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Climate shock impacts on supply chains: the case of the truckload spot market

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ABSTRACT

Climate shocks increasingly disrupt supply chains, yet research has focused primarily on mitigation strategies (i.e., carbon reduction), leaving adaptation strategies comparatively understudied. We begin to fill this gap by studying how transportation managers within a supply chain respond to climate-related shocks, defined as a month in which a state's exposure to extreme temperature or precipitation events rises significantly, measured by the custom University of Tennessee Climate Index (UTCI), which combines anomalies in high/low temperature and heavy precipitation with population exposure. Drawing on structured interviews with transportation managers, we uncover beliefs that shippers tend to be less demand-responsive in the short-term to climate-related shocks, often prioritizing the desire to move freight at any reasonable cost. Motor carriers, in contrast, are more sensitive to price. To test these qualitative assessments, we regress monthly state-level truckload spot market data from the contiguous 48 states on the UTCI in reduced-form two-way fixed effects specifications, finding that a one-standard-deviation increase in climate shocks increases freight prices by 1.9%, with minimal effects on freight volume, indicating that market adjustments occur primarily through price rather than quantity. We further estimate IV specifications based on three-stage least squares (3SLS) models to disentangle the net causal effects from the reduced form specification. Consistent with our interviews, we find motor carriers are more sensitive than shippers to climate shocks. The results have important implications, offering shippers, carriers, and brokers with concrete price-change benchmarks they can use to budget transportation spend, design contract–spot portfolios, and plan capacity during climate shocks.

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1. Introduction

Freight transportation managers regularly observe that extreme weather causes sudden, short-term spikes in truckload spot prices, but it is not well understood why these spikes occur or whether they reflect changes in demand, supply, or both. Winter storms, heat waves, and heavy rain routinely disrupt capacity, alter lane balances, and increase operating costs—but the magnitude and mechanism of price adjustment in the truckload spot market remain empirically underexplored. Despite a rapidly growing literature on climate risk, most supply chain work focuses on long-run mitigation or network redesign rather than the near-term economic consequences of climate shocks for freight markets.

Climate shocks, as defined here, are considered to be a month in which a state's exposure to extreme temperature or precipitation events rises significantly. This is measured by the University of Tennessee Climate Index (UTCI), which combines anomalies, unusually hot/cold days and/or heavy-rain days relative to 2001–2020 norms, with population exposure. Climate shocks impact the freight market by increasing demand uncertainty, constraining carrier capacity, reducing asset productivity, and elevating operational risk (Brusset & Bertrand, 2018; Cao et al., 2024; Pankratz & Schiller, 2024). For transportation managers, who must choose between securing scarce spot capacity at elevated prices or delaying shipments, the key puzzle is how these shocks translate into observed spot-price dynamics.

Climate shocks are especially visible in the area of distribution. For example, Winter Storm Uri of 2021 led to frozen roads, halting freight transportation in the area (McEntire 2021). More broadly, heavy precipitation increases accident frequency and congestion (Koetse and Rietveld 2009, Andrey et al. 2003, Doll et al 2014, Pregnolato et al., 2017) as well as route disruptions, detours, and delays (Fournier Gabela and Sarmiento 2020, Dalziell and Nicholson 2001, Ding and Wu 2023). Heat stress, fog, and wind also increase the probability of traffic accidents (Stern and Zehavi 1990, Edwards, 1996, Hermans et al., 2006). Since freight transportation depends on consistent and on-time deliveries, these disruptions increase transport costs and echo downstream.

Transport managers face the challenging task of responding and adapting to climate shocks. These involve trade-offs, such as increasing reserve capacity, purchasing one-off capacity through spot markets, or absorbing the costs of climate-related delays. Decision support for these adaptation choices remains thin compared with the extensive literature on mitigation and carbon accounting (e.g., Ellram and Tate, 2025). Although existing research shows that freight spot markets provide resilience, flexibility, and additional capacity (Pellegrino et al 2021), there is limited evidence on how effectively these markets adapt to climate shocks. Our contribution is to quantify the financial impact of climate shocks on freight spot prices, translating risk into concrete, managerial cost benchmarks.

Most empirical studies focus on specific weather events. For example, Hurricane Harvey negatively impacted the distance and time traveled for outbound freight (Gard and Famofo-Idowu, 2019). Tropical Storm Imelda reduced freight lane accessibility as well as daily freight tender volumes (Bilginsoy 2021). Hurricane Sandy substantially impacted the route choice for freight transportation in the Port of New York and New Jersey (Fialkoff et al. 2017). Hurricane landfalls are also linked to increases in long-haul, dry van trucking spot rates inbound to the affected state, but the increase is only significant in "tight" spot market conditions (Acocella et al. 2020, Kulpa 2024, Rana et al. 2025). By contrast to these studies, our paper examines the cost impact of extreme temperature and precipitation, providing a broader view of how climate variability translates into price dynamics.

To ground the study in practice, we first conducted interviews with 9 major freight carriers, shippers, and brokers to understand how climate shocks impact spot prices. Practitioners reported that shippers were willing to move freight at any cost during shocks, while motor carriers demonstrated greater price sensitivity. To test these narratives, we assembled a unique climate dataset constructed by our team's climatologist from the ECMWF ERA5 reanalysis and merged it with state-level, monthly outbound truckload spot price and quantity data for the contiguous United States from 2016 to 2021. This strategy used reduced-form two-way fixed effects models, controlling for macroeconomic and highway conditions.

We find that climate shocks increase freight prices by 1.9% without a significant effect on market volume, which is consistent with industry accounts that adjustments occur primarily through price rather than quantity. Additional econometric specifications using an explicit supply–demand system explain the observed market dynamics, reinforcing the conclusion that motor carriers are significantly more impacted than shippers, also consistent with industry interviews.

The remainder of the paper is structured as follows: we review the relevant literature on freight pricing models, present the narrative evidence from industry interviews, state our hypotheses, and then detail our empirical model and findings. We close by discussing the implications of our results, highlighting how the price benchmarks we estimate can support expectation management and resilience planning during climate shocks.

From a supply chain economics perspective, our study connects to work on freight pricing and capacity allocation in truckload markets, where spot prices transmit short-run scarcity and contract markets provide stability (Masten, 2009; Scott, 2015, 2018, 2019; Miller, Scott, & Williams, 2021; Li et al., 2022). However, this literature has largely examined endogenous fluctuations in demand, input costs, or regulatory regimes rather than exogenous climate shocks. From a climate adaptation standpoint, our work complements research on supply chain resilience and climate risk management (Christopher & Peck, 2004; Tukamuhabwa et al., 2015; Ghadge et al., 2020; Pankratz & Schiller, 2024) by treating the truckload spot market as a specific operational adaptation mechanism. In contrast to studies that focus on long-run network redesign or mitigation (e.g., Ellram & Tate, 2025), we quantify how short-run climate shocks are absorbed through prices versus quantities in a decentralized transportation market. In doing so, we position spot pricing as a key lever in firms' climate adaptation strategies within logistics.

Research question: How do defined climate shocks (UTCI spikes) affect state-level truckload spot prices and volumes?**Results:** Prices rise by 1.9%; volumes are statistically unchanged on average, with evidence pointing to inelastic shipper demand and price-responsive carrier supply.

2. Freight spot markets: literature review

2.1. Freight price behavior

The freight market includes the contract and spot markets, the former of which provides network stability by securing long-term transportation agreements (Masten, 2009), and the latter which offers higher linehaul rates for shippers in urgent need of capacity (Scott, Parker, and Craighead, 2017). Freight spot pricing may be higher for carriers with limited price knowledge or facing challenges in obtaining outbound loads, both of which impose dynamic transactions costs (Li et al., 2022). Both shippers and carriers take these factors, as well as potential costs, into account when deciding to secure capacity through the spot market.

Within the transportation market, spot prices represent real-time signals about the availability of transport capacity. During disruptions, spot markets reflect existing demand–supply movements (Lindsey and Mahmassani, 2017). In this way, the spot market represents a mechanism for achieving resilience through potential price adjustment.

In the context of freight transportation, spot prices adjust based on real-time market conditions, which include the availability of transport capacity and other factors, such as route characteristics, distance, and truck type requirements (Lindsey et al., 2013). The freight transportation spot price can be categorized as a state-dependent adjustment that is renegotiated with each transaction (Scott 2015, 2018). When there are exogenous shocks, the freight spot market may demonstrate either rising spot prices due to shrinking supply or expanding demand or decreasing spot prices due to expanding supply or shrinking demand (Miller et al 2021). Outbound backhauls, fluctuating fuel costs, and changes in asset productivity magnify these price adjustments, creating a process that is more pronounced during periods of disruption. Since price adjustment behavior under disruption in the freight spot market is understudied, it is unclear ex ante whether spot prices will rise or fall in the face of an exogenous shock.

2.2. Freight pricing models

There are several economic models of freight pricing, which are depicted at the microeconomic level. For example, Shah and Brueckner (2012) model price and frequency competition among freight carriers, where freight carriers maximize profit by setting prices, frequencies, and vehicle carrying capacities. Lin and Lee (2018) model an individual carrier's hub under cost minimization and profit maximization motives and Lindsey and Mahmassani (2017) employ a cost minimization model for third-party brokers operating in the spot market. Brokers identify carriers who will accept the lowest price for each shipment bundle. The objective is to minimize the cost across bundles and carriers. Finally, Papadopoulos et al. (2021) model Pareto-improving pricing schemes within a general transportation network. The authors use a microeconomic model to define the expected total monetary cost of truck drivers in the network.

Our research extends the freight pricing literature by empirically examining how climate disruptions influence pricing mechanisms in the spot market, where short-term price fluctuations reflect rapid adjustments to supply constraints rather than strategic pricing competition. Predictable demand with low variability is highly desirable in this industry to maintain profitability (Scott et al., 2017; Miller and Muir, 2020). Conversations with carriers, shippers, and brokers reveal that climate shocks disrupt predictable demand patterns on affected lanes and can increase empty miles. As a result, carriers may reject potentially high-cost contractual loads, forcing shippers to turn to the spot market (Kulpa 2024; Rana and Caplice, 2019). In other words, shippers tend to be less demand-responsive in the short term to climate-related shocks, being willing to move freight at any reasonable cost. Motor carriers, in contrast, are more sensitive to price. We incorporate these factors into our model.

Our evidence complements transportation economics on spot-market price formation and capacity allocation, where prices indicate near-term scarcity (Masten, 2009; Lindsey & Mahmassani, 2017; Scott, 2015, 2018, 2019; Miller, Scott, & Williams, 2021) by showing that defined climate shocks are resolved via price rather than quantity adjustment. It also extends supply-chain resilience/adaptation research (Christopher & Peck, 2004; Tukamuhabwa et al., 2015; Ghadge et al., 2020) by quantifying a repeatable, state-month cost effect and reconciling it with practitioner narratives about carrier rejection behavior and empty-mile risk. The literature hence indicates that near-term adaptation in trucking is mediated by the spot market's pricing function, with quantity adjustments muted on average while localized surges occur in the immediate aftermath of events.

2.3. Narrative evidence

As noted, price adjustment behavior under disruption in the freight spot market is understudied, therefore it is unclear ex ante whether spot prices will rise or fall in the face of an exogenous shock. To bridge this theoretical gap, the team adopted a narrative approach to describing the decision making of real-world actors (Leonard, 2018). A narrative is a sense-making story about some economically relevant topic that is shared by members of a group and suggests certain patterns of actions (Roos and Reccius, 2024). By exploring narratives, researchers can better understand the relevant factors, perceived causal linkages, and sequencing of decisions that underlie actors' decisions. In this way, narratives provide an understanding of actors' informal theories for action. The team interviewed senior transportation executives from nine companies, representing shippers, carriers, and brokers. Interviews enabled the team to appropriately assign factors to specify supply and demand, while avoiding confounding effects (Ramey, 2011). Interviews also enabled the team to understand the impact of climate shocks on freight spot price adjustments from the perspective of managers, adding context to the interpretation of statistical results.

Narrative data was collected using semi-structured interviews (Casell, 2015). Semi-structured interviews combine structured questions with opportunities for deeper discussion, allowing respondents to express detailed thoughts beyond the interview guide. This method suits data collection when researchers lack clear theoretical knowledge and are seeking understanding from practitioner insights. The research team used these interviews to capture diverse perspectives from shippers, carriers, and brokers. Additional details about the interview methodology, including the interview guide, respondent demographic data, and trustworthiness checks, are presented in the appendix. Over the course of interview data collection, the responses of market participants converged on the narrative presented below.

2.3.1. Before the event

Interviews showed that, prior to the event, spot market prices remain stable or trend down. Firms in the transportation market can typically anticipate when and where a climate shock will occur, and are therefore usually able to prepare. Shippers' and carriers' ability to prepare for an event shapes their decision making, which in turn shapes spot market prices. Prior to an event, carriers are primarily concerned with maintaining driver safety and protecting operating equipment. As a result, capacity in the anticipated area of impact typically contracts. Inbound shipments are slowed or halted while outbound shipments are accelerated. The capacity that otherwise would have been deployed in the anticipated area of impact becomes available in the broader transportation network. This increase in available network capacity may have a moderating effect on spot market prices. In other words, localized supply–demand imbalances may not impact overall market pricing signals prior to an event.

Key factors during this pre-event phase include the location and scope of the impending disruption. First, the downward effect on overall market prices tends to be more pronounced when an event is anticipated to impact a major shipping lane (e.g., New York-Philadelphia). This is because trucks that regularly move along major shipping lanes tend to be more easily redeployed elsewhere. When an event is anticipated to impact a minor shipping lane, trucks are more often underutilized rather than redeployed. Second, the scope of the expected weather event may influence how much displaced capacity becomes available elsewhere prior to the event. Geographically larger events tend to displace more capacity, smaller events tend to displace less capacity. Third, shippers may seek to position inventory in areas adjacent to the anticipated area of impact, to speed inbound deliveries after the event. This action may result in increased volume in adjacent areas, though not necessarily increased spot prices. Finally, shipper decisions can be sector specific. Construction and emergency relief supplies sometimes represent inbound traffic prior to the event, although volumes tend to be low. Consumer products, food and beverages, and medical supplies represent a significant portion of pre-positioning in adjacent areas.

Importantly, the expectation of a climate shock typically does not pull capacity into the spot market, either dedicated or new. That is, available spot capacity, rather than total spot capacity, shifts prior to an event as a redistribution of existing capacity. Overall, the picture that emerges in discussions with transportation executives is that total network demand remains relatively constant, while supply-side shifts in available, rather than total, capacity drive any observed spot market price changes.

2.3.2. During and immediately following the event: Supply-demand imbalances (excess demand) intensify in the area of impact

During an event, shipments are slowed or halted in the area of impact. At the same time, the need for shipments, particularly of inbound goods, builds. The result is an imbalance of transportation supply and demand, with excess demand in impacted areas. The imbalance increases with the intensity and duration of the climate shock.

An important driver of these imbalances is the involvement of FEMA, which may require transportation services for disaster relief. FEMA typically obtains transportation services from pre-approved private sector carriers through the FEMA Tender of Service Program (FEMA STOS Program). Carriers that apply to participate in the FEMA STOS Program can be called on to provide capacity. FEMA's entry into the market can significantly impact spot prices. In addition to absorbing capacity, FEMA contracts may entail unpredictable schedules and long wait times at loading sites. As a result, carrier capacity contracted by FEMA is effectively kept out of the spot market for an indeterminate amount of time. Interviewees suggested FEMA involvement extends the timeframe for resolving supply–demand imbalances after an event.

Overall, cost pressures begin to build during an event. The gap between supply and demand, exacerbated by FEMA's entry into the market, builds upward pressure on spot market prices. In addition, weather related disruptions constrain fuel, warehousing, and other infrastructure. In sum, during an event, the stage is set for a spike in spot market prices as soon as shipments into the impacted area are able to resume.

2.3.3. After the event

After the event, spot market prices spike with the swift return of shipments. After a severe weather event, the area of impact sees a swift return of shipping activity. It might be expected that capacity displaced prior to the event would simply absorb this uptick in activity, without much effect on spot market prices. Even so, a number of factors contribute to generating a spike in spot market prices immediately after an event.

On the demand side, shippers prioritize customer commitments over cost. One executive described shipper attitudes after an event as "whatever it takes to meet our obligations." Pressure from shippers to immediately resolve supply–demand imbalances built up during the event gives carriers upward pricing flexibility. That is, carriers can increase prices to quickly draw in needed capacity.

On the supply side, several operational challenges combine to increase prices immediately after an event. First, shipments are overwhelmingly inbound, with impacted businesses requiring little outbound movement. Shippers must therefore increase prices to compensate highly savvy, price-sensitive carriers for the lack of outbound backhauls. Second, fuel costs in the area of impact tend to be elevated, leading to higher shipping costs. Third, asset productivity declines. Impact on infrastructure increases drive times and roadway incidents. Damaged and/or understaffed receiving facilities increase dwell times. Communication disruptions increase co-ordination costs. In sum, asset turnover decreases and costs increase. Finally, FEMA may absorb capacity that would otherwise enter the spot market, constraining supply.

Overall, the picture that emerges after an event is one in which shippers adopt a “whatever it takes” attitude toward meeting demand, putting pressure on carriers to draw capacity into a constrained environment quickly. These conditions reinforce a “price surge” phenomenon within the spot market that persists until network capacity and demand normalize. This spike typically occurs 24 h after an event, as businesses assess their operations and begin making orders. The magnitude of the post-event spike tends to be larger when the severe weather impacts a major shipping lane. Rising prices in a major shipping lane can also provide cover for price hikes in smaller lanes, creating a broader network effect. Supply-demand imbalances typically resolve after 1 to 2 weeks, with prices settling back to a more normal level.

Narrative data aligns generally with assertions based on freight price adjustment literature that rising spot prices signal shrinking supply or expanding demand (Miller et al 2021). Still, these general predictions do not capture the factors driving price adjustments before, during, and after climate shocks. Narrative evidence suggests that generally, localized, rather than market-wide, supply–demand imbalances drive price adjustments. Thus, increased prices do not necessarily signal total network supply or demand conditions, but rather the aggregated impact of changes in the distribution of supply or demand across disruption areas. Further investigation that incorporates data on weather events and pricing onto geographies is required to explore this topic.

3. Hypotheses development

Climate shocks impose supply-side constraints that ripple through freight markets, leading to price and quantity adjustments. Based on conclusions from freight price adjustment literature (Section 2) and evidence from past disruptions (Section 2.3), we expect that climate shocks will impact market outcomes in two major ways.

Hypothesis 1. (*Climate shocks increase spot prices.*) *Transportation professionals are highly aware of the responsiveness of spot market prices to capacity constraints. Supply chain climate disruptions usually lead to price increases as shippers focus on delivery continuity, absorbing higher costs to secure capacity. This price insensitivity among shippers, along with carrier limitations, results in upward price adjustments that serve to rebalance supply and demand.*

Hypothesis 2. (*Climate shocks have ambiguous effects on spot volumes ex ante; empirically, average effects are near zero.*) *In addition to price changes, shifts in freight volume represent another market reaction. Depending on how the disruption plays out, freight quantities may either contract due to limited carrier availability (supply shock) or expand as demand surges post-event for restocking and emergency shipments. There is theoretical potential for movement in either direction, requiring empirical measurement.*

4. Model development

To test these qualitative assessments, we build a unique, custom state-level climate index, quantifying a state’s exposure to climate shocks. We regress monthly state-level truckload spot market data from the contiguous 48 states on the climate index in reduced form two-way fixed effects specifications. We also estimate instrumental variables specifications based on three-stage least squares (3SLS) models to disentangle the net causal effects from the reduced form specification.

4.1. Data sources

In order to understand the effect of climate shocks on the over-the road freight market, we examine lane-level truckload (TL) dry-van spot market data from DAT Freight & Analytics. Prices are for specific lanes, where lane origin and destination are aggregated to the state-level from 2016 to 2021. Arbitrage of loads and capacity between the spot and contract markets, as well as between different modes (Kulpa 2024), ensure the truckload spot market prices are representative of freight markets as a whole. As a measure of quantity, we use the number of dry-van truckload shipments along each lane during a given month, also obtained from DAT Freight & Analytics. We also derive average destination variables on price and quantities based on the weighted average prices of outbound loads, and the average destination freight flows (outbound-inbound). These are important variables to control for how a particular lane fits in the wider network of freight flows. For example, a lane that terminated in a backhaul markets (where inbound loads are greater than outbound loads) should expect to pay higher freight prices because of these network imbalances.

Our key explanatory variable of interest, o_climate (d_climate), is an index of climate related events at the origin (destination) state. The University of Tennessee Climate Index (UTCI) is a dataset developed by researchers at the authors’ institution (Ferrada and Fu 2023) to assess the impact of climate shocks on populations. The index incorporates four meteorological variables—daily maximum and minimum temperatures, hourly and daily precipitation, and snow accumulation—derived from high-resolution ERA5 reanalysis data (Hersbach et al., 2020) using downscaling methods detailed in Ashfaq et al. (2022), Rastogi et al. (2022), and Rastogi et al. (2023). The UTCI spans 2000–2022 and is benchmarked against a 20-year climatological baseline (2001–2020) representing average climate conditions. To account for exposure, the UTCI integrates gridded global population data from NASA’s SEDAC (2020), producing a monthly and yearly index at a spatial resolution of $0.25^\circ \times 0.25^\circ$.

Climate shocks are identified as days when temperatures or precipitation significantly deviate from the 20-year climatological baseline (2001–2020). A very hot day is one in which the daily maximum temperature exceeds 35 °C and is at least 5 °C above its local climatological value; a very cold day is one in which the daily minimum temperature is below –8°C and at least 10 °C below climatology. These dual (absolute + anomaly) conditions prevent normal seasonal heat in already hot regions from being classified as extreme and avoid counting mild winter anomalies that do not meaningfully stress infrastructure, energy systems, or economic activity. For precipitation, the UTCI follows World Meteorological Organization guidelines for heavy rain, defining extreme events as days with maximum hourly precipitation above 25 mm/hr or daily totals above 96 mm.

During the construction of the UTCI, multiple alternative heat, cold, and precipitation thresholds were tested, including variants based solely on absolute cutoffs and variants based solely on deviations from climatology. Many of these alternatives produced unrealistic temporal and spatial patterns—for example, labeling nearly all summer days in hot states as "extreme" or flagging modest winter anomalies as disruptive events. The final thresholds were selected because they produced spatial and temporal patterns of extreme events that align with known major weather episodes, FEMA disaster declarations, and documented operational impacts. In this study, we aggregate the UTCI to the state level for the continental U.S., focusing on areas affected by climate shocks, using its monthly temporal resolution (and yearly aggregations where appropriate). For additional details on the UTCI methodology, please refer to the appendix/supplemental materials.

We validated the UTCI by comparing state-level peaks in the index with known extreme weather events. The index effectively captures climate shocks, including hurricanes, and is particularly sensitive to rare and anomalous meteorological events such as winter storms and heat waves. For example, when Hurricane Harvey made landfall in late August 2017, Texas's climate index measured 0.06. However, in May 2018, two severe storms that caused over one billion dollars in damage struck the state and the index rose to 0.19. By comparison, Texas's average UTCI value over the sample period is 0.02. These UTCI spikes correspond closely with observed disruptions in the freight market and FEMA disaster declarations (McEntire 2021), demonstrating the index's real-world relevance. Furthermore, the UTCI and its components align with best practices in climatological methodology (Jin et al., 2024). As climate change continues to drive increasingly extreme and irregular weather events, this index offers a valuable tool for assessing climate-related disruptions.

4.2. Control variables

In modeling the effects of climate events, it is useful to separate our control variables into demand controls (variables which affect a shipper's desire to move freight) and supply controls (variables which affect a motor carrier's ability to move freight). As demand controls, we use origin and destination state-level gross domestic product and population to control for income and market size. We also use the average lane distance to control for the cost of shipper's inventory in transit, on the assumption that longer routes take more time. We use origin manufacturing, and agricultural sector output, and destination retail and construction sector output to control for demand flows from particularly freight-intensive economic sectors. To control for supply conditions for motor carriers, we use transportation sector output at the origin, and average state-level retail diesel prices. Because spot-rates reflect "all in" transportation prices (i.e., there are no explicit fuel surcharges), diesel prices appear as a line item costs for motor carriers, therefore acting as a supply shifter.[1] We also control for supply network variables including destination lane balance, and destination average outbound spot price. Finally, motor carriers are biased in favor of routes that return drivers home (Yang 2024). To control for this, we use the number of heavy-truck registrations at the destination.

In most cases we log transform variables so that regression estimates can be interpreted as elasticities. The exceptions are destination lane balance (which may be negative) and −o_climate which may be 0. Variable names, descriptions, reporting frequencies, sources and summary statistics are reported in Table 1 Fig 1 provides a map of cross-sectional average spot prices and climate. Climate events are concentrated in California, and the northern Midwest and plains area, while the highest average spot prices occur in California, the Midwest and Mid-Atlantic States.

4.3. Reduced-form specification

This study employs a reduced-form econometric model to assess the impact of climate shocks on freight spot market prices and volumes. Specifically, we estimate a two-way fixed-effects regression model, controlling for state and time fixed effects to capture unobserved heterogeneity across states and time periods.

The general form is as follows:

$$Y_{ijt} = \boldsymbol{X}_{ijt}\beta + \delta Climate_{ijt} + \gamma_i + \varphi_j + \tau_t + \epsilon_{ijt}, \tag{1}$$

Where:

- Y_{ijt} is the dependent variable (alternatively spot price or quantity), from origin i to destination j at time t.
- $\boldsymbol{X}_{ijt}$ is a $1 \times k$ vector of control variables,
- $\boldsymbol{\beta}$ is a $k \times 1$ vector of coefficients to be estimated,
- γ_i, φ_j are state-specific fixed effects at the origin and destination, respectively,
- τ_t are time fixed effects, and
- δ is the conditional covariance weighted average causal effect of climate events on the truckload spot market.

[1] Of course diesel prices also affect the demand for transportation services through the price of transportation services. Prior research has shown that fuel costs may be passed through with an additional markup (Balthrop et al. 2025).

Table 1
Summary statistics and variable descriptions.

Variable	Description	Source	Freq	Mean	Std. Dev.	Min	Max
l_spot	ln(avg. spot price ($/mi.))	DAT	M	0.567	0.302	−0.413	1.467
l_q	ln(dry-van truckld. moves)	DAT	M	5.179	1.265	2.079	9.477
o_climate	climate event index	U Tenn	M	0.019	0.043	0.000	0.515
Dry-van Truckload Demand Controls							
l_gdp_o	ln(state GDP at orig,)	BEA	Q	12.741	0.921	10.235	14.890
l_pop_o	ln(pop. at orig,)	BEA	Q	15.635	0.848	13.262	17.493
l_gdp_d	ln(state GDP at dest.)	BEA	Q	12.702	0.927	10.235	14.890
l_pop_d	ln(pop. at dest.)	BEA	Q	15.591	0.866	13.262	17.493
l_miles	ln(avg. route distance)	DAT	M	6.963	0.475	6.312	8.077
l_ag_o	ln(agricultural GDP at orig,)	BEA	Q	8.305	0.992	4.943	11.080
l_man_o	ln(manuf. GDP at orig,)	BEA	Q	10.620	0.983	7.728	12.916
l_con_d	ln(construction GDP at dest.)	BEA	Q	9.367	0.927	6.568	11.486
l_ret_d	ln(retail GDP at dest.)	BEA	Q	9.919	0.888	7.509	12.002
Dry-van Truckload Supply Controls							
l_fuel	ln(diesel price at orig,)	OPIS	M	0.927	0.157	0.057	1.347
d_balance	outbd.-inbd. moves at dest.	DAT	M	101	6774	−25640	36,389
l_dest_p	ln(avg. spot price at dest.)	DAT	M	1.056	0.241	0.154	2.190
l_trac_d	ln(regd. tractors at dest.)	FHWA	A	10.722	1.023	7.739	12.730
l_tnsp_o	ln(trans. GDP at orig,)	BEA	Q	9.226	0.932	5.970	11.291

M = monthly, Q = quarterly, A = annually

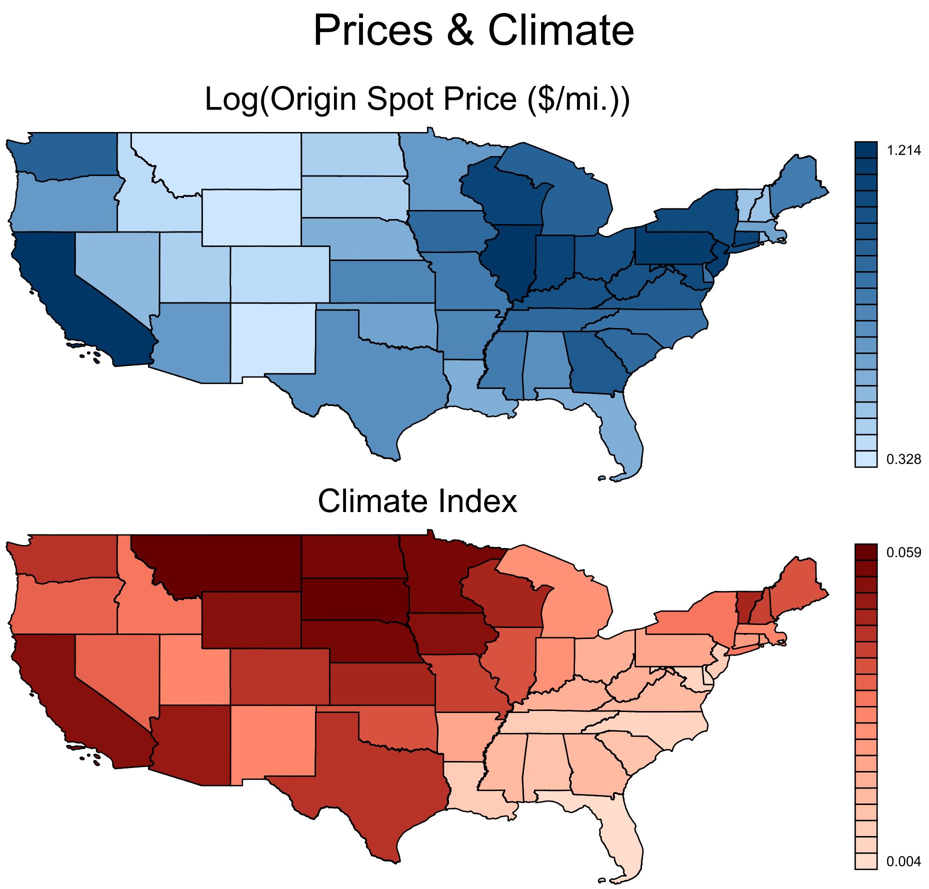

Fig. 1. Map of State Level Price and Climate Averages.

Intuitively, this model is closely analogous to a staggered difference-in-difference estimator, where before and after market outcomes of states experiencing climate events are compared to states which do not experience climate events.

4.4. Alternate empirical model of demand and Supply: 3SLS

While Eq. (1) gives the most straightforward and compelling observational estimates of climate events and market outcomes, the specification is theoretically agnostic, and so the mechanics of *how* the market is affected are hidden. We therefore pursue an alternate empirical strategy resting on stronger assumptions.

Price and quantity are simultaneously determined by demand and supply functions, so that $q^d(p) = q(p) = q^s(p)$. While we observe market quantities, q, and prices, p, we do not, strictly speaking, observe the functions $q^d(p)$ and $q^s(p)$. Yet empirically-grounded estimates of these theoretical objects are immensely useful for modeling, understanding, and predicting the market system. Intuitively, it is possible to estimate these equations in a two-step process using two-stage least squares (Hayashi, 2000; Wooldridge 2002). For the supply curve, we need to first obtain price variation that is exogenous to motor carrier supply decisions. We do this by estimating the effect of demand variation on price,

$$p_{ijt} = \boldsymbol{X}^{D}_{ijt}\beta + \epsilon_{ijt}, \tag{2}$$

where $\boldsymbol{X}^{D}_{it}$ are a vector of demand shifters. After estimating this first-stage equation, we obtain the fitted values $\widehat{p_{it}}$ predicted from the demand variation. We then use these fitted values in the estimation of the supply curve in the second stage,

$$q_{ijt} = \boldsymbol{X}^{S}_{ijt}\beta + \theta\widehat{p_{ijt}} + \delta Climate_{ijt} + \epsilon_{ijt}, \tag{3}$$

where $\boldsymbol{X}^{S}_{ijt}$ is a vector of supply determinants. The two-stage process addresses the simultaneity problem of regressing market quantity on market price because $\widehat{p_{ijt}}$ is now predetermined with respect to q_{ijt}. The demand curve is obtained in the opposite fashion, by first regressing market prices on supply determinants, obtaining fitted prices, then regressing quantity on these fitted prices along with demand determinants. The equations can be more efficiently estimated simultaneously as a system,

$$q^{S}_{ijt} = \theta_1 p_{ijt} + \boldsymbol{X}^{S}_{ijt}\boldsymbol{\beta}_1 + \delta_1 Climate_{ijt} + \epsilon_{1,ijt}$$

$$q^{D}_{ijt} = \theta_2 p_{ijt} + \boldsymbol{X}^{D}_{ijt}\boldsymbol{\beta}_2 + \delta_2 Climate_{ijt} + \epsilon_{2,ijt} \tag{4}$$

The order condition necessary for identifying the system is that there is at least one exogenous variable in $\boldsymbol{X}^{S}_{ijt}$ not in $\boldsymbol{X}^{D}_{ijt}$, and vice versa (Wooldridge 2002). It is also possible to allow for cross-equation correlation in the error term using three-stage least squares (3SLS) (Thiel and Zellner 1962).

It is worth comparing the reduced-form specification in Eq. (1) to the 3SLS specification in Eqs. (4). The reduced-form specification is compellingly causal because climate-related shocks, such as intense rainfall, are exogenous to spot-market prices; i.e. problems of reverse causality (e.g., the spot price in Texas does not affect climate) can be ruled out. But because Eq. (1) does not attempt to address the simultaneous determination of price and quantity, it gives no indication as to how the burden of climate disruption is shared between shippers and motor carriers. Simultaneous treatment of price and quantity (as in (4)) can answer this, but adds complications, not because price and quantity are endogenous with the climate index, but because they are endogenous with each other. Unlike Eq. (1), estimates from the system of Eqs. in (4) require assumptions about exclusion restrictions that are not empirically testable. For example, we have assumed that the demand-shifting variables in $\boldsymbol{X}^{D}_{ijt}$ do not affect supply, except through market price (and vice-versa). These restrictions are not required for causal assessment of Eq. (1); nonetheless, given their validity, the system specifies a regional econometric model allowing deeper interpretations.

4.5. Results

Our analysis shows that climate shocks do significantly impact freight spot prices, validating Hypothesis 1, *Climate shocks increase spot prices*. A one-standard deviation increase in the climate index results in a 1.9% increase in spot prices. To put this into context, the within-lane standard deviation of price is 18.2%, so while climate shocks are important, their effects can be hidden within the usual variation. Given monthly average spot market expenditures of $1.03 billion in our dataset, climate shocks account for $8.55 million in increased expenditure, on average. Climate shocks do not significantly impact quantity, indicating that adverse climate shocks to supply are partially offset by increased–or highly inelastic–demand. Price elasticity is consistent with predictions from freight price adjustment literature, which suggests that exogenous supply shocks raise prices but not quantities in markets facing inelastic demand. The result is also consistent with the narratives provided by industry practitioners, who stated that they must maintain service levels even at higher spot prices. Climate events therefore effect a transfer of economic rents from shippers to motor carriers.

4.6. Reduced-form specification

We first examine the results of the reduced form specification (Eq. (1) as laid out in Table 2. Columns (1) and (2) present simple models with log price as the dependent variable, origin and destination climate and origin, destination and time dummy variables (column 2). Climate shocks tend to increase spot market prices at the origin. From column (2) a one standard deviation increase in climate-related shocks (0.043) results in a 0.043*0.437 = 0.019, or a 1.9% increase in the average spot price over the course of the month. Destination climate shocks tend to reduce price, although the effect is weaker. A one standard deviation increase in the climate index results in a marginally significant 0.1% reduction in price. The significance of coefficient estimates are robust to the inclusion of a battery of supply and demand estimates in columns (3).[2] While destination price effects become larger and more statistically significant in (3), a one standard deviation shock still results in less than a 1% reduction in price. Conversely, while origin affects attenuate slightly, their effect remains more than twice as strong as destination shocks. In column (4) we restrict the sample prior to COVID-19 to ensure there are no confounding effects. The pattern of coefficient estimates is similar to column (2) but with attenuated origin effects. Columns (5)-(8) look at the effect of climate shocks on market volume (number of truckloads). Here we see weaker effects, with origin climate shocks having an insignificant effect on quantity except during Covid. Destination climate shocks achieve marginal statistical significance in columns (6) and (7), but the size of the effect remains small. The overall conclusion from reduced form estimates in Table 2 is that market adjustments to climate shocks occur predominately through price rather than quantity. It also appears that climate events have stronger effects on the spot market when occurring at the origin of routes as opposed to their destinations.

Change in economic well-being owing to climate shocks can be measured by changes in total surplus, proportionate to $\Delta P \Delta Q$. Because the overall change in volume (ΔQ) is close to 0, climate shocks have little effect on overall economic welfare, at least within the context of the truckload spot market. Instead, Table 2 results indicate that climate shocks result in a transfer of economic rents from shippers to motor carriers. Unfortunately, our data do not give insight on whether increased transportation costs are ultimately passed on from shippers to their customers.

4.7. Three-stage least squares specification (demand and supply)

We next implement our simultaneous equations model via three-stage least squares (3SLS) specification to separate shipper and motor carrier responses. 3SLS results are consistent with OLS estimates above, showing a similar positive price response at the origin due to climate shocks. Rather than being a robustness test of Eq. (1), however, the 3SLS specification is better interpreted as an unpacking of the effects of the reduced form equation by treating demand and supply sides of the market *separately*. Taken together, the estimated 3SLS responses can be used to recover net effects measured in Eq. (1).

Table 3 details and estimates the supply–demand system. Columns (1)-(4) provide parsimonious models relying on two-way fixed effects. Columns (5)-(8) provide models grounded on observable economic variables to better understand climate shocks and market dynamics. Column (1) provides a baseline model, where demand is identified by income at the origin and supply is identified by diesel prices and origin transportation expenditures. First stage instruments are strongly correlated with price as indicated by first-stage F-tests (F = 1288, 2407, $p < 0.001$). These instruments are used to estimate demand and supply elasticities in the second stage. Demand in column (1) is strongly inelastic ($|\theta_2| < 1$), and statistically indistinguishable from 0. Supply is elastic ($\theta_1 > 1$): other things equal, a 1% increase in price results in an 8.5% increase in truckload carriage supplied.

Columns (3–4) add origin and destination climate shocks to the model. These shocks appear to operate mainly through market supply, with no significant effects apparent in the demand equation (column (3)). A one standard deviation climate shock at the origin reduces quantity supplied by 12.9%. This adverse supply effect is consistent with increased spot prices in Table 2, columns (1)-(4). Destination climate shocks apparently increase supply: a one standard deviation destination shock increases quantity supplied by 5.8%. This estimate is also consistent with destination climate shocks reducing price in Table 2. The inclusion of climate variables does not noticeably affect specification statistics: instruments are strong in the first-stage, while p-values for the Hansen-Sargan test-statistic for overidentification remain insignificant. Eqs. (1)–(4) indicate that freight is positively correlated with economic output. A 1% increase in origin GDP increases freight demand by 0.8%. Supply is increasing in origin competition, as measured by origin transportation expenditures (l_tnsp_o). Surprisingly, origin fuel prices tend to increase motor carrier supply. This unexpected result may be partially explained by overshifting of fuel costs by motor carriers to shippers (Balthrop et al. 2025). Given much of the variation in fuel price is cross-sectional, the inclusion of state-fixed effects may absorbing some of the relevant effect. Finally, the negative R-squared value in column (4) indicates the supply curve, when interpreted independently, has lower predictive value than regression on a constant-only model (i.e., making prediction using the mean of the dependent variable).[3] Nonetheless, the inclusion of climate variables represents a slight increase in the overall model performance relative to columns (1)-(2), having a slightly reduced RMSE.

Estimates in columns (1)-(4) rely heavily on place and time fixed effects and minimal instrumentation in order to provide an empirically rigorous, but theoretically agnostic model. The result is a model very close to the reduced-form specifications in Table 2 columns (2), (6), but with the addition of price elasticities linking price to quantity. The drawback of these models is that they are identified primarily with "catch-all" fixed effect terms, which do not explain why price and quantity vary. Given stronger theoretical assumptions, however, it is possible to build a theoretically richer model based on spatial-temporally varying explanatory variables that more deeply characterize freight market dynamics. We include a broader battery of supply and demand shifters in Table 3,

[2] Control variables are included to show robustness against omitted variables concern. Reduced form coefficients for the control variables do not have direct economic meaning. Interpretation requires information about price elasticities in Table 3 (Wooldridge 2002).

[3] It is possible to have negative R-squared because it is the actual value of the regressors, not the fitted values from instrumentation, that are used in the second-stage calculation.

Table 2
Two-way fixed effects estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	l_spot	l_spot	l_spot	l_spot	l_q	l_q	l_q	l_q
o_climate	0.433***	0.437***	0.393***	0.349***	−0.0539	−0.0342	−0.0146	0.146**
	(0.0132)	(0.0133)	(0.0111)	(0.0122)	(0.0557)	(0.0550)	(0.0478)	(0.0600)
d_climate		−0.0203*	−0.157***	−0.0330***		−0.108*	−0.0844*	0.0317
		(0.0119)	(0.0108)	(0.0120)		(0.0578)	(0.0486)	(0.0627)
l_gdp_o			0.634***	−0.000310			0.658***	−0.0791
			(0.0297)	(0.0475)			(0.125)	(0.247)
l_pop_o			−1.401***	−0.927***			0.481*	1.671***
			(0.0609)	(0.0968)			(0.262)	(0.522)
l_gdp_d			0.0354	−0.245***			0.637***	0.436*
			(0.0299)	(0.0465)			(0.116)	(0.230)
l_pop_d			−1.328***	−0.470***			−0.302	0.523
			(0.0666)	(0.0974)			(0.279)	(0.498)
l_miles			−0.206***	−0.206***			−1.025***	−1.050***
			(0.00130)	(0.00146)			(0.00695)	(0.00824)
l_ag_o			−0.000683	0.0361***			0.00736	0.00874
			(0.00276)	(0.00477)			(0.0132)	(0.0275)
l_man_o			0.249***	0.127***			−0.0964**	−0.130**
			(0.0104)	(0.0129)			(0.0444)	(0.0643)
l_con_d			−0.0161**	0.0189**			0.174***	0.102**
			(0.00795)	(0.00949)			(0.0386)	(0.0514)
l_ret_d			0.159***	0.495***			0.0904	−0.152
			(0.0161)	(0.0283)			(0.0748)	(0.141)
l_fuel			−0.119***	0.116***			0.177***	0.233***
			(0.00611)	(0.00845)			(0.0293)	(0.0452)
d_balance			−2.59e-06***	−1.52e-06***			−2.13e-06**	−2.09e-06
			(1.58e-07)	(2.15e-07)			(8.74e-07)	(1.31e-06)
l_dest_p			0.477***	0.254***			−0.0768***	−0.118***
			(0.00700)	(0.00720)			(0.0214)	(0.0276)
l_trac_d			0.0319***	0.0281***			0.0322*	0.0416
			(0.00412)	(0.00951)			(0.0192)	(0.0546)
l_tnsp_o			−0.0797***	−0.106***			0.0924**	0.229***
			(0.00775)	(0.0141)			(0.0373)	(0.0772)
Constant	0.429***	0.429***	31.65***	20.12***	4.327***	4.329***	−10.26*	−27.57***
	(0.00451)	(0.00453)	(1.140)	(1.698)	(0.0226)	(0.0227)	(5.371)	(9.501)
Sample	Full	Full	Full	Pre-Covid	Full	Full	Full	Pre-Covid
Origin, Dest. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,716	94,716	94,716	67,248	94,716	94,716	94,716	67,248
R-squared	0.744	0.744	0.837	0.839	0.688	0.688	0.775	0.774

Robust standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

columns (5)-(8). As demand controls we use origin and destination income (*l_gdp_o, l_gdp_d)* origin and destination population (*l_pop_o, l_pop_d)*, and distance between origin and destination (*l_miles*). We use state-level manufacturing and agricultural output (*l_man_o, l_ag_o)* to control for freight sources and destination construction and retail output to control for freight sinks *(l_con_d, l_ret_d)*. As supply controls, we use fuel cost (*l_fuel),* state-level transportation output (*l_tnsp_o),* destination lane balance (*d_balance)*, outbound price at destination (*l_dest_p),* and number of registered vehicles at the destination (*l_trac_d)*.

We provide results for the baseline model without climate shocks in columns (5)-(6). Demand is price inelastic, while supply is elastic, similar to specifications in columns (1)-(4). The main difference is that supply becomes noticeably less elastic, after controlling for destination market conditions such as lane balance, destination price, and destination vehicle registries. The signs of supply shifters are also as expected, with higher fuel prices tending to reduce supply, while transportation output and destination desirability tend to increase supply. On the demand side, we find evidence that freight is an inferior good, with both origin and destination income variables negative. Given much of the variation in income is cross-sectional, this implies Mississippi (lowest GDP per capita, and heavily reliant on agriculture, forestry and manufacturing), consumes more truckload freight per capita, than does New York (highest GDP per capita, with finance and insurance as the most important economic sectors). Freight demand increases with population/ market size, and decreases with distance, as expected. Origin manufacturing and agricultural output, and destination construction and retail output, also have the expected sign and significance.

We include origin and destination climate shocks in both demand and supply specifications in columns (7) and (8). Whereas climate shocks do not significantly affect demand, they do result in significant supply reductions, whether the shock occurs at the origin or at the destination. To put this into context, a one-standard deviation climate shock at the origin results in an 8.4% reduction in quantity supplied, other things equal. That destination climate shocks also reduce supply, contrasts results in Table 3 columns (3)-(4) relying on two-way fixed effects.

Table 3
Three-stage least squares (3SLS) estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	qDemand	qSupply	qDemand	qSupply	qDemand	qSupply	qDemand	qSupply
o_climate			0.156	−3.098***			−0.0480	−1.958***
			(0.249)	(0.909)			(0.0621)	(0.0816)
d_climate			−0.0127	1.350***			0.0685	−1.299***
			(0.120)	(0.394)			(0.0593)	(0.0790)
l_spot	−0.304	8.516***	−0.229	9.765***	−0.563***	2.220***	−0.550***	2.265***
	(0.756)	(2.151)	(0.738)	(2.760)	(0.0191)	(0.0218)	(0.0193)	(0.0219)
Demand Controls								
l_gdp_o	0.811***		0.800***		−0.525***		−0.548***	
	(0.135)		(0.131)		(0.0147)		(0.0150)	
l_pop_o					0.802***		0.830***	
					(0.0149)		(0.0152)	
l_gdp_d					−0.113***		−0.125***	
					(0.0178)		(0.0179)	
l_pop_d					0.407***		0.436***	
					(0.0172)		(0.0174)	
l_miles					−0.927***		−0.928***	
					(0.00613)		(0.00616)	
l_ag_o					0.149***		0.145***	
					(0.00298)		(0.00296)	
l_man_o					0.457***		0.458***	
					(0.00680)		(0.00683)	
l_con_d					0.400***		0.398***	
					(0.0113)		(0.0113)	
l_ret_d					0.0257		0.0164	
					(0.0167)		(0.0167)	

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

One caveat is that columns (5)-(8) are significantly overidentified according to Sargan-Hansen test statistics, meaning second stage residuals are correlated with first-stage instruments, in apparent violation of identifying orthogonality conditions.[4] The over-identification test might be "failed" for multiple reasons. First, it is reasonable to expect that underlying parameters (such as the price elasticity of supply) are heterogeneous across states, in which case, different instruments identify unique parameters for the different states. If so, the overidentification test is itself invalid (Angrist and Pischke, 2009; Parente and Silva, 2012). Second, columns (5)-(8) represent a partial-equilibrium regional economic model, where the instruments (various forms of state- level GDPs, fuel prices and vehicle registrations, etc.) are endogenous, in that they are influenced by the truckload transportation spot market. For example, booming spot markets may feedback to influence variables like state-level GDP and vehicle registrations, but this feedback is likely to be small compared to the direct effect of how general economic activity (i.e., state income) affects the spot market.[5] At a deeper level, the structural model in (7)-(8) is not strictly causal—state GDP does not directly affect spot markets, only shipper and motor carriers' decisions do—nonetheless, it is a useful application of organizing economic constructs. We can take estimates from Eqs. (7) and (8) and recover estimates very similar to the measured effects from Eq. (1). A one-standard deviation climate shock results in a (0.043*-1.958)/(−0.550–2.220) = 0.031, or a 3.1% increase in spot prices. This is comparable to the 1.9% origin price increase from a one-standard deviation shock estimated in the reduced form model in Table 2. Where reduced form and structural estimates diverge is on the effect of destination shocks, with reduced-form models predicting market softening, while the structural model (Table 3, columns (7)-(8)) predict market tightening from reduced supply. It is possible to dismiss the structural model in this case, given its failure of the overidentification test; however, another reasonable interpretation is that the divergence between estimates is driven by the inclusion of state fixed effects, and that the two approaches give different perspectives on market response to climate shocks. The more empirically rigorous reduced-form model better accounts for the fixed regional patterns in trade flows; the structural model more clearly characterizes the underlying economic dynamics and so is of more theoretical interest.

5. Discussion

5.1. Overview

This study theorizes and tests the effects of climate shocks on dry van TL spot market prices. We use a multi-method approach that combines narrative evidence from interviews with shippers, carriers, and freight brokers with a robust regression model estimated with detailed data on climate shocks and the trucking spot market. The quantitative evidence suggests that outbound spot prices across all distances increase by 1.9% on average over a month in lanes affected by a climate shock. The increased prices do not translate into significant effects on the number of outbound spot TLs (i.e., capacity), holding other factors constant. These findings confirm the narrative evidence that suggests that practitioners are willing to pay higher spot prices to keep their on-time delivery promises to their customers, without necessarily generating higher outbound spot freight demand. The implications of these findings for theory, research, and practice are discussed next.

Our study contributes to the transportation literature by quantifying how climate shocks affect economic outcomes (i.e., price and demand) in the freight TL spot market (Leicht and Leicht, 2024, p. 174; Gössling et al., 2023; Patnala et al., 2023; Ghadge et al 2020). Our study quantifies the price effects of climate shocks on the spot market, shedding light on the economic effects of climate variability, an increasingly relevant topic in supply chain research (e.g., Ghadge et al., 2020).

The study also contributes to the TL transportation literature by showing how climate shocks impact spot prices and truck movements. Because the TL industry is driven by economies of scope rather than economies of scale (Caplice, 2007, Holzhacker et al., 2024), predictable demand with low variability is highly sought after to maintain profitable and productive utilization of assets (Scott et al., 2017; Miller and Muir, 2020). Our narrative evidence suggests that climate shocks disrupt the predictable demand patterns on affected lanes and can increase empty miles because of the imbalances created by the climate shock (Caplice, 2007; Rothkopf et al., 2024). Thus, carriers may reject contractual loads due to increased costs of operating in the affected area and desperate shippers may need to use the spot market.

Our findings suggest that climate shocks increase spot prices yet, interestingly, these increased prices do not necessarily translate into significantly increase spot truckload volumes. Indeed, this corroborates the predictions about the functioning of the spot market that "some service option is better than no service option, suppliers [carriers] with high prices provide value to the buyer because the value of delivering the load on-time nearly always exceeds the cost to get it there" (Scott, 2019, p. 2611). Thus, our study's findings suggest a corollary to the *extent* to which carriers will have a "temptation to deviate" (Acocella and Caplice 2023) from contractual business when spot market prices increase – namely, that short-term increases in spot market prices do not necessarily translate to increased TL spot market activity. These findings are in line with a growing body of evidence that the TL spot market is viewed more as a "safety valve" for shippers willing to pay higher prices to move loads under capacity constrained environments (Acocella et al., 2020; Scott et al., 2017; Scott 2019).

[4] The usual interpretation is that one or more of the instruments are invalid. However, there is not a good way of determining which instrument is the source of the problem; reducing the model to a just-identified set of parameters does not admit for the possibility of empirical falsification (Kiviet, 2020).

[5] A full general equilibrium transportation model (e.g., Redding and Turner, 2015) would explicitly account for these feedbacks, but this would add little additional understanding of the effect of climate shocks on the freight spot market.

5.2. Practical implications

The findings of the study have relevant implications for shippers, carriers, and brokers. Transportation managers are increasingly required to develop strategies for dealing with frequent and severe climate events related to climate change (Brusset and Bertrand, 2018; Rowan et al., 2013) without sufficient understanding of costs. One common question (or a close variant) we received from practitioners during our interviews was "How can we better use the spot market in planning our transportation spend and strategy?" The findings of the study provide some guidance to each of these groups. First, for shippers, our primary findings suggest an approximately 1.9% increase in outbound spot prices for a one standard deviation increase in the UTCI. While this effect is statistically significant, the price increase is relatively insignificant from a market-wide perspective. However, underlying these average effects (and corroborated by the evidence) is the fact that shippers without enough capacity will pay very high rates on the spot market to maintain their customer commitments. Because climate shocks are associated with higher contract tender rejection rates by carriers (Caza and Shekhar, 2022), shippers could deepen their portfolio of contract carriers to try to avoid exposure to the more expensive and volatile spot market prices. Indeed, one large shipper of high value products we interviewed mentioned having over forty contract carriers in their portfolio and only very rarely had to use the spot market even after climate shocks.

Second, our findings suggest that carriers could seek to shift more capacity to the spot market to haul loads at a premium price. Still, because carrier profitability is highly reliant on stable and balanced load schedules (Acocella and Caplice 2023), carriers should be aware of potential network imbalances that result from climate shocks and how these imbalances create both opportunities and risks of using the spot market. As our results suggest, carriers have a potential revenue opportunity from servicing shippers in extreme weather affected areas but, operating in these areas can expose carriers to damages to equipment, time and fuel spent navigating around infrastructure damage, and higher potential for accidents (Kulpa 2024). Carriers need to ensure that if they pursue opportunities on the spot market during a climate shock, they can cover their costs associated with hauling these loads and have a sufficient customer base in or around the affected area to find outbound loads.

Third, the findings of our study suggest that freight brokers may have significant opportunities to improve their spot market revenues during climate shocks. Freight brokers tend to set prices between asset-based carriers and shippers based on spot market rates thus their performance is tied to their ability to manage spot market dynamics (Acocella and Caplice 2023). Additionally, freight brokers may be better suited to meet the needs of shippers impacted by climate shocks given their ability to pool truckload capacity across a network of carriers (Acocella and Caplice 2023; Scott 2019; Scott, 2018). Our study highlights that freight brokers would be well served by closely monitoring climate shocks. Indeed, one carrier-broker we interviewed in the study mentioned that they increased their cold-calling activity to shippers affected by climate shocks. Thus, brokers can use climate shocks to not only temporarily provide capacity to shippers that have been unable to secure it, but this also may lead to an opportunity to continue to serve those new customers for future business.

5.3. Limitations

As with all studies, this research has limitations to explain the effects of climate shocks in other contexts or transportation modes. In this study, we examine how climate shocks affect the dry-van, truckload spot market. While this is the most widely used mode of trucking transportation, there are several other types of trucking transportation such as LTL, refrigerated, and flatbed among others. Climate shocks would likely affect spot market activity of these other trucking equipment types but, the effects might be in different directions or of different magnitudes. For example, one could hypothesize that climate shocks might have a stronger effect on flatbed spot market activity because flatbed equipment could be used to transport construction materials or machinery to a climate shock-affected area where rebuilding activity may need to take place. Additionally, one could hypothesize a similar direction and magnitude for refrigerated trucking because of the increased demand for perishable food products, pharmaceuticals, or other temperature sensitive goods. Thus, future research should examine the effects of climate shocks on the spot market activity of other trucking equipment types.

While it is relatively straightforward that climate shocks would affect spot market activity of other transportation modes (e.g., containerized water freight, air freight, rail, intermodal, etc.) the direction or size of the effect is less clear. For example, following the logic we draw on in this study, one could expect that climate shocks will have a positive effect on intermodal spot prices if an affected lane is disrupted. However, the size of the effect is less clear because the intermodal spot market (as well as other modes) is relatively small. Future research should examine the effect of climate shocks on other transportation modes. Interestingly, other research could also consider how climate shocks lead to modal switching behavior such as shifting from slower rail transportation to faster truck transportation as a response to climate shocks.

This research also has data limitations. First, while we have spot market data that is relatively granular at the state-to-state level, we did not have access to data at regional or market area levels (i.e., Dallas to Atlanta). Future studies should re-examine the analysis conducted herein to estimate effects at more local levels. Second, our narrative evidence was conducted with a convenience sample (as is almost as the case) of practitioners that were willing to participate in the research. Most participants were from relatively large shippers, carriers, and brokers. While it is these larger firms that make up the majority of the market in terms of volume, market dynamics are likely determined by smaller "marginal" shippers and carriers (Balthrop 2021). Future studies could try to use more perspectives from smaller companies. Third, while the narrative and quantitative evidence corroborates our predictions, future research could use other methods such as behavioral experiments that may be able to better understand the decision making behind pricing and capacity adjustments in the TL spot market during a climate shock. Finally, our study focuses on the US dry-van truckload spot market. Future studies could examine whether our results are similar in other countries or regions. Dry-van truckload transportation is the most widely used commercial transportation mode in the US but, this is not the case in other countries or regions that are geographically smaller or rely more on other transportation modes thus, results may vary.

5.4. Directions for future research

Beyond addressing the limitations of this study, research could explore several future extensions of this paper. First, future research could test the extent to which tight or soft market conditions (Acocella et al., 2020) play a moderating role in the relationship between climate shocks and TL spot prices and volume adjustments. Second, future research could examine testing differences in high vs. low volume lanes as a moderator in how prices and volumes might adjust during a climate shock. Third, extending our analyses with more granular data on spot bidding behavior differences between carriers and brokers would also be of interest given that carriers are more susceptible to the network imbalances caused by climate shocks relative to brokers. Finally, future research could examine how the length-of-haul moderates the average relationships that we document in this study as prior research has documented how long-haul spot loads tend to be more impacted by hurricanes than short haul loads (Rana and Caplice, 2019; Kulpa 2024).

6. Conclusion

This study shows how climate shocks affect freight spot market prices, with each standard deviation increase in the University Climate Index resulting in an approximate 1.9% increase in spot prices. We use a unique data set on climate shocks combined with data from the freight spot price market to make evident the strategic role of the spot market as a "safety valve" as indicated by narrative insights from industry practitioner. This clearly illustrates the role of the spot price mechanism that balances supply and demand when exogenous disruptions occur.

We contribute to the literature on transportation pricing by showing that spot prices act as real-time indicators of supply–demand imbalances. Our results can be contrasted with prior studies that have focused on steady-state pricing. This highlights the importance of spot pricing not just as a reflection of market conditions but as a functional tool for operational resilience.

Our research has multiple practical implications. Shippers may benefit from diversifying their carrier portfolios to reduce reliance on the spot market during disruptions. Carriers should weigh the operational costs and risks associated with conducting business in disrupted areas, while freight brokers could make use of their capacity-matching capabilities to strengthen relationships with shippers affected by climate shocks.

CRediT authorship contribution statement

Sara Hsu: Writing – original draft, Project administration, Conceptualization. **Andrew Balthrop:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Dan Pellathy:** Writing – original draft, Investigation. **Travis Kulpa:** Writing – original draft, Conceptualization. **Gonzalo Andrew Ferrada:** Methodology, Data curation. **Joshua Fu:** Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tre.2025.104609.

Data availability

The data that has been used is confidential.

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