0.36)	(14.44)	(3.71)	(2.42)	(0.85)	(0.91)	(1.10)	(1.50)	(0.80)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	216	216	216	216	216	216	216	216	216	216	157	216
R^2	.957	.957	.957	.957	.957	.957	.957	.957	.956	.956	.979	.957

(b) Cass Freight Index

	Cass Rates											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-1	SPEI-1	SRI-1	LnBalnce	LakeLvl
Drought Measure	0.0003	0.0002	0.0002	0.0004	0.0424	-0.0428	-0.0230	-0.0114*	-0.0089	-0.0068	0.0092	0.0176***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	216	216	216	216	216	216	216	216	216	216	157	216
R^2	.969	.968	.969	.968	.968	.969	.969	.969	.969	.968	.979	.97

Table A.22: **Robustness – Alternative Measures of Water Scarcity: Firm Operating Expenses and Market Power**

Notes. This table shows the operating-expense specification in Table 8 re-estimated with a different measure of water scarcity in each column. The dependent variable is the natural logarithm of operating expenses over revenues. The measures are the ERA5 rainfall anomaly, dry days (rainfall below the 10th percentile of its daily distribution), the CHIRPS anomaly, CHIRPS dry days, log potential evaporation, log ERA5 and log CHIRPS precipitation, the standardized precipitation, precipitation-evaporation, and runoff indices at nine months, the log water balance (precipitation less potential evaporation), and the minimum level of Lake Gatun. Measures are accumulated over the fiscal quarter and the two before it $(q-2, q)$, and the standardized indices are their native nine-month versions. Each measure is interacted with the combined market share of the five largest firms in the firm's NAICS 4-digit industry, averaged at the firm level. The sample excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by fiscal quarter-end date, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Ln(Operating Expenses / Revenues)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-9	SPEI-9	SRI-9	LnBalnce	LakeLvl
Drought Measure	0.0007***	0.0001	0.0003**	0.0003	0.1184*	-0.0719***	-0.0259**	-0.0060***	-0.0058***	-0.0062***	-0.0392***	-0.0009
	(3.02)	(0.61)	(2.45)	(1.51)	(1.90)	(-3.03)	(-2.22)	(-2.89)	(-2.96)	(-2.81)	(-2.81)	(-0.70)
Drought × Top 5 Market Share	-0.0005***	-0.0001	-0.0003**	-0.0002	-0.1243**	0.0563***	0.0284**	0.0050***	0.0047***	0.0050**	0.0289***	0.0028***
	(-2.80)	(-0.58)	(-2.60)	(-1.38)	(-2.35)	(2.81)	(2.53)	(2.64)	(2.66)	(2.38)	(2.67)	(2.69)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	156061	156061	156061	156061	156061	156061	156061	156061	156061	156061	156061	156061
Firms	5088	5088	5088	5088	5088	5088	5088	5088	5088	5088	5088	5088
R^2	.789	.789	.789	.789	.789	.789	.789	.789	.789	.789	.789	.789

Table A.23: **Robustness – Exposed, Unexposed, and Unmatched Firms**

Notes. This table shows OLS regressions of firm revenues and operating income on drought, estimated separately by data availability and canal exposure. The dependent variable is revenues (operating income) standardized by the firm's mean and standard deviation in columns 1 to 3 (4 to 6). Drought is the rainfall anomaly accumulated over the fiscal quarter and the two before it $(q-2, q)$. Higher values mean drier conditions. Canal exposure is the combined share of import and export shipment value passes through the canal, measured over the full sample period in Panel A, over 2012 to 2014 in Panel B, and over the 36 months before the fiscal quarter in Panel C. Columns (1) and (4) cover only firms without exposure data, columns (2) and (5) firms with zero exposure, and columns (3) and (6) firms with positive exposure. The p-value is from a one-sided test that drought lowers the outcome more for firms with positive exposure than for firms with zero exposure, from a pooled regression with fixed effects interacted with the exposure indicator. The sample covers fiscal years 2000 to 2024 and excludes transportation, financial, real estate, and unclassified firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-quarter, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Standardized Revenues			Standardized Operating Income		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full-Period Exposure						
Rainfall Anomaly (q-2,q)	-0.0006	-0.0003	-0.0018***	-0.0015**	-0.0012*	-0.0025***
	(-0.68)	(-0.34)	(-2.97)	(-2.43)	(-1.76)	(-3.63)
p-value			0.001			0.024
Observations	181210	49250	193903	200944	50187	189535
Firms	7057	1077	2914	7698	1119	2937
Panel B: 2012–2014 Exposure						
Rainfall Anomaly (q-2,q)	-0.0008	-0.0010	-0.0019***	-0.0014**	-0.0022***	-0.0025***
	(-0.93)	(-1.35)	(-2.95)	(-2.38)	(-3.13)	(-3.51)
p-value			0.044			0.252
Observations	237419	56440	130536	257653	55731	127313
Firms	8523	843	1684	9207	856	1694
Panel C: Trailing Three-Year Exposure						
Rainfall Anomaly (q-2,q)	-0.0009	-0.0027***	-0.0022**	-0.0017***	-0.0027**	-0.0025**
	(-1.25)	(-2.83)	(-2.57)	(-3.23)	(-2.15)	(-2.53)
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
p-value			0.720			0.557
Observations	344294	6696	71683	361716	6488	70685
Firms	10708	472	1920	11396	461	1929

Table A.24: **Robustness – Alternative Measures of Water Scarcity: Short Interest**

Notes. This table shows the short-selling specification in Table 10 re-estimated with a different measure of water scarcity in each column. The dependent variable is the Markit short-selling score (a) and short interest as a percentage of float (b). Measures are the ERA5 rainfall anomaly, dry days (rainfall <10 pct of its daily distribution), the CHIRPS anomaly, CHIRPS dry days, log evaporation, log ERA5 and log CHIRPS precipitation, standardized precipitation, precipitation-evaporation, the log water balance as precipitation less evaporation, and the minimum level of Lake Gatun. Each is contemporaneous and monthly. The sample excludes ocean shipping firms and financial firms. Fixed effects are listed in the table. t-statistics, based on standard errors clustered by year-month, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Markit Score

	Markit Score											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-1	SPEI-1	SRI-1	LnBalnce	LakeLvl
Drought Measure	0.0002	0.0034**	0.0001	0.0007	0.0631	-0.0276*	-0.0084	-0.0071**	-0.0074**	-0.0015	0.0088	-0.0057*
	(1.15)	(2.10)	(0.82)	(0.43)	(1.07)	(-1.75)	(-0.90)	(-2.59)	(-2.30)	(-0.34)	(1.22)	(-1.66)
Drought × > Median Value (Imp)	0.0004***	0.0020	0.0003***	0.0031***	0.1283***	-0.0449***	-0.0295***	-0.0088***	-0.0091***	-0.0141***	-0.0075	-0.0080***
	(4.65)	(1.53)	(4.24)	(3.11)	(2.81)	(-4.34)	(-4.32)	(-3.63)	(-3.34)	(-4.51)	(-1.06)	(-5.13)
Drought × > Median Value (Exp)	-0.0002	0.0003	-0.0002*	0.0008	-0.0312	0.0266	0.0148	0.0051	0.0045	0.0021	0.0002	-0.0024
	(-1.51)	(0.14)	(-1.82)	(0.44)	(-0.46)	(1.63)	(1.62)	(1.34)	(1.01)	(0.43)	(0.02)	(-0.86)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	179328	179328	179328	179328	179328	179328	179328	179328	179328	179328	129856	179328
Firms	1438	1438	1438	1438	1438	1438	1438	1438	1438	1438	1434	1438
R^2	.525	.525	.525	.525	.525	.525	.525	.525	.525	.525	.531	.525

(b) Short Interest as % of Float

	% of Float Shorted											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Higher value = drier					Higher value = wetter						
	Anomaly	DryDays	C-Anomly	C-DryDay	LnPotEv	LnPrecip	C-LnPrec	SPI-1	SPEI-1	SRI-1	LnBalnce	LakeLvl
Drought Measure	-0.0010	0.0123	-0.0013**	-0.0054	-0.3827	0.0618	0.1242**	-0.0089	-0.0101	0.0465*	0.0676	-0.0075
	(-1.23)	(1.35)	(-2.41)	(-0.81)	(-1.05)	(0.65)	(2.25)	(-0.47)	(-0.47)	(1.67)	(1.53)	(-0.54)
Drought × > Median Value (Imp)	0.0027***	0.0067	0.0022***	0.0191***	0.9953***	-0.2708***	-0.2054***	-0.0345*	-0.0382*	-0.0827***	-0.0835	-0.0802***
	(4.26)	(0.67)	(3.95)	(2.80)	(2.83)	(-3.06)	(-3.68)	(-1.70)	(-1.68)	(-2.87)	(-1.63)	(-7.48)
Drought × > Median Value (Exp)	0.0018***	0.0149*	0.0014**	0.0207***	0.9450***	-0.2236***	-0.1801***	-0.0305*	-0.0345*	-0.0855***	-0.0854*	-0.0769***
	(2.75)	(1.68)	(2.49)	(2.70)	(2.85)	(-2.63)	(-3.32)	(-1.70)	(-1.75)	(-3.48)	(-1.81)	(-6.35)
Firm-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Profitability-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	179970	179970	179970	179970	179970	179970	179970	179970	179970	179970	130314	179970
Firms	1420	1420	1420	1420	1420	1420	1420	1420	1420	1420	1420	1420
R^2	.587	.587	.587	.587	.587	.587	.587	.587	.587	.587	.592	.587