Climate Shocks, Trade Credit, and Firm Resilience in Chile

Facundo Luna

Rutgers University

March 2026

Abstract

How does the short-term financial architecture of production networks shape the propagation of climate shocks? Using the universe of electronic invoices and wildfire alerts in Chile (2015–2024), I reconstruct monthly buyer–supplier links for the formal economy and estimate how pre-existing trade credit positions determine whether firms absorb or transmit wildfire-induced disruptions. A Local Projections DiD design identifies horizon-specific effects across three exposure margins: direct, upstream, and downstream. Trade credit received operates as state-contingent liquidity insurance: it broadly buffers downstream shocks by bridging payment delays, selectively mitigates upstream shocks by financing emergency procurement, and offers narrow protection against direct physical destruction. Trade credit supplied amplifies vulnerability by locking working capital in receivables that become illiquid when customers are in distress. A size gradient —buffering for small firms, absent for large firms — confirms that the mechanism operates through binding financial constraints. Aggregating across exposure margins, indirect network losses exceed direct losses. A counterfactual in which all indirectly exposed firms hold slack payables positions reduces aggregate losses by nearly two-thirds, implying that the distribution of interfirm financial positions is a determinant of aggregate climate resilience.

1 Introduction

Climate-related disasters are becoming increasingly frequent and severe, and wildfires have emerged as a significant source of production risk. Particularly in Chile, the 2017 and 2023 fire seasons burned exceptionally large areas and generated pervasive disruptions to local activity, logistics, and air quality (Cordero et al., 2024), with adverse effects on regional economic conditions (Chan et al., 2022; Faúndez Pinilla et al., 2023). For firms operating in supply chains, these shocks are not merely local events: they propagate through input-output linkages, depressing the performance of upstream suppliers and downstream customers (Barrot and Sauvagnat, 2016; Carvalho et al., 2021; Boehm et al., 2019).

In this setting, do pre-existing working capital arrangements, especially trade credit positions set before the shock, mitigate the real effects of climate disasters and help preserve supply chain stability? Trade credit is a central source of short-term financing and often expands when bank credit tightens, providing relationship-specific liquidity and insurance (Cuñat, 2007; Garcia-Appendini and Montoriol-Garriga, 2013). Recent work shows that when suppliers are hit by operating shocks, trade credit within networks is reallocated to keep transactions going (Ersahin et al., 2024). Likewise, after natural disasters, greater access to trade credit is associated with stronger post-disaster performance (Lai et al., 2022).

What remains less clear is whether resilience depends on firms' ex ante trade credit positions than on post-shock adjustments. Does a firm's position in accounts payable and receivable predict its ability to absorb shocks that arrive directly or through suppliers and customers? And does trade credit buffer shocks differently depending on whether the firm primarily receives credit or extends it, and on where the disruption occurs in the production network?

This paper examines the effects of wildfires in Chile on firm performance and supply chain stability, focusing on how pre-shock trade credit conditions shape resilience. I explicitly treat trade credit as a state-contingent instrument whose stabilizing or amplifying power depends on where the shock lands in the network and on the firm's ex ante position in payables and receivables. I utilize a novel dataset that contains the universe of interfirm transactions in Chile from 2015 to 2024, enabling the recovery of the buyer-supplier network at scale. The analysis distinguishes three exposure margins: direct hits to the focal firm, upstream exposure via affected suppliers, and downstream exposure via affected customers. For each margin, I test whether pre-shock trade credit conditions, measured by a higher share of purchases or sales financed with trade credit and longer average payment terms in the six months before the shock, buffer or amplify the impact.

Empirically, I implement a Local Projections Difference-in-Differences design that estimates horizon-specific treatment effects while constructing clean control sets to address contamination from staggered timing (Dube et al., 2025).

The main results show that wildfires generate persistent declines in sales, purchases, and employment that propagate extensively through the production network. Trade credit received operates as state-contingent liquidity insurance that mitigates this propagation. In the face of downstream disruptions, firms with strong payables positions bridge payment delays, thereby avoiding the cascading deterioration in sales and supplier retention observed in constrained firms. For upstream disruptions, this financial slack protects real output and employment by financing the adjustment costs of alternative sourcing, even as the emergency procurement premium is borne symmetrically across all firms. In contrast, trade credit supplied works through a fundamentally different channel: receivables provide no real-side protection and actively amplify exit risk when customers are in distress, effectively tightening the liquidity constraint precisely when cash is most needed. These patterns are validated by a strict size gradient—buffering is comprehensive for small firms but absent for large firms—confirming that the mechanism operates through binding financial constraints rather than unobserved firm quality.

These micro-level frictions have aggregate consequences. A back-of-the-envelope aggregation reveals that indirect network losses exceed direct physical losses, yielding a network multiplier of approximately 3.1. Under a counterfactual in which all indirectly exposed firms held top-quartile payables positions, aggregate losses would fall by nearly two-thirds. This implies that the distribution of interfirm financial positions—a margin typically outside the scope of disaster policy—is a first-order determinant of how climate shocks translate into aggregate output costs. While physical destruction sets the initial damage, it is the supply chain's financial architecture that determines the magnitude of the resulting economic contraction.

These patterns align with evidence that firms with liquidity expand trade credit provision in crises and perform better (Garcia-Appendini and Montoriol-Garriga, 2013), but they reveal an important distinction: ex ante liquidity positions determine buffering capacity without requiring stressed partners to extend additional credit during the crisis. This contrasts with recent findings that trade credit flows increase following operating shocks (Ersahin et al., 2024), suggesting that pre-existing financial arrangements and post-shock adjustments operate as complementary rather than substitute mechanisms.

This paper contributes to three strands of the literature. First, on trade credit and corporate liquidity (Petersen and Rajan, 1997; Cuñat, 2007; Garcia-Appendini and Montoriol-Garriga, 2013; Jacobson and von Schedvin, 2015; Breza and Liberman, 2017; Amberg et al., 2021; Benguria et al., 2023; Giannetti, 2024; Ersahin et al., 2024), I show that the buffering role of trade credit is state-contingent and fundamentally asymmetric across the direction of credit flows and exposure margins. Better ex ante payables conditions help firms mitigate shocks transmitted through their networks, most notably via affected suppliers, yet offer limited insulation when the focal firm is directly hit, and physical capacity binds. More generous receivables positions worsen performance by tying up liquidity and transmitting stress from customers, amplifying negative effects while preserving network connections. This asymmetry suggests that trade credit operates simultaneously as liquidity insurance and relationship-specific investment, with the net effect depending critically on shock location and the firm's network position.

Second, related to production networks and the propagation of operational shocks (Barrot and Sauvagnat, 2016; Carvalho et al., 2021; Boehm et al., 2019), I uncover where along buyer-supplier links the chain absorbs rather than transmits disturbances. I document stronger buffering on the upstream margin, connecting financing slack to the preservation of relationships and sales, and show that the location of the shock within the network determines whether trade credit mechanisms can effectively stabilize transactions. This finding complements existing evidence by demonstrating that network position and shock direction jointly determine whether interfirm credit flows mitigate or propagate disruptions.

Third, on climate disasters and firm resilience, using firm-level evidence from wildfires, I show that pre-existing, relationship-embedded working capital stabilizes network outcomes after shocks but does not insure directly hit firms against physical disruption. This complements work on disaster impacts and post-disaster performance (Tsuruta, 2013; Lai et al., 2022; Ersahin et al., 2024; Fatica et al., 2024; Hu et al., 2025) and shifts the resilience literature beyond bank credit and public relief toward private, relationship-based liquidity inside supply chains, with particular attention to the timing dimension: arrangements made before shocks matter.

Methodologically, the paper also contributes by employing a Local Projections DiD framework that sharpens identification relative to traditional event study designs commonly used in prior work (Barrot and Sauvagnat, 2016; Ersahin et al., 2024; Lai et al., 2022; Alfaro et al., 2021; Amberg et al., 2021; Costello, 2020). By leveraging LP DiD, I estimate horizon-specific responses and use control sets that avoid contamination from timing and overlapping treatments. This framework is well-suited for tracing how buffering evolves over time, for example, peaking in the short run for upstream shocks yet fading for direct hits, and for probing heterogeneity across firms that differ in financial constraints or network position. It also complements advances that clarify identification in event studies with heterogeneous treatment effects and staggered adoption, ensuring that dynamic patterns are interpreted against credible counterfactuals (Callaway and Sant'Anna, 2021).

The remainder of the paper is organized as follows. Section 2 develops a simple conceptual framework that guides the empirical analysis and generates testable hypotheses. Section 3 describes the data, including how I construct direct and network exposures from electronic invoices and wildfire records. Section 4 lays out the empirical strategy, detailing the local-projection difference-in-differences framework and its measurement. Section 5 reports the main results on direct and propagated effects and examines heterogeneity. Section 6 presents a simple aggregation exercise and policy implications. Section 7 concludes.

2 Conceptual Framework: Trade Credit as a State-Contingent Shock Absorber

This section develops a stylized framework to guide the empirical analysis and generate testable hypotheses. The model features a supply chain with financial frictions to rationalize how a stronger position in received trade credit—defined by a higher proportion of purchases financed via trade credit (ϕ) and longer payment terms (τ)—mitigates three types of shocks: direct shocks to a focal firm, upstream shocks hitting its suppliers, and downstream shocks hitting its customers.

The framework is deliberately partial equilibrium and static. Trade credit terms are treated as predetermined state variables reflecting pre-existing supplier relationships rather than objects of optimization. The purpose is not to model the endogenous formation of trade credit contracts, but to discipline the sign and relative strength of shock transmission and mitigation mechanisms that are subsequently estimated in reduced-form regressions.

2.1 Model Setup

Technology. The focal firm F produces output using upstream inputs x and labor ℓ via a Cobb–Douglas technology:

$$y \;=\; A\,x^{\alpha}\ell^{1-\alpha}, \qquad \alpha \in (0,1). \tag{1}$$

Financial environment. A share $\phi \in [0,1]$ of input purchases cx is financed through trade credit. The deferred payment carries an effective discount $\kappa \in (0,1)$, which captures in reduced form the financial advantage of longer payment terms τ: a higher τ lowers κ, reflecting greater discounting of the deferred obligation.[1]

Liquidity constraint. At the production stage, the firm must cover the cash portion of inputs, the wage bill, and any emergency spending $E \geq 0$ (defined below):

$$(1-\phi)\,cx + w\ell + E \;\leq\; W + \bar{B}, \tag{2}$$

where W is liquid wealth and $\bar{B}$ is a fixed bank credit limit. I focus on financially constrained firms for which (2) binds, with shadow value $\lambda > 0$.

Upstream disruptions and emergency procurement. When a key supplier is disrupted, the firm must replace a shortfall through emergency procurement at a cost premium. Emergency procurement must be financed with cash—it cannot draw on existing trade credit arrangements, since it involves transactions outside the firm's established supplier relationships.[2] I represent the per-unit procurement surcharge as $\chi(s, E)$, where $s \in [0,1]$ indexes the severity of the upstream shock and E is emergency spending:

$$\chi_s > 0, \quad \chi_E < 0, \quad \chi_{EE} > 0, \quad \chi_{sE} < 0. \tag{3}$$

[1] Formally, one can microfound $\kappa(\tau) = (1 + r_{TC})^{-\tau}$ with r_{TC} the implicit trade credit rate. Since τ enters all results exclusively through κ, the reduced-form treatment is without loss for the comparative statics that follow.

[2] This assumption is conservative: if emergency inputs could also be partially financed by trade credit, the mitigation mechanism would be stronger.

The first three properties are standard: more severe disruptions raise per-unit costs, while emergency spending lowers them with diminishing returns. The cross-partial $\chi_{sE} < 0$ means emergency spending is more productive when disruptions are severe; when disruptions are negligible, there is little scope for emergency measures, whereas severe disruptions make investments in alternative sourcing yield larger marginal benefits.[3]

Profits. In present-value terms, profits are

$$\Pi \;=\; pA\,x^{\alpha}\ell^{1-\alpha} \;-\; (1-\phi)\,cx \;-\; \kappa\,\phi\,cx \;-\; w\ell \;-\; (1+r)\bar{B} \;-\; E \;-\; \chi(s,E)\,x. \tag{4}$$

The surcharge $\chi(s,E)\,x$ applies to total input use, a simplification that captures the disruption as raising average procurement costs across the firm's input bundle.[4]

Optimality conditions. The Lagrangian is $\mathcal{L} = \Pi + \lambda\big(W + \bar{B} - (1-\phi)\,cx - w\ell - E\big)$. The first-order conditions are:

$$pA\alpha\,x^{\alpha-1}\ell^{1-\alpha} \;=\; c\Big[(1-\phi)(1+\lambda) + \phi\kappa\Big] + \chi(s,E), \tag{5}$$

$$pA(1-\alpha)\,x^{\alpha}\ell^{-\alpha} \;=\; w(1+\lambda), \tag{6}$$

$$-\chi_E(s,E^\star) = \frac{1+\lambda}{x}. \tag{7}$$

Equations (5)–(7) jointly with the binding constraint (2) determine $(x^\star, \ell^\star, E^\star, \lambda^\star)$.

Equation (7) makes the emergency spending trade-off transparent: when liquidity is scarce (high λ), the effective cost of emergency cash rises, so the firm chooses lower $E^\star$ for any given scale x.

Liquidity-weighted marginal cost of inputs. From (5), the liquidity-weighted marginal cost of regular inputs is

$$MC_x(\phi,\kappa;\lambda) \;=\; c\Big[(1-\phi)(1+\lambda) + \phi\kappa\Big]. \tag{8}$$

[3]This property holds for natural specifications. For example, $\chi(s,E) = s\cdot g(E)$ with $g' < 0$ yields $\chi_{sE} = g'(E) < 0$.

[4]In practice, only a fraction of inputs may be disrupted. Replacing $\chi(s,E)\,x$ with $\chi(s,E)\,\tilde{x}$ for disrupted quantity $\tilde{x} \le x$ would preserve all qualitative results while scaling the upstream shock magnitude.

Higher received trade credit reduces marginal cost under a cash constraint. A larger ϕ shifts spending from the cash-constrained portion bearing cost $(1+\lambda)$ to the deferred portion bearing cost $\kappa < 1 < 1+\lambda$:

$$\frac{\partial MC_x}{\partial \phi} = c\big[\kappa - (1+\lambda)\big] < 0. \tag{9}$$

A lower κ (longer payment terms, higher τ) further reduces the cost of the deferred portion:

$$\frac{\partial MC_x}{\partial \kappa} = c\,\phi > 0 \quad \Longleftrightarrow \quad \frac{\partial MC_x}{\partial \tau} < 0. \tag{10}$$

These partial derivatives hold λ fixed. However, λ is endogenous: a higher ϕ relaxes the cash constraint for given (x, ℓ, E), reducing λ and increasing feasible scale. This effect reinforces the direct effect, so that $\partial x^\star / \partial \phi > 0$ at the equilibrium of the full system (see Appendix A).

Trade credit supplied (receivables). Accounts receivable $AR \geq 0$ represent funds locked in customer credit that cannot be collected quickly when a shock hits. On impact, liquid wealth available for constraint (2) is reduced to $W^{liq} = W - AR$. This tightens the liquidity constraint, raises λ, and amplifies sensitivity to shocks. Thus, while extending trade credit may strengthen customer relationships, it increases real losses when shocks hit by reducing the firm's financial buffer.

2.2 Shock Transmission and Mitigation

Shocks that reduce liquid wealth W or raise required cash outlays increase λ. The marginal value of received trade credit is therefore amplified when liquidity becomes scarce, generating state-contingent mitigation.

All three shock types work through a common structure. Let $\theta \in \{\delta, s, d\}$ denote a generic shock that (i) may reduce the marginal revenue product of inputs and (ii) tightens the liquidity constraint, raising λ. Higher ϕ attenuates channel (ii) because a larger share of input costs is deferred and thus insulated from the liquidity wedge. The shocks differ in which channels are active and whether trade credit opens an additional margin (emergency spending).

2.2.1 Direct Shocks

A direct shock $\delta \in [0, 1)$ reduces productivity and destroys liquid wealth:

$$A = A(\delta), \;\; A_\delta < 0; \qquad W = W(\delta), \;\; W_\delta < 0.$$

Both channels reduce optimal inputs: lower A reduces the marginal product, while lower W tightens the constraint and raises λ. Received trade credit attenuates the liquidity component—the increase in λ has a smaller effect on MC_x when ϕ is large—but cannot substitute for impaired productive capacity.

Proposition 1 (Direct Shock Mitigation)**.** *Stronger received trade credit attenuates the negative effect of direct shocks on inputs, employment, and output:* $\partial^2 x^\star/(\partial\delta\,\partial\phi) > 0$*. The mitigation operates primarily through the liquidity channel and is stronger when shocks predominantly affect liquid wealth rather than productivity. (Proof in Appendix A.)*

2.2.2 Upstream Shocks

An upstream disruption s increases procurement costs through $\chi(s, E)$. Beyond the common liquidity mechanism, trade credit opens an additional margin. From (7), higher ϕ lowers λ, reducing the effective cost of emergency spending and allowing the firm to invest more in alternative sourcing ($E^\star_\phi > 0$). Higher $E^\star$ directly reduces realized procurement costs $\chi(s, E^\star)$.

Proposition 2 (Upstream Shock Mitigation)**.** *Stronger received trade credit attenuates the negative effect of upstream shocks on inputs, employment, and output:* $\partial^2 x^\star/(\partial s\,\partial\phi) > 0$*. The mechanism operates through both lower effective input costs and greater capacity to finance emergency procurement. (Proof in Appendix A.)*

2.2.3 Downstream Shocks

A downstream shock d reduces demand and delays payments:

$$p = p(d), \;\; p_d < 0; \qquad W = W(d), \;\; W_d < 0.$$

The demand channel (lower p) reduces the marginal revenue product directly. The liquidity channel (delayed customer payments lower W and raise λ) causes additional contraction. Trade credit mitigates the liquidity component by decoupling input payment timing from delayed customer payments, but the demand effect is unaffected.[5]

Proposition 3 (Downstream Shock Mitigation)**.** *Higher ex ante received trade credit attenuates the negative effect of downstream shocks on inputs, employment, and output:* $\partial^2 x^\star/(\partial d\, \partial\phi) > 0$*. The mitigation operates on the financial channel; the demand channel is unaffected. (Proof in Appendix A.)*

Remark 1 (Extension to τ and output). Since τ enters only through κ and $\partial MC_x/\partial\tau < 0$, all mitigation results hold replacing ϕ with τ. Since x and ℓ are complements under Cobb–Douglas and both face the liquidity wedge $(1+\lambda)$, all results extend to labor and output (see Appendix A).

2.3 Empirical Predictions

The framework generates the following testable hypotheses.

Hypothesis 1 (Direct Impact). Firms in wildfire-affected municipalities experience declines in sales, input purchases, and employment. This follows from Proposition 1: the direct shock reduces productivity and liquid wealth, raising λ and contracting optimal scale.

Hypothesis 2 (Network Propagation). Firms with commercial exposure to affected partners experience declines even without direct exposure. This follows from Propositions 2 and 3: supplier disruptions raise procurement costs, while customer shocks reduce demand and delay payments.

Hypothesis 3 (Trade Credit Mitigation). Among exposed firms, stronger pre-shock trade credit positions (higher ϕ, longer τ) attenuate losses[6]. The framework predicts heterogeneous mitigation: upstream shocks activate both the liquidity and emergency spending channels, downstream shocks activate the liquidity channel only, and direct shocks face the additional constraint of impaired physical capacity. The number of active channels need not map into a strict ranking of

[5] If maintaining scale through trade credit also helps preserve customer relationships that support demand, an indirect demand-side benefit may arise. This second-order general equilibrium effect lies outside the partial equilibrium model but connects to Hypothesis 4 below.

[6] This prediction is driven by the cross-partials derived in Appendix A

estimated magnitudes, since the relative importance of each channel is an empirical question; what the theory pins down is the sign of the cross-partial for all three shock types

3 Data

3.1 Data Sources

I combine two main sources. The first is the Electronic Invoice system administered by the Chilean Tax Authority (Servicio de Impuestos Internos), which provides mandatory digital records of all formal business-to-business transactions.[7] From this source, I observe transaction-level data for 2015–2024, including invoice values, stated payment terms, and the economic activity and municipality of both parties. I complement invoices with monthly value-added tax returns and employer wage reports from the same authority to construct firm-level sales, payroll, and employment.

The second source is CONAF's wildfire database, which records event dates, burned area, and municipality-level location.[8] I link wildfires to firms through their registered municipality, constructing three exposure measures: (i) *direct exposure* if the firm operates in a municipality with a Red Alert wildfire declaration in month t; (ii) *upstream exposure*, aggregating suppliers' direct exposure weighted by pre-shock purchase shares; and (iii) *downstream exposure*, aggregating customers' direct exposure weighted by pre-shock sales shares. Network weights are computed from the universe of transactions among firms with at least one formal employee.

I reconcile firm identifiers across invoice and tax files, drop observations with missing or inconsistent information, and winsorize extreme payment values (p1 and p99). Following standard practice, I exclude financial firms, government institutions, and utilities (Barrot and Sauvagnat, 2016; Ersahin et al., 2024).

The resulting panel tracks firms, their trading partners, and wildfire exposure over time. Transaction records provide the network structure and pre-shock trading weights; wildfire events deliver plausibly exogenous variation in shock timing and location; administrative filings supply consistent outcome measures. This structure enables separating direct impacts from network-mediated effects and testing how pre-shock trade credit conditions shape shock propagation.

[7] `https://www.sii.cl/servicios_online/1039-como_fact_elect-1182.html`

[8] Corporación Nacional Forestal, the agency responsible for Chile's forestry policy under the Ministry of Agriculture.

3.2 Exposure Measures and Trade Credit Conditions

Direct exposure. A municipality is treated in month t if SENAPRED declares at least one Red Alert for wildfire during that month.[9] Formally, $A_{ct} = \mathbf{1}\{\text{Red Alert in municipality } c \text{ in month } t\}$, and firm-level treatment is $D_{it} = A_{c(i)t}$, where $c(i)$ is firm i's registered municipality.

Red Alert offers some advantages over arbitrary hectare thresholds. First, it reflects severity and proximity to population centers and infrastructure, aligning with the economic channels of interest: logistics disruptions, evacuations, and localized financial stress. A fixed surface threshold ignores location and can misclassify small but destructive fires near industrial areas as irrelevant while treating large remote fires as equally harmful. Also, Red Alerts are declared in real time, providing a uniform, time-stamped signal without look-ahead bias, whereas hectares burned are measured ex post and depend on suppression outcomes. Additionally, Red Alerts trigger full emergency deployment, marking precisely when economic costs and supply chain disruptions become salient. Appendix E shows robustness to alternative surface-burned thresholds.

Indirect exposure. Following Alfaro et al. (2021), I construct upstream and downstream exposure indices capturing shock transmission through trading relationships.

Downstream exposure measures the share of firm i's customers in affected municipalities, weighted by prior-year sales:

$$w_{c,i,t} = \frac{\text{Sales}_{i,c,t-1}}{\sum_{c' \in \mathcal{C}_i} \text{Sales}_{i,c',t-1}}, \qquad \text{E}^D_{i,t} = \sum_{c \in \mathcal{C}_i} w_{c,i,t} \cdot T_{c,t},$$

where $T_{c,t} = 1$ if customer c's municipality experiences a shock at t.

Upstream exposure measures the share of firm i's suppliers in affected municipalities, weighted by prior-year purchases:

$$w_{s,i,t} = \frac{\text{Purchases}_{i,s,t-1}}{\sum_{s' \in \mathcal{S}_i} \text{Purchases}_{i,s',t-1}}, \qquad \text{E}^U_{i,t} = \sum_{s \in \mathcal{S}_i} w_{s,i,t} \cdot T_{s,t}.$$

In the main analysis, a firm is indirectly exposed if $\text{E}^U_{i,t} \geq 5\%$ or $\text{E}^D_{i,t} \geq 5\%$; robustness checks vary this threshold.

[9] The National Service for Disaster Prevention and Response (SENAPRED) is the technical agency responsible for coordinating emergency response to natural and human-caused disasters.

Pre-shock trade credit conditions. For each firm i and month t, I measure trade credit conditions over the six months before the shock, $[t-6, t-1]$, using two margins: (i) the share of transactions conducted on credit, and (ii) the value-weighted average contractual days to payment. I compute these separately for received credit (on purchases) and provided credit (on sales). The indicator TC_{it}^{R} (TC_{it}^{P}) equals one if firm i is in the top quartile of both the share and payment terms distributions for received (provided) trade credit during the pre-shock window:

$$TC_{it}^{\{R,P\}} = \mathbf{1}\Big\{\text{Share and Terms in top quartile over } [t-6, t-1]\Big\}.$$

These constructions guarantee that exposure indices and trade credit measures are predetermined with respect to the shock. The network weights are fixed using pre-shock transaction shares, so E_{it}^{U} and E_{it}^{D} vary only with partners' treatment status, not with firm i's outcomes.

3.3 Spatial distribution of wildfire exposure by municipality (2015–2024)

Figure 1 provide a descriptive map of wildfire intensity at the municipality level over the full sample period (2015–2024). Panel A plots the cumulative number of red-alert events issued in each municipality, while Panel B plots the cumulative burned area (hectares) recorded over the same period. In both panels, municipalities are grouped into quantiles of the underlying distribution, so the color scale is designed to highlight spatial concentration rather than absolute differences in levels.

Wildfire activity is highly spatially concentrated, with a small cluster of municipalities repeatedly appearing in the upper quantiles while vast regions remain unaffected. Crucially, the maps reveal that frequency and severity are distinct dimensions: some areas endure frequent alerts with minimal physical damage, while others suffer extensive burned areas from fewer events. This divergence reflects heterogeneity in fire size and containment effectiveness, motivating treating wildfire exposure as a multidimensional phenomenon rather than a single aggregate measure.

These maps help visualize where wildfire risk is systematically elevated in the sample and clarify why the empirical design focuses on network-linked exposure: firms can be economically affected even when located outside the darkest areas if they transact with suppliers or customers in high-intensity municipalities.

Figure 1: Spatial distribution of wildfire activity across municipalities (2015–2024).

(a) Cumulative burned area (hectares), 2015–2024.

(b) Cumulative red alerts, 2015–2024.

3.4 Summary Statistics

Table 1 presents descriptive statistics for the sample, comparing firms in municipalities with at least one Red Alert declaration during the sample period (treated) with those in municipalities without such declarations (control). The sample is large on both sides (approximately 12 million control and 13.5 million treated firm-months), supporting precise estimation.

At baseline, treated firms are somewhat smaller: average monthly sales are roughly 1,907 UF for treated versus 2,203 UF for controls, and average employment is 19 versus 21 workers.[10] De-

[10]The Unidad de Fomento (UF) is an inflation-indexed unit of account in Chile, adjusted daily by the Central

spite these level differences, short-run dynamics are similar: month-to-month growth in sales and employment centers near 1% with comparable dispersion.[11]

Trade credit conditions differ modestly across groups. On the receiving side, control firms conduct a slightly higher share of purchases on credit with shorter terms than treated firms (57% vs. 54%; 27 vs. 25 days). On the supplying side, treated firms extend credit somewhat more often at similar maturities (72% vs. 70%; 24 days for both). Importantly, the composite trade credit indicator combining share and maturity is balanced across groups, supporting identification.

Network exposure is sparse on average but exhibits a thick tail: mean upstream and downstream exposure shares are low, with standard deviations an order of magnitude larger. This pattern aids identification, as most firm-months have negligible exposure while a nontrivial subset experiences meaningful partner shocks, generating sharp within-cell variation after fixed effects are absorbed.

Composition differences are limited. Control municipalities have a lower fraction of micro firms and a higher share in agriculture and forestry, with similar participation in commerce and services. The empirical specifications absorb these differences with sector-by-month and region-by-month effects, so identification comes from within-cell comparisons. The balance on trade credit margins supports a clean test of whether pre-shock credit positions moderate shock transmission.

Appendix B presents the same statistics stratified by trade credit conditions. Additionally, I examine the determinants of trade credit terms, revealing a fundamental asymmetry: larger firms extract more favorable terms from suppliers while imposing stricter terms on customers, consistent with bargaining-power explanations (Giannetti, 2024; Breza and Liberman, 2017). Network structure also matters: firms with more customers impose tighter payment conditions, reflecting reduced relationship-specific dependencies (Barrot and Sauvagnat, 2016; Ersahin et al., 2024). Market concentration uniformly reduces trade credit provision, as firms in concentrated sectors exploit market power to shift terms in their favor (Costello, 2020). These patterns imply that pre-shock trade credit positions are not randomly assigned but reflect underlying firm characteristics and market structure. The empirical specifications account for this selection by including firm fixed effects and by measuring trade credit conditions before shocks occur, ensuring identification from comparing differentially exposed firms with similar predetermined credit positions rather than from cross-sectional variation

Bank. As of early 2025, 1 UF ≈ 39,000 Chilean pesos ≈ USD 40.

[11] Size categories follow SII criteria based on annual sales: Micro <2,400 UF; Small 2,400–25,000 UF; Medium 25,000–100,000 UF; Large >100,000 UF.

Table 1: Baseline characteristics: Control vs. Treated firms

	Control		Treated	
Variable	*Mean*	*SD*	*Mean*	*SD*
Total Sales (UF)	2,203.858	6,898.330	1,907.498	6,480.520
Δ Total Sales	0.013	0.810	0.007	0.850
Firm Sales (UF)	1,864.404	6,082.020	1,598.891	5,678.420
Δ Firm Sales	0.030	1.020	0.032	1.050
Purchases (UF)	899.990	2,898.510	695.076	2,569.460
Δ Purchases	0.042	1.010	0.033	1.060
Employment	20.697	169.530	18.958	199.220
Δ Employment	0.013	0.348	0.013	0.350
Share TC received	0.566	0.350	0.539	0.370
Avg TC term rec.	27.121	18.850	25.239	17.410
Share TC supplied	0.699	0.420	0.715	0.420
Avg TC term supp.	24.011	15.580	24.098	14.970
TC^P	0.114	0.320	0.092	0.290
TC^R	0.274	0.450	0.275	0.450
Upstream exposure	0.011	0.070	0.005	0.040
Downstream exposure	0.014	0.100	0.005	0.050
Δ suppliers	0.054	0.440	0.051	0.460
Δ customers	0.024	0.410	0.026	0.420
Micro	0.306	0.460	0.366	0.480
Small	0.532	0.500	0.498	0.500
Medium	0.109	0.310	0.093	0.290
Large	0.053	0.220	0.043	0.200
Agriculture & Forestry	0.124	0.330	0.069	0.250
Industry	0.271	0.440	0.286	0.450
Commerce	0.325	0.470	0.337	0.470
Service	0.280	0.450	0.307	0.460
Observations	13,509,026		12,073,130	
Number of Firms	478,607		208,572	

in who receives generous terms.

4 Empirical Methodology

I estimate dynamic wildfire effects using Local Projections Difference-in-Differences (LP-DiD) (Dube et al., 2025). This approach suits settings where treatment is a sharp, unit-time intervention with persistent outcomes: in a given municipality-month, a fire occurs or not, but consequences persist over subsequent months.

Standard event studies with two-way fixed effects suffer from well-documented problems when treatment timing varies: coefficients on leads and lags can be contaminated by effects from other periods, and apparent pre-trends can arise from treatment effect heterogeneity alone (Sun and Abraham, 2021). LP-DiD corrects this by constructing valid comparison groups at each horizon, separating anticipation from post-treatment dynamics, and avoiding the negative weighting problem of conventional staggered designs (Dube et al., 2025).

Let Y_{it} denote the outcome of firm i at month t and D_{it} indicate that firm i's municipality experiences a Red Alert in month t. For horizon $h \in \{-Q, \dots, 0, \dots, H\}$, I estimate:

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_0 + \beta_1^h D_{it} + \alpha^h X_{i,t-1} + \gamma_i + \lambda_{s(i),t} + \delta_{r(i),t} + \varepsilon_{it}, \tag{11}$$

where $Y_{i,t+h} - Y_{i,t-1}$ is the change in outcome from the month before treatment to horizon h, and β_1^h measures the average treatment effect at that horizon.

To examine heterogeneity by pre-shock trade credit, I augment equation (11):

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_0 + \beta_1^h D_{it} + \beta_2^h (D_{it} \times TC_{it}^{\{R,P\}}) + \beta_3^h TC_{it}^{\{R,P\}} + \alpha^h X_{i,t-1} + \gamma_i + \lambda_{s(i),t} + \delta_{r(i),t} + \varepsilon_{it}, \tag{12}$$

where $TC_{it}^{\{R,P\}}$ indicates whether firm i is in the top quartile of both trade credit share and payment terms (received or provided) during the six months before the shock. The coefficient β_2^h captures whether pre-shock trade credit buffers ($\beta_2^h > 0$) or amplifies ($\beta_2^h < 0$) the impact at horizon h. The total effect for high trade credit firms is $\beta_1^h + \beta_2^h$, and the profile $\{\beta_2^h\}_h$ reveals whether mitigation is short-lived, delayed, or persistent.

Following Dube et al. (2025), I restrict estimation to clean treated and clean control observations. Clean treated units satisfy $D_{it} = 1$ at t with $D_{i,t-j} = 0$ for $j \in \{1, \dots, L\}$, where $L = 6$ months is the pre-event exclusion window. Clean controls satisfy $D_{i\tau} = 0$ for all $\tau \in [t - L, t + h]$. This construction ensures control units provide valid counterfactuals and eliminates contamination from overlapping treatments.

Sample Restrictions Following Dube et al. (2025), I restrict estimation to clean treated and clean control observations. Clean treated units satisfy $D_{it} = 1$ at t with $D_{i,t-j} = 0$ for $j \in \{1, \ldots, L\}$, where $L = 6$ months is the pre-event exclusion window. Clean controls satisfy $D_{i\tau} = 0$ for all $\tau \in [t-L, t+h]$. This construction ensures control units provide valid counterfactuals and eliminates contamination from overlapping treatments.

Fixed Effects Structure Firm fixed effects (γ_i) absorb time-invariant heterogeneity (managerial quality, technology, baseline risk), so identification comes from within-firm changes. Sector-by-month effects ($\lambda_{s(i),t}$) control for product market shocks (demand swings, commodity prices, sector-specific regulations). Region-by-month effects ($\delta_{r(i),t}$) absorb location-specific conditions (regional fluctuations, disaster response intensity, local policies). With this structure, estimation compares firms within the same sector-month and region-month cells, isolating differential exposure from aggregate, sectoral, or regional shocks.

Indirect Exposure The same logic extends to network spillovers. Let E_{it}^{U} and E_{it}^{D} denote upstream and downstream exposure indices mapping partners' shocks to firm i using pre-shock transaction weights. Replacing D_{it} in equations (11)–(12) with these indices yields horizon-specific effects of partner shocks under analogous clean comparison rules.

Inverse Probability Weighting Treated firms are not a random draw from the firm population. Firms embedded in denser and more geographically dispersed supply chains are mechanically more likely to experience network shocks, and these firms tend to be larger, faster-growing, and more productive than the average control firm. If these observable differences correlate with differential outcome trajectories, they can generate spurious pre-trends and bias the estimated treatment effects.

To address this compositional concern, I augment the LP-DiD estimator with inverse probability weights following Sant'Anna and Zhao (2020) and Callaway and Sant'Anna (2021). I estimate a propensity score model for the probability of direct or indirect exposure conditional on pre-shock firm characteristics—including lagged sales growth, purchase growth, employment growth, exit probability, network size, and firm scale—along with region and sector indicators. Control observations receive weights equal to $\hat{p}/(1-\hat{p})$, where $\hat{p}$ is the estimated propensity score, while treated observations receive unit weights. Weights are trimmed at the 99th percentile to limit the influence of extreme values and normalized to sum to the sample size (Busso et al., 2014). This reweighting adjusts the control group to resemble the treated group on observable pre-shock characteristics, improving the credibility of the parallel trends assumption for the indirect exposure margins.

Outcomes and Inference I measure firm performance using year-on-year growth rates of sales, purchases, and employment, which capture changes in activity while dampening seasonality. To assess supply chain stability, I use year-on-year changes in the number of distinct customers and suppliers, as well as exit probabilities.

Standard errors are clustered at the municipality level for direct exposure specifications and at the firm level for indirect exposure. For the heterogeneity results, I present the estimates from the pooled LP model, which Dube et al. (2025) shows is algebraically equivalent to the stacked difference-in-differences estimator of Cengiz et al. (2019), improving efficiency while preserving causal interpretation.

5 Results

This section presents the dynamic effects of wildfire exposure on firm outcomes and market exit.[12] The analysis proceeds in two steps. First, I estimate impulse response functions for the average effects of direct, upstream, and downstream exposure on sales, purchases, and employment. Second, I explore heterogeneity based on pre-shock trade credit conditions, distinguishing between credit received (accounts payable) and credit extended (accounts receivable) to isolate the liquidity buffer from relational components.

The results generally confirm the theoretical predictions. Trade credit received buffers upstream and downstream shocks (Propositions 2 and 3). Buffering for direct shocks is more limited (Proposition 1), consistent with physical capacity constraints dominating financial frictions. The asymmetry

[12] Throughout Section 5, I interpret statistical significance based on whether 95% confidence intervals exclude zero for multiple consecutive horizons, indicating economically meaningful persistent effects.

between trade credit received and supplied validates the state-contingent nature of interfirm credit: received credit operates as liquidity insurance, while supplied credit creates relationship-specific capital at the cost of counterparty risk exposure.

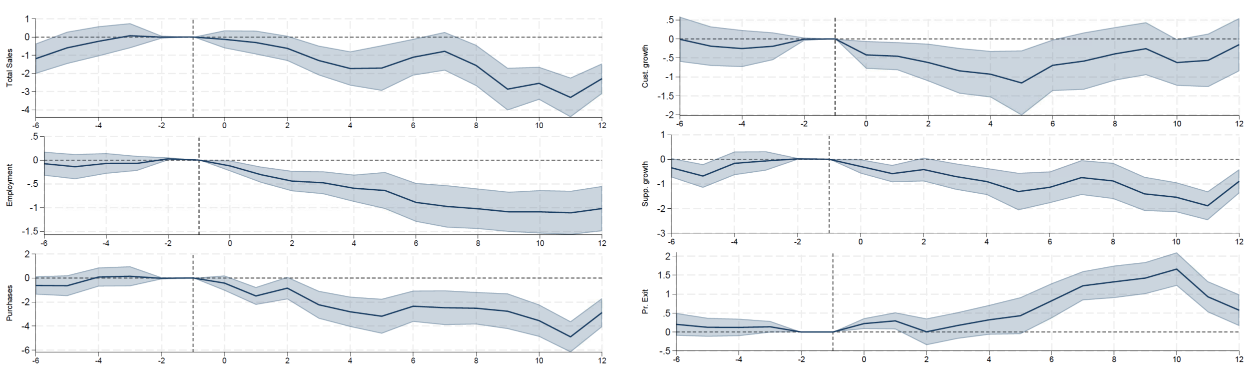
In Appendix C, a detailed discussion and test about the Pre-trends assumption is presented.

5.1 Average Dynamic Effects of Wildfire Exposure

Figure 2 documents the dynamic adjustment of firms directly exposed to wildfires. As shown in Panel (a), real activity contracts persistently. Sales deteriorate in the months following the shock, stabilizing at approximately -2% by horizon 12. Employment exhibits a sluggish but monotonic decline, becoming statistically negative and settling around -1%. Input purchases follow a similar downward trajectory, declining by roughly 3%. The absence of divergent pre-trends across all real outcomes supports the identification strategy.

Panel (b) highlights the propagation of distress through the production network. Supplier growth declines significantly, indicating that directly affected firms sever upstream relationships. In contrast, customer growth initially decreases but then remains statistically indistinguishable from zero at the end of the year, suggesting that while firms cut upstream orders, they struggle to retain downstream clients only at the margin. Financial distress is evident in the extensive margin: exit probability rises gradually, reaching a plateau of 1.5 percentage points by horizon 10.

Figure 2: Dynamic Effects of Direct Exposure on Firm Outcomes



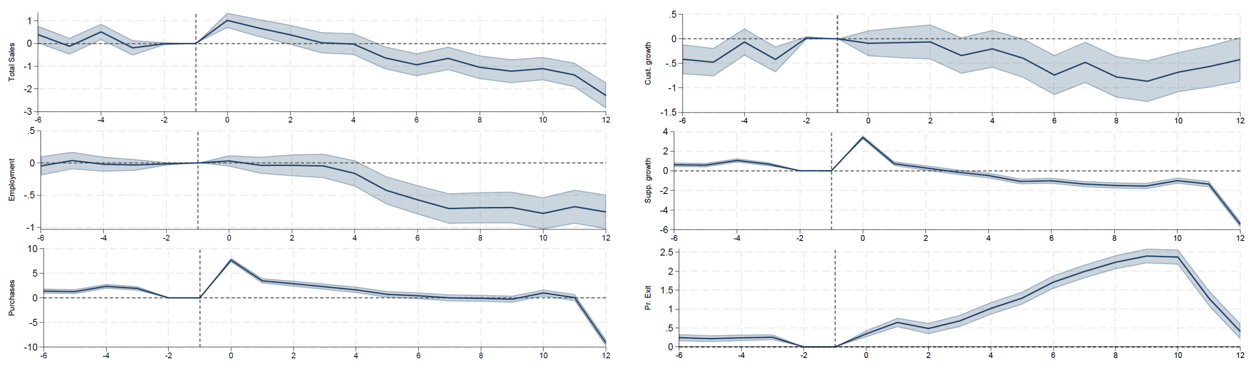
(a) Real Effects

(b) Network Stability

Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the municipality level.

Figures 3 and 4 illustrate how these shocks propagate along the supply chain. For firms with *upstream exposure* (Figure 3), the dominant feature is a sharp, transient spike in input purchases of approximately 10% at impact. Because these values are deflated, this surge reflects the theoretical "emergency procurement" mechanism ($\chi(s, E)$): firms facing supplier disruptions incur premiums to secure expedited inputs from alternative sources. This cost shock transmits to real activity, with sales turning negative after a brief lag (-2% by horizon 12) and employment eroding gradually. Supplier growth spikes initially—consistent with emergency switching—before contracting by 5% as relationships stabilize at a lower level [13].

Figure 3: Dynamic Effects of Upstream Exposure on Firm Outcomes



(a) Real Effects

(b) Network Stability

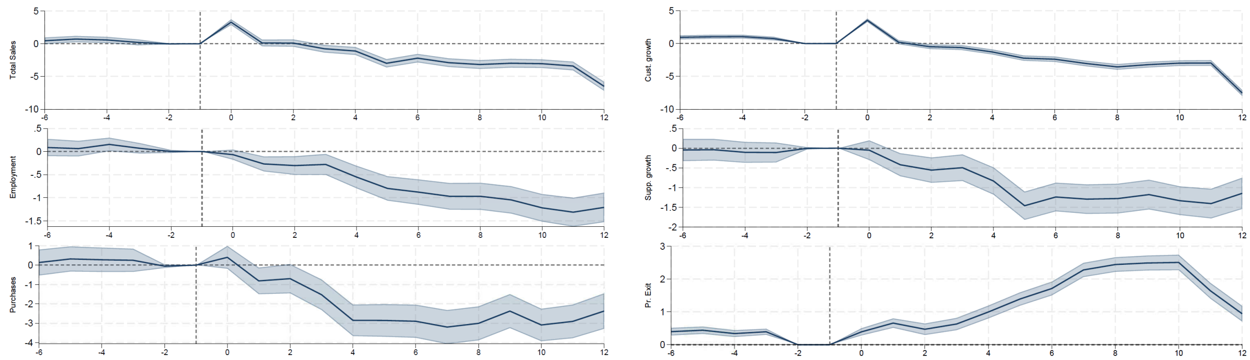
Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the firm level.

Downstream exposure (Figure 4) operates as a demand shock. Following a fluctuation at impact, total sales experience the steepest decline among all groups, deepening to -5% by horizon 12. Employment and purchases track this contraction, falling by 1% and 2%, respectively. Notably, the purchase response lacks the emergency spike observed in the upstream case, confirming that demand-constrained firms simply scale back operations rather than seeking alternative inputs. The network impacts confirm this demand channel: customer growth collapses (-6% by horizon 12) as downstream buyers exit or shrink, while exit probability rises to 2.5 percentage points, comparable to the upstream case.

Together, these patterns validate the distinct transmission channels predicted by theory. While all exposure types generate liquidity-driven attrition, the intermediate mechanics differ: upstream exposure triggers a cost-push shock visible in emergency procurement, whereas downstream exposure

[13]In Appendix F, I present a formal test to support the emergency procurement channel

Figure 4: Dynamic Effects of Downstream Exposure on Firm Outcomes



(a) Real Effects

(b) Network Stability

Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the firm level.

acts as a pure demand contraction. The persistence of these effects highlights the role of adjustment frictions—such as search costs and relationship specificity—in slowing post-disaster recovery.

5.2 Heterogeneity by Trade Credit Received

The theoretical framework suggests that trade credit serves as a state-contingent safety net, alleviating liquidity constraints that amplify real contractions. Table 2 tests this by interacting each exposure treatment with a firm's standardized pre-shock trade credit payables (TC^P), using inverse probability weights to adjust for observable differences between exposed and control firms. The horizon-by-horizon impulse responses, reported in Appendix D, complement the pooled estimates by revealing how buffering evolves dynamically over the twelve months following the shock. The pooled coefficients are consistent with the average of the horizon-specific effects, and the IRFs confirm that the patterns are not driven by any single post-shock month.

For firms hit directly (Panel A), trade credit provides meaningful but selective protection. The interaction offsets the baseline declines in sales and purchases, and firms with stronger payables positions retain more suppliers through the disruption. Yet the effect on employment remains statistically indistinguishable from zero, and the exit interaction is small and insignificant. The impulse responses reinforce this picture: the sales and supplier-retention gaps between high- and low-TC^P firms emerge gradually over the first four months and persist through the remainder of the estimation window, while the employment paths remain largely overlapping regardless of trade credit position. This aligns with the intuition that while liquidity can ease procurement and cash management during a crisis, it cannot substitute for impaired productive capacity. The supplier-retention result suggests that financially buffered firms actively maintain upstream relationships rather than severing them under stress, preserving supply chain connections that support eventual recovery.

The downstream exposure results (Panel B) provide the broadest evidence of buffering. The TC^P interaction is significant and positive for sales and purchases, and firms with greater financial slack also retain more suppliers and face lower exit probability. The only margin where trade credit fails to help is employment, consistent with the theoretical prediction that deferred supplier obligations reduce the immediate cash burden of a liquidity crunch but cannot restore the revenue needed to sustain payroll when downstream demand contracts. The impulse responses for this panel are revealing. For sales, high-TC^P firms remain essentially at their pre-shock trajectory throughout the twelve-month window, while low-TC^P firms experience a deepening decline that reaches roughly five percentage points by the final horizon. The divergence is progressive rather than instantaneous, suggesting that the liquidity channel operates cumulatively: firms with financial slack avoid the cascading deterioration that compounds as customer payments are delayed and then partially defaulted. The exit dynamics mirror this pattern in reverse—low-TC^P firms face steadily rising exit probability, while high-TC^P firms experience declining exit risk over time, generating the largest absolute separation of any outcome-panel combination by the end of the estimation window.

For upstream exposure (Panel C), trade credit mitigates the shock on the two margins most directly connected to the liquidity mechanism: sales and employment. The sales interaction is the largest across all panels, implying that well-positioned firms essentially avoid the upstream-induced revenue decline. The employment buffering is also strong and highly significant. Exit probability falls for firms with higher payables. However, the interaction on purchases is not statistically significant. The impulse responses clarify this null result: both high- and low-TC^P firms exhibit a sharp procurement spike at impact, consistent with the model's emergency sourcing channel. This spike is of similar magnitude for both groups, confirming that the emergency procurement premium $\chi(s, E)$ is incurred regardless of a firm's trade credit position. The divergence appears in what happens next: low-TC^P firms see purchases collapse after the initial spike, falling steadily through the estimation window, while high-TC^P firms stabilize near zero. The pooled interaction averages these two phases resulting in an insignificant coefficient despite the economically important difference in medium-run dynamics. The sales and employment IRFs show a cleaner pattern: a steady and widening gap between the two groups that opens within the first two months and grows monotonically, consistent with the highly significant pooled coefficients.

Taken together, these results confirm the theoretical predictions while revealing an important dynamic structure. Trade credit buffering operates comprehensively for downstream exposure, where the liquidity timing mismatch between delayed customer payments and ongoing supplier obligations is the primary friction and where the effects compound progressively over time. It operates selectively for upstream exposure, protecting the real outcomes that depend on a firm's ability to finance adjustment costs, even as the emergency procurement channel operates symmetrically across trade credit positions. And it provides narrow protection for direct exposure, where physical constraints dominate. Across all three margins, the pattern is consistent with trade credit relaxing a binding cash constraint whose relevance varies with the nature of the shock, and the horizon-specific evidence confirms that the buffering is persistent rather than temporary.

5.3 Heterogeneity by Trade Credit Supplied

The theoretical framework predicts a sharp difference between the credit a firm receives and the credit it supplies. While receiving credit relaxes a firm's cash constraints, supplying credit to customers (accounts receivable, TC^R) ties up working capital, which can make a firm more financially vulnerable during a crisis. Table 3 tests this by interacting the wildfire treatments with a firm's pre-shock receivables, and the horizon-by-horizon impulse responses in Appendix D complement the pooled estimates. The results confirm the theoretical asymmetry: trade credit supplied provides no protection for real activity and, for downstream exposure, actively amplifies vulnerability on the exit margin.

For direct exposure (Panel A), all TC^R interaction coefficients are statistically indistinguishable from zero. The impulse responses confirm this: the paths for high- and low-receivables firms are nearly indistinguishable across sales, employment, purchases, and exit, with confidence bands overlapping throughout the twelve-month window. This contrasts with the results TC^P, where sales, purchases, and the number of sellers were significantly buffered. Receivables lock up working capital without providing the financial slack needed to manage a direct disruption.

Table 2: Exposure Effects by Trade Credit Received

	(1) Δ% Sales	(2) Δ% Purchases	(3) Δ% Employment	(4) Pr. Exit	(5) Δ% Sellers	(6) Δ% Buyers
Panel A: Direct Exposure						
Treatment	-1.157***	-2.266***	-0.507***	0.425***	-0.758**	-0.347
	(0.407)	(0.691)	(0.171)	(0.153)	(0.360)	(0.229)
Treatment × $TC^{\{P\}}$	0.994*	1.581*	0.187	-0.132	0.580*	0.138
	(0.568)	(0.799)	(0.237)	(0.391)	(0.337)	(0.393)
Observations	10,934,502	10,379,174	10,934,502	16,537,370	10,379,174	6,280,117
R^2	0.781	0.801	0.651	0.643	0.806	0.805
Panel B: Downstream Exposure						
Treatment	-1.360***	-1.558***	-0.531***	1.448***	-0.600***	-1.152***
	(0.181)	(0.250)	(0.0839)	(0.0622)	(0.110)	(0.120)
Treatment × $TC^{\{P\}}$	0.731**	2.021***	0.0475	-0.275**	0.442**	0.0882
	(0.368)	(0.507)	(0.175)	(0.138)	(0.225)	(0.263)
Observations	7,340,046	6,821,922	7,340,046	10,307,272	6,821,922	5,633,648
R^2	0.807	0.819	0.680	0.712	0.826	0.802
Panel C: Upstream Exposure						
Treatment	-0.392***	1.332***	-0.396***	1.273***	-0.137	-0.0998
	(0.139)	(0.187)	(0.0672)	(0.0500)	(0.0854)	(0.120)
Treatment × $TC^{\{P\}}$	1.282***	0.575	0.434***	-0.287***	0.199	-0.210
	(0.310)	(0.414)	(0.145)	(0.111)	(0.187)	(0.252)
Observations	9,385,555	9,016,636	9,385, 555	14,968,988	9,016,636	5,287,452
R^2	0.784	0.801	0.652	0.648	0.807	0.800
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month–Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Month–Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel A standard errors are clustered at the county level. Panels B and C standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The downstream panel (Panel B) provides the clearest evidence of what trade credit supplied actually does. The TC^R interactions on sales, purchases, and employment are all insignificant—the impulse responses confirm largely overlapping paths on these real margins, with both groups experiencing comparable declines. The exit interaction, however, is positive and highly significant, indicating that firms with large outstanding receivables face higher exit risk when customers are hit. This is the mirror image of what TC^P delivers: where payables reduce exit probability, receivables increase it. The mechanism is straightforward—when customers are disrupted, payment delays lengthen and some receivables become uncollectable, draining working capital precisely when the firm needs it most. At the same time, the interaction on the number of sellers is positive and significant, and the impulse responses for supplier growth show a persistent and widening gap: high-TC^R firms maintain their upstream relationships while low-TC^R firms experience steady supplier attrition. This suggests that firms embedded in dense credit networks—extending credit downstream, receiving it upstream—benefit from mutual dependencies that keep suppliers engaged even under stress.

For upstream exposure (Panel C), a similar pattern holds. The TC^R interactions are uniformly insignificant, with only a marginal positive effect on employment. Impulse responses show that both high- and low-TC^R firms exhibit a characteristic spike in emergency procurement at impact and a subsequent decline in purchases, with essentially overlapping paths. The emergency procurement channel requires cash, and receivables are not cash: firms with large outstanding customer credit cannot convert those claims into the liquidity needed to fund alternative sourcing.

In sum, credit received and credit supplied serve fundamentally different purposes. Credit received acts as liquidity insurance: it provides financial slack to maintain procurement, preserve employment, and reduce exit risk, with effects that compound progressively over time. Credit supplied does not buffer real activity and can amplify vulnerability by tying up cash in customer obligations that become illiquid under stress. The downstream exit result makes this concrete: the same firms that benefit from generous payment terms are endangered by extending those terms to their customers. For a firm in a disaster zone, the balance between payables and receivables determines whether trade credit functions as a tool for operational continuity or a source of additional fragility.

The brief spike in sales at impact, visible for both downstream and upstream exposure, likely reflects emergency transactions in the immediate aftermath of the fire — accelerated orders from affected customers and inventory liquidation toward disrupted supply chains — before the persistent contractionary effects dominate from the second month onward.

5.4 Sectoral Heterogeneity

The theoretical framework predicts that trade credit buffering should be strongest where shocks operate through liquidity channels and where emergency procurement is feasible. These conditions vary sharply across sectors due to differences in input specificity, inventory management, and the nature of customer relationships. In Appendix E, I test these predictions by estimating the model separately for primary, industrial, commercial, and service sectors.

The commercial sector offers the clearest validation of the liquidity channel. Because retail and

Table 3: Exposure Effects by Trade Credit Supplied

	(1) Δ% Sales	(2) Δ% Purchases	(3) Δ% Employment	(4) Pr. Exit	(5) Δ% Sellers	(6) Δ% Buyers
Panel A: Direct Exposure						
Treatment	-1.190***	-2.210***	-0.511***	0.316**	-0.751**	-0.465
	(0.381)	(0.696)	(0.174)	(0.159)	(0.352)	(0.282)
Treatment × $TC^{\{R\}}$	0.606	0.621	0.106	0.364	0.288	0.430
	(0.614)	(0.716)	(0.288)	(0.235)	(0.290)	(0.422)
Observations	10,934,502	10,379,174	10,934,502	16,537,370	10,379,174	6,280,117
R^2	0.781	0.801	0.651	0.643	0.806	0.805
Panel B: Downstream Exposure						
Treatment	-1.310***	-1.386***	-0.467***	1.288***	-0.674***	-1.227***
	(0.194)	(0.265)	(0.0909)	(0.0688)	(0.116)	(0.132)
Treatment × $TC^{\{S\}}$	0.226	0.596	-0.166	0.313***	0.482**	0.323
	(0.332)	(0.476)	(0.155)	(0.114)	(0.208)	(0.229)
Observations	7,340,046	6,821,922	7,340,046	10,307,272	6,821, 922	5,633, 648
R^2	0.802	0.794	0.623	0.681	0.787	0.782
Panel C: Upstream Exposure						
Treatment	-0.280*	1.518***	-0.389***	1.239***	-0.114	-0.0888
	(0.144)	(0.192)	(0.0699)	(0.0528)	(0.0885)	(0.128)
Treatment × $TC^{\{S\}}$	0.319	-0.406	0.231*	-0.0331	0.0356	-0.161
	(0.287)	(0.381)	(0.135)	(0.0933)	(0.171)	(0.224)
Observations	9,385,555	9,016,636	9,385,555	14,968,988	9,016,636	5,287,452
R^2	0.784	0.801	0.652	0.648	0.807	0.800
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month–Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Month–Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel A standard errors are clustered at the county level. Panels B and C standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

wholesale firms manage fungible inventories with high turnover, their primary constraint during a shock is often cash flow rather than the specificity of physical inputs. Consequently, trade credit received (TC^P) generates comprehensive buffering against both direct and downstream shocks. For direct exposure, TC^P significantly attenuates losses in sales and purchases, reduces exit probability by 1.1 percentage points, and expands the supplier base. For downstream exposure, the buffering is even broader being this is the most comprehensive set of TC^P results for any sector under any exposure type. However, upstream TC^P buffering is limited to exit probability, and the TC^R results reveal an important counterpoint: for upstream shocks, firms with high receivables suffer significantly deeper sales and purchase declines. In a sector with thin margins, tying up working capital in customer debts while also facing supply disruptions creates a compounding liquidity squeeze. Downstream, TC^R raises exit risk (0.834, $p < 0.01$), confirming that receivables become liabilities when customers are in distress.

In the primary sector (agriculture and extraction), the binding constraints are geographic specificity and seasonality. Here, trade credit received acts as insurance for procurement and survival across multiple exposure types. For downstream exposure, the interaction coefficient on purchases is the largest across all sectors, suggesting that financial slack enables firms to maintain critical input flows that would otherwise be cut—a key margin given that missed planting or harvesting windows cannot be recovered. The TC^P interactions on sales, exit, and number of sellers confirm that buffering extends beyond procurement into broader operational and network resilience. For upstream exposure, TC^P significantly buffers sales and sharply exit risk. This is the only sector where direct exposure interacted with TC^P significantly reduces exit probability (-1.835, $p < 0.01$), likely reflecting the structure of primary supply chains: producers operating in fire-prone regions who maintain strong trade credit relationships with processors benefit from mutual incentives to preserve the relationship even when the producing area is physically damaged. The TC^R interactions for buyer retention are positive and significant across downstream and upstream exposure, and the direct panel shows a similar pattern. However, TC^R is also associated with deeper employment losses across downstream and upstream exposure, showing the same trade-off between relationship preservation and operational vulnerability as in the baseline results.

In contrast, the industrial sector shows limited real-side buffering from TC^P, a result consistent with input specificity. Manufacturing and construction rely on specialized components and certified suppliers that cannot be easily replaced on spot markets, regardless of a firm's liquidity. The "emergency spending" mechanism is less effective when the necessary replacement inputs simply do not exist. Trade credit keeps industrial firms alive and connected, even when it cannot restore their production volumes. The TC^R results are distinctive in this sector. For upstream exposure, firms with high receivables suffer a large and significant decline in purchases and lose sellers, suggesting that receivables lock up the working capital needed to manage supply disruptions. For downstream exposure, TC^R raises exit risk, confirming the "liquidity squeeze": capital-intensive firms with long production cycles and large outstanding receivables are especially vulnerable when customers default.

The service sector presents the weakest evidence for the TC^P channel on indirect exposure, consistent with its production structure. Service firms typically have low input intensity, minimal inventories, and simultaneous production and consumption. When downstream demand fades, the constraint is the fundamental absence of customers, not a lack of cash to buy inputs. Consequently, TC^P provides no significant buffering against downstream or upstream shocks. However, for direct exposure, TC^P generates significant positive interactions on sales, purchases, and the number of sellers, suggesting that when the shock is local and financial constraints bind, even service firms benefit from liquidity slack. The most distinctive feature of the service sector is the role of TC^R under downstream exposure. Services is the only sector in which trade credit supplied generates broad positive real effects: sales, number of sellers, and number of buyers all improve significantly. Unlike goods-producing firms, where receivables represent sunk costs tied to shipped merchandise, service receivables often correspond to ongoing contractual relationships—consulting engagements, maintenance agreements, recurring subscriptions—where maintaining the financial link helps retain clients through the crisis. Yet this does not extend to upstream exposure, where TC^R raises exit risk, indicating that even in services, receivables create vulnerability when suppliers are disrupted.

In summary, trade credit functions as a shock absorber only under specific boundary conditions. It is most effective in Commerce, where inputs are fungible and financial constraints bind across multiple margins of adjustment. It is effective in Primary sectors for preserving critical procurement and reducing exit risk, driven by the irreversibility of seasonal production. It is limited in Industry, where input specificity prevents the liquidity channel from translating into real production gains, though it consistently supports survival and network maintenance. And it is weakest in Services for indirect exposure, where demand rather than liquidity constrains adjustment—though services uniquely benefit from TC^R as relationship capital under downstream shocks. Across all sectors, the survival value of trade credit remains consistent: even where it cannot restore immediate output, financial slack prevents firm exit, preserving the network architecture through which the eventual recovery must proceed.

5.5 Heterogeneity by Firm Size

The theoretical framework rests on a binding liquidity constraint: trade credit buffers shocks by relaxing the cash requirement for input procurement and emergency spending. A direct implication is that buffering should be strongest among firms for which this constraint binds most tightly—that is, small firms with limited internal resources and less access to external finance. As firms grow larger and accumulate financial buffers, retained earnings, and diversified credit lines, the shadow value of liquidity falls, and the marginal benefit of trade credit as a shock absorber diminishes. In Appendix E, I test this prediction by separately estimating trade credit interactions for small, medium, and large firms.

The results confirm a size gradient. Trade credit received generates comprehensive real-side buffering for small firms, selective but strong buffering for medium firms, and essentially no buffering for large firms. This gradient provides validation of the model's core mechanism: trade credit matters precisely because it relaxes a constraint that binds differentially across the firm size distribution.

Small firms exhibit the broadest and most consistent evidence of mitigation, consistent with their position as the most financially constrained segment of the economy. For direct exposure, trade credit received (TC^P) generates significant positive interactions for sales , purchases , and employment. The employment result is particularly notable: this is the only size category in which trade credit significantly buffers the employment response to direct shocks, suggesting that small firms face binding cash constraints on payroll that larger firms can absorb through internal resources.

The upstream exposure results for small firms are the most comprehensive in the analysis. The TC^P interaction is positive and highly significant across real margins, and the number of sellers. In fact, the magnitude of the sales interaction exceeds the baseline treatment effect, implying that well-positioned small firms essentially avoid the upstream shock entirely. This pattern aligns with the emergency spending mechanism: when small firms have sufficient financial slack from deferred supplier payments, they can fund the search for alternative inputs and expedited logistics that would otherwise be foreclosed by their limited cash reserves.

Medium firms occupy an intermediate position in the financial constraint distribution, and their results reflect this status: buffering is present but concentrated in fewer margins. For direct exposure, TC^P generates the largest point estimate for sales interaction across all size categories, suggesting that medium firms face binding constraints specifically on the revenue side while maintaining sufficient internal buffers for employment and procurement. Their upstream results are also strong, with significant buffering for real variables. This suggests that medium firms suits in the middle where financial slack translates most effectively into supply chain resilience.

Large firms represent the theoretical counterfactual: what happens when the liquidity constraint is slack. If trade credit buffering operates through the shadow value of liquidity, it should vanish when that value is small—and this is precisely what the data show. Across all three exposure types, the TC^P interactions for real outcomes are uniformly insignificant, except for a reduction in exit probability under upstream exposure. Large firms do not need trade credit to maintain production when shocks hit because they can draw on retained earnings, diversified credit lines, and internal capital markets to finance adjustments.

Summarizing these findings, the size gradient in trade credit buffering supports the model's core mechanism. The data conform to the theoretical prediction with consistency: small firms—where liquidity constraints bind most tightly—exhibit comprehensive buffering; medium firms show selective but strong resilience; and large firms—where constraints are slack—show no buffering and significant amplification through receivables. This pattern also addresses potential endogeneity concerns: if trade credit interactions simply captured unobserved firm quality, the buffering effect would not vary systematically with size. The fact that it does strengthens the causal interpretation that trade credit buffers shocks precisely by relaxing binding financial constraints.

5.6 Robustness checks

Appendix E presents additional Pooled LP estimates using alternative cutoffs for defining directly affected firms (specifically, burned areas exceeding 200 and 500 hectares). It also considers alternative thresholds for indirect exposure, ranging from strictly positive ($> 0\%$) to 10%, to complement the baseline 5% cutoff used for upstream and downstream exposure. Across all specifications, the results exhibit patterns consistent with the baseline estimates.

Additionally, there is a potential concern regarding the implementation of Law 21.131 (2019), which mandated 30-day payment terms and could threaten the identification in this analysis. However, the law generated minimal disruption to the aggregate trade credit distribution. Comparing the pre- and post-2020 periods, the average days-to-payment declined only marginally (from 28.2 to 24.5 days), while the standard deviation slightly increased (from 17.7 to 18.4 days). This persistence of heterogeneity confirms that the distinction between firms with high and low trade credit remains a valid source of identification throughout the full sample period.

6 Aggregation and Policy Implications

6.1 Aggregate Implications and the Network Multiplier

The micro-level estimates can be used to gauge the macroeconomic relevance of network propagation. I construct a simple accounting exercise that combines the estimated treatment effects on sales with the observed distribution of exposure across the Chilean firm population, weighting firms by their sales.

Direct versus indirect losses. Averaged across 120 months, directly exposed firms account for 2.05% of total sales, downstream-exposed firms for 3.15%, and upstream-exposed firms for 2.05%. Combining these shares with the pooled treatment effects yields a decomposition of aggregate sales losses per period:

$$\text{Direct loss} \approx 0.0205 \times (-1.16\%) = -0.024 \text{ pp},$$

$$\text{Downstream loss} \approx 0.0315 \times (-1.36\%) = -0.043 \text{ pp},$$

$$\text{Upstream loss} \approx 0.0205 \times (-0.39\%) = -0.008 \text{ pp}.$$

The baseline estimate implies that the average monthly wildfire shock reduces aggregate output by 0.075%. Indirect network spillovers drive roughly two-thirds of this decline (-0.051 pp), exceeding the direct physical component.[14]

The estimated network multiplier—defined as the ratio of total aggregate losses to direct losses—is approximately **3.1** (0.075/0.024). This magnitude is consistent with the production network literature, comparable to the multiplier of 4.7 estimated by Carvalho et al. (2021) for the Great East Japan Earthquake and the 2.4 multiplier in Barrot and Sauvagnat (2016) . However, unlike Barrot and Sauvagnat (2016), who find propagation primarily downstream due to technological specificity, my results document significant bi-directional propagation. This highlights that *financial frictions* operate as a distinct transmission mechanism: constraining customers via input scarcity

[14]This accounting exercise assumes that the estimated relative effects represent net aggregate losses. This assumption is conservative if the general equilibrium effect of the disaster is negative (e.g., regional infrastructure disruptions absorbed by fixed effects). However, it may overestimate losses if non-exposed firms purely substitute the sales of exposed firms (business stealing). Given the high degree of input specificity documented, which limits short-run substitution, the business-stealing channel is likely second-order relative to the direct disruption.

and suppliers via liquidity shortages.

The trade credit counterfactual. To quantify the stabilizing potential of trade credit, I compute the implied loss under a counterfactual in which all indirectly exposed firms possess top-quartile payables positions ($TC^P = 1$).

$$\text{Counterfactual downstream loss} \approx 0.0315 \times (-0.63\%) = -0.020 \text{ pp},$$

$$\text{Counterfactual upstream effect} \approx 0.0205 \times (+0.89\%) = +0.018 \text{ pp}.$$

Under this counterfactual, the total aggregate loss decreases from 0.075% to 0.026%. Interpreted through the lens of Bigio and La'o (2020), this result suggests that financial frictions account for nearly 65% of the aggregate transmission. By relaxing the working capital constraint, trade credit reduces the "liquidity wedge" that would otherwise propagate through the production network, leaving only the residual loss driven by physical destruction, which liquidity cannot mitigate.

6.2 Policy Implications

The results presented in this paper carry the following policy implications:

Beyond Geographic Targeting. Standard interventions typically target geographically defined "emergency zones." However, the aggregate accounting shows that physically distant firms drive the bulk of economic losses. Disaster relief programs should therefore incorporate supply chain exposure into targeting criteria. Verifiable administrative data—such as the VAT records used in this paper—can identify firms with critical commercial links to disaster zones, allowing support to reach the nodes where propagation is most severe.

Targeted Liquidity vs. General Stimulus. The counterfactual analysis demonstrates that liquidity is the binding constraint for propagation. However, the heterogeneity results show that this buffering is concentrated among SMEs. This implies that broad, untargeted liquidity injections (e.g., universal low-rate loans) are inefficient, as large firms do not pass liquidity through the chain. Instead, government-backed working capital guarantees should be specifically targeted at SMEs with demonstrated network exposure to fund the "emergency procurement" necessary to maintain operations.

Mitigating Contagion via Receivables. The results reveal a specific vulnerability for liquidity providers: firms extending trade credit import distress from their customers. To prevent this "contagion via generosity," policy should focus on asset monetization. Instruments that facilitate the rapid conversion of accounts receivable into cash—such as state-subsidized factoring or supply chain finance guarantees—would allow suppliers to preserve customer relationships without jeopardizing their own solvency. Chile's universal electronic invoicing system provides the ideal digital infrastructure to implement such a program at scale.

Sectoral Specificity. Finally, the limits of financial adaptation for direct shocks and the sectoral heterogeneity dictate a subtle approach. For the primary sector, where harvest cycles bind, speed of disbursement is paramount. For commerce, working capital is highly effective. For services, where demand is the constraint, liquidity provision is insufficient and must be paired with demand-side stimulus. Crucially, for direct physical damage, financial tools are ineffective; resilience requires ex-ante investments in physical adaptation and insurance markets.

7 Conclusion

As climate-related disasters become more frequent, understanding how private firms absorb or propagate these shocks is critical for economic stability. Using the universe of firm-to-firm transactions in Chile combined with precise wildfire records, this paper provides comprehensive evidence on the role of pre-existing financial arrangements in shaping supply chain resilience.

The core finding is that wildfires generate persistent network-propagated losses. Trade credit received acts as state-contingent liquidity insurance: it buffers customer shocks by bridging payment delays and mitigates supplier shocks by financing the adjustment costs of emergency procurement. However, when the firm itself is physically hit, the scope for financial mitigation narrows: liquidity helps maintain procurement and supplier relationships but cannot substitute for destroyed productive capacity. Trade credit supplied works through a fundamentally different channel. Receivables provide no real-side protection and, when customers are in distress, actively amplify exit risk by locking working capital in obligations that become illiquid precisely when cash is most needed.

The aggregate accounting highlights the macroeconomic impact of these micro-level findings. Indirect losses transmitted through supply chains account for roughly two-thirds of the total output impact, yielding a network multiplier of approximately 3.1—comparable to estimates from the Great East Japan Earthquake and U.S. natural disasters. A counterfactual in which all indirectly exposed firms held top-quartile payables positions would reduce aggregate losses by nearly two-thirds, implying that financial frictions within the production network—rather than physical destruction alone—drive climate disaster costs. The distribution of interfirm financial positions, a margin typically invisible to policymakers focused on the banking sector, is a first-order determinant of aggregate resilience.

The heterogeneity analysis reinforces the causal interpretation. Buffering follows a strict size gradient—comprehensive for small firms where liquidity constraints bind tightly, selective for medium firms, and absent for large firms with access to alternative financing—confirming that trade credit matters because it relaxes a constraint that binds differentially across the firm distribution. Sectoral variation further disciplines the mechanism: buffering is broadest in commerce, where inputs are fungible, and the liquidity channel operates across multiple margins; effective in primary sectors for preserving irreversible seasonal procurement; limited in industry, where input specificity prevents liquidity from translating into production gains; and weakest in services for indirect shocks, where demand rather than cash constrains adjustment.

These results speak to several active debates. For the production networks literature, the paper provides micro-level evidence that short-term financial positions at individual nodes determine whether shocks amplify or attenuate as they propagate. For the trade credit literature, the findings demonstrate that the stabilizing role of interfirm credit is state-contingent: the same instrument that buffers shocks through payables amplifies vulnerability through receivables, and the boundary conditions for effective buffering depend on the interaction between shock type, firm size, and sectoral production structure. For climate economics, the evidence shifts the focus of resilience policy from ex-post relief toward the ex-ante financial arrangements embedded in supply chains, which shape how much of a disaster's cost materializes in aggregate output.

The policy implications are concrete. Disaster relief should incorporate supply chain exposure into targeting criteria, using the administrative transaction data that already exists in countries with electronic invoicing. Liquidity support should be directed at financially constrained SMEs with demonstrated network exposure rather than disbursed broadly. Instruments that facilitate the rapid monetization of receivables—such as state-backed factoring linked to electronic invoice platforms—would allow firms to preserve customer relationships without importing their distress. And for direct physical damage, where financial tools reach their limits, resilience requires ex-ante investment in adaptation infrastructure and insurance markets.

The analysis has limitations that point toward future work. The partial equilibrium framework does not capture general equilibrium reallocation across firms or regions, and the aggregation exercise treats exposure margins as additively separable. A structural production network model that endogenizes trade credit positions and their interaction with network topology would allow welfare analysis and optimal policy design. The paper also abstracts from the dynamic response of trade credit terms themselves—how suppliers and customers renegotiate payment conditions after a shock—which is an important margin that the same invoice-level data could elucidate. Finally, extending the framework to other types of aggregate shocks—monetary policy, trade disruptions, pandemics—would test whether the mechanisms identified here generalize beyond climate disasters to the broader class of shocks that propagate through production networks under financial frictions.

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A Derivations and Proofs

This appendix derives the comparative statics stated in Section 2. Throughout, assume an interior solution, standard differentiability, and second-order conditions sufficient for the implicit function theorem.

A.1 Equilibrium System

With the binding liquidity constraint, equilibrium $(x^\star, \ell^\star, E^\star, \lambda^\star)$ solves:

$$\begin{aligned} pA\alpha\, x^{\alpha-1}\ell^{1-\alpha} &= c\Big[(1-\phi)(1+\lambda) + \phi\kappa\Big] + \chi(s, E), && \text{(A.1)} \\ pA(1-\alpha)\, x^{\alpha}\ell^{-\alpha} &= w(1+\lambda), && \text{(A.2)} \\ -\chi_E(s, E) &= \frac{1+\lambda}{x}, && \text{(A.3)} \\ W + \bar{B} &= (1-\phi)\, cx + w\ell + E. && \text{(A.4)} \end{aligned}$$

A.2 Properties of the Shadow Value of Liquidity

Rather than assuming properties of λ in response to shocks and trade credit, we derive them from the equilibrium system.

Lemma 1 (Liquidity responds to wealth shocks)**.** *If a shock reduces liquid wealth ($W_\theta < 0$ for $\theta \in \{\delta, d\}$), then $\lambda_\theta > 0$ in the constrained regime.*

Proof sketch. Differentiate (A.4) with respect to θ:

$$W_\theta = (1-\phi)\, c\, x_\theta + w\, \ell_\theta + E_\theta.$$

From (A.1)–(A.3), an increase in λ raises the effective cost of all inputs, reducing x, ℓ, and E. Hence, to absorb the negative wealth shock ($W_\theta < 0$) while maintaining the binding constraint with lower scale, the system requires a higher λ. Formally, applying the implicit function theorem to the system yields $\lambda_\theta = -W_\theta/\Delta_\lambda > 0$, where $\Delta_\lambda > 0$ under second-order conditions. □

Lemma 2 (Trade credit reduces the shadow value of liquidity)**.** *In the constrained regime, $\lambda_\phi < 0$: higher ϕ relaxes the cash constraint and reduces the scarcity value of cash.*

Proof sketch. At given (x, ℓ, E), increasing ϕ reduces the left-hand side of the cash requirement $(1-\phi)\,cx$ in (A.4), creating slack. To restore the binding constraint at the new equilibrium, λ falls, which expands scale until the constraint binds again. □

Lemma 3 (Cross-property: trade credit attenuates liquidity response to shocks)**.** *For shocks that reduce liquid wealth, $\lambda_{\theta\phi} \leq 0$: the increase in λ caused by the shock is weakly smaller when ϕ is higher.*

Proof sketch. The sensitivity of λ to a wealth shock depends on how tight the cash constraint is per unit of lost wealth. When ϕ is higher, a smaller share of input costs must be financed with cash, so the constraint is less sensitive to reductions in W. Formally, differentiating the IFT expression for λ_θ with respect to ϕ and using $\partial[(1-\phi)\,c]/\partial\phi = -c < 0$ yields $\lambda_{\theta\phi} \leq 0$. □

A.3 Direct Shocks

Proof of Proposition 1. Set $s = 0$, $E = 0$, $\chi = 0$. Define the input FOC residual:

$$F(x, \ell, \lambda; \delta, \phi) \equiv pA(\delta)\alpha\, x^{\alpha-1}\ell^{1-\alpha} - c\Big[(1-\phi)(1+\lambda) + \phi\kappa\Big].$$

Differentiate with respect to δ (holding equilibrium variables fixed for the partial):

$$F_\delta = pA_\delta\alpha\, x^{\alpha-1}\ell^{1-\alpha} - c(1-\phi)\lambda_\delta < 0,$$

where both terms are negative ($A_\delta < 0$ and $\lambda_\delta > 0$ by Lemma 1).

Differentiate F_δ with respect to ϕ:

$$F_{\delta\phi} = c\,\lambda_\delta - c(1-\phi)\lambda_{\delta\phi}.$$

The first term is positive ($\lambda_\delta > 0$); the second is non-negative ($\lambda_{\delta\phi} \leq 0$ by Lemma 3). Hence $F_{\delta\phi} > 0$.

Under second-order conditions ($F_x < 0$ locally), the implicit function theorem yields $x_{\delta\phi} \propto -F_{\delta\phi}/F_x > 0$. □

A.4 Upstream Shocks

Lemma 4 (Trade credit relaxes the emergency spending margin)**.** *In the constrained regime, $E_\phi > 0$: higher received trade credit increases optimal emergency spending.*

Proof. From (A.3): $-\chi_E(s, E) = (1 + \lambda)/x$. By Lemma 2, $\lambda_\phi < 0$, which reduces the right-hand side. Since $\chi_{EE} > 0$ (diminishing returns), a lower marginal cost of emergency spending implies higher optimal $E^\star$. □

Proof of Proposition 2. Define the residual $G \equiv pA\alpha\, x^{\alpha-1}\ell^{1-\alpha} - MC_x - \chi(s, E)$.

Differentiate with respect to s: $G_s = -\chi_s < 0$, confirming $x_s < 0$.

For the cross-partial:

$$G_{s\phi} = -\chi_{sE} \cdot E_\phi.$$

By Lemma 4, $E_\phi > 0$. By (3), $\chi_{sE} < 0$. Hence $G_{s\phi} > 0$.

Under second-order conditions, the IFT yields $x_{s\phi} > 0$. □

A.5 Downstream Shocks

Proof of Proposition 3. Set $s = 0$, $E = 0$. Define:

$$H(x, \ell, \lambda; d, \phi) \equiv p(d)\, A\alpha\, x^{\alpha-1}\ell^{1-\alpha} - c\Big[(1 - \phi)(1 + \lambda) + \phi\kappa\Big].$$

Differentiate with respect to d:

$$H_d = p_d\, A\alpha\, x^{\alpha-1}\ell^{1-\alpha} - c(1 - \phi)\lambda_d < 0,$$

where $p_d < 0$ and $\lambda_d > 0$ (Lemma 1, since $W_d < 0$).

Differentiate H_d with respect to ϕ:

$$H_{d\phi} = c\,\lambda_d - c(1 - \phi)\lambda_{d\phi} > 0,$$

by the same argument as the direct shock case (Lemma 3).

Under second-order conditions, $x_{d\phi} > 0$. Note the demand channel ($p_d < 0$) is not mitigated by ϕ. $\square$

A.6 Extensions

Labor and output. Since ℓ faces the liquidity wedge $w(1+\lambda)$ in (A.2) and is complementary to x under Cobb–Douglas, all shocks that reduce $x^\star$ also reduce $\ell^\star$, and attenuation of the x response by ϕ propagates to ℓ and to output $y = Ax^\alpha \ell^{1-\alpha}$: $\ell_{\theta\phi} > 0$ and $y_{\theta\phi} > 0$ for $\theta \in \{\delta, s, d\}$.

Payment terms. Since τ enters only through κ and $\partial MC_x/\partial\tau < 0$, a longer τ also relaxes the cash constraint and reduces λ. All comparative statics derived for ϕ hold with τ: $x_{\theta\tau} > 0$, $\ell_{\theta\tau} > 0$, $y_{\theta\tau} > 0$.

Trade credit supplied. Accounts receivable AR reduce effective liquid wealth to $W^{liq} = W - AR$, tightening the constraint and raising λ. By analogous application of Lemmas 1–3 (replacing ϕ with AR and reversing signs), high receivables amplify shock transmission: $x_{\theta,AR} < 0$ for all θ. This generates a testable asymmetry: the interaction of shocks with accounts payable (received trade credit) should have a positive coefficient, while the interaction with accounts receivable (supplied trade credit) should have a negative coefficient.

Connecting to empirical specifications. The reduced-form regressions estimate:

$$y_{it} = \beta_1 \,\text{Shock}_{it} + \beta_2 \,(\text{Shock}_{it} \times \phi_{i,t-1}) + \gamma X_{it} + \alpha_i + \mu_t + \varepsilon_{it}.$$

The theory predicts $\beta_1 < 0$ and $\beta_2 > 0$. The magnitude of β_2 reflects the strength of the liquidity channel relative to other transmission mechanisms (productivity destruction for direct shocks, demand reduction for downstream shocks) that are not mitigated by trade credit.

B Descriptive Statistics by Trade Credit Conditions and their determinants

Table 4: Baseline characteristics by Trade Credit Received

	$TC^{\{P\}}=\mathbf{1}$		$TC^{\{P\}}=\mathbf{0}$	
Variable	*Mean*	*SD*	*Mean*	*SD*
Total Sales (UF)	4,885.855	10,067.658	1,723.223	6,095.666
Δ Total Sales	−0.007	0.755	0.013	0.858
Employment	41.177	218.998	17.336	181.478
Δ Employment	0.005	0.308	0.014	0.358
Share TC received	0.892	0.178	0.513	0.368
Avg TC term rec.	41.858	22.538	24.283	16.608
Share TC supplied	0.761	0.378	0.702	0.420
Avg TC term supp.	27.918	16.708	23.564	15.008
Upstream exposure	0.010	0.068	0.009	0.050
Downstream exposure	0.010	0.078	0.010	0.088
Δ suppliers	0.041	0.398	0.055	0.458
Δ customers	0.013	0.398	0.028	0.428
Micro	0.138	0.344	0.362	0.488
Small	0.496	0.500	0.517	0.500
Medium	0.221	0.418	0.088	0.288
Large	0.147	0.358	0.037	0.198
Agriculture & Forestry	0.142	0.358	0.091	0.298
Industry	0.254	0.434	0.283	0.458
Commerce	0.407	0.491	0.323	0.478
Service	0.202	0.408	0.306	0.468
Observations	2,621,917		22,960,239	

Table 5: Baseline characteristics by Trade Credit Supplied

	$TC^{\{R\}} = \mathbf{0}$		$TC^{\{R\}} = \mathbf{1}$	
Variable	*Mean*	*SD*	*Mean*	*SD*
Total Sales (UF)	2,232.715	7,310.430	1,557.364	4,593.620
Δ Total Sales	0.011	0.80	0.009	0.900
Employment	21.610	211.670	14.937	85.490
Δ Employment	0.012	0.330	0.015	0.370
Share TC received	0.553	0.360	0.549	0.370
Avg TC term rec.	26.035	18.880	26.407	18.820
Share TC supplied	0.525	0.450	0.978	0.130
Avg TC term supp.	20.138	18.010	29.860	6.450
Upstream exposure	0.008	0.060	0.008	0.060
Downstream exposure	0.009	0.070	0.010	0.080
Δ suppliers	0.049	0.430	0.060	0.380
Δ customers	0.036	0.430	0.007	0.390
Micro	0.353	0.480	0.299	0.460
Small	0.508	0.500	0.560	0.500
Medium	0.097	0.290	0.107	0.310
Large	0.043	0.200	0.033	0.180
Agriculture & Forestry	0.087	0.280	0.117	0.320
Industry	0.260	0.440	0.335	0.470
Commerce	0.368	0.480	0.234	0.470
Service	0.287	0.450	0.314	0.460
Observations	18,560,958		7,021,198	

Table 6: Determinant of Trade Credit Conditions

	Panel A. Receives better TC ($TC_{it}^{\{P\}}$)					**Panel B. Provides better TC** ($TC_{it}^{\{R\}}$)				
	All	Micro	Small	Medium	Large	All	Micro	Small	Medium	Large
Small	0.0214***					0.0465***				
	(0.000819)					(0.00134)				
Medium	0.0980***					0.0341***				
	(0.00220)					(0.00246)				
Large	0.147***					-0.0655***				
	(0.00383)					(0.00385)				
$\ln(\text{sales}_{t-1})$	0.00544***	0.00299***	0.00461***	0.0131***	0.0105***	0.0175***	0.0315***	0.0163***	0.0118***	-0.0364***
	(0.000351)	(0.000299)	(0.000447)	(0.00119)	(0.00263)	(0.000446)	(0.000702)	(0.000611)	(0.00122)	(0.00214)
$\ln(\text{cust}_{t-1})$	0.0164***	0.0370***	0.0363***	-0.000316		-0.0847***	-0.0842***	-0.0934***	-0.0942***	-0.0523***
	(0.000723)	(0.000880)	(0.00155)	(0.00210)		(0.000691)	(0.00175)	(0.000886)	(0.00142)	(0.00242)
$\ln(\text{sup}_{t-1})$	0.0154***	-0.00895***	0.00618***	0.0377***	0.0902***	-0.0616***	-0.0534***	-0.0593***	-0.0611***	-0.0527***
	(0.000690)	(0.000762)	(0.00229)	(0.00477)	(0.00601)	(0.000879)	(0.00136)	(0.00106)	(0.00253)	(0.00424)
Sector HHI	0.710**	1.422***	1.213***	-0.0940	-3.653*	-4.666***	-4.998***	-3.606***	-2.781***	-6.184***
	(0.345)	(0.345)	(0.433)	(0.515)	(2.094)	(0.657)	(0.805)	(0.745)	(1.019)	(1.524)
N	14,680,640	3,654,292	7,999,213	1,983,173	1,043,962	14,680,640	3,654,292	7,999,213	1,983,173	1,043,962
R^2	0.101	0.024	0.057	0.066	0.055	0.161	0.130	0.183	0.156	0.114
municipality FE			Yes					Yes		
Sector FE			Yes					Yes		
Month FE			Yes					Yes		

C Pre-Trends and the Conservative Nature of Network Estimates

A central assumption in difference-in-differences is the parallel trends assumption—that treated and control groups would have evolved similarly in the absence of the shock. Table 7 evaluates this assumption by estimating the treatment effects in the pre-exposure period (from $t-6$ to $t-2$ in relation to $t-1$), using inverse probability weights to reweight the control group toward the observable characteristics of exposed firms.

For firms facing direct physical exposure (Panel A), the baseline treatment coefficient is statistically insignificant for sales, purchases, employment, and network variables. The one exception is exit probability, which enters negatively (-0.221, $p < 0.01$), suggesting that firms in municipalities about to experience wildfires had slightly *lower* pre-shock exit rates—a pattern that, if anything, biases against finding a post-shock increase in exit. The trade credit interactions are largely clean: TC^P

interactions are uniformly insignificant except for a marginal effect on buyers (-0.525, $p < 0.10$), and TC^R interactions show a significant negative coefficient on employment (-0.433, $p < 0.01$) and a marginal effect on exit (-0.151, $p < 0.10$). These pre-period TC^R coefficients are negative, opposite in sign to the amplification effects documented in the post-shock period, reinforcing rather than undermining the post-shock interpretation.

For downstream exposure (Panel B), sales and employment pre-trends are statistically indistinguishable from zero, while purchases show a marginally negative coefficient (-0.333, $p < 0.10$)—opposite in sign to the large positive emergency procurement spike that characterizes upstream exposure, and thus not a concern for the downstream demand-shock interpretation. Exit probability enters negatively (-0.106, $p < 0.01$) and buyer growth positively (0.376, $p < 0.01$), consistent with the interpretation that firms with downstream network links are embedded in expanding commercial relationships prior to the shock. The TC^P interaction on purchases (1.309, $p < 0.01$) and on the number of sellers (0.401, $p < 0.05$) is significant in the pre-period, which warrants caution in interpreting the corresponding post-shock coefficients for downstream exposure. However, the TC^P interactions on sales, employment, and exit—which constitute the core evidence for downstream buffering—are all insignificant in the pre-period, supporting a causal interpretation for these margins. The TC^R interactions are uniformly insignificant, confirming that the post-shock relationship-capital effects of trade credit supplied are not driven by pre-existing differential trends.

For upstream exposure (Panel C), the baseline pre-trends show that the purchases coefficient (1.485, $p < 0.01$) is large and positive, reflecting the fact that firms with upstream network links engage in higher and growing procurement volumes. Seller growth is also positive (0.546, $p < 0.01$), consistent with expanding supply chains. These baseline pre-trends do not compromise the identification of the post-shock *interaction* effects, which are the paper's central contribution. The TC^P interaction pre-trends are insignificant for sales, purchases, and employment—the three real outcomes where post-shock buffering is documented. The significant pre-trend interactions (exit at 0.305, $p < 0.05$; buyers at -0.416, $p < 0.05$) concern margins where the post-shock TC^P coefficients are themselves either insignificant or carry opposite signs, limiting the scope for contamination. The TC^R interactions show a negative exit coefficient (-0.177, $p < 0.01$) and a positive buyer coefficient (0.447, $p < 0.05$); the exit pre-trend is opposite in sign to the post-shock amplification pattern, while the buyer pre-trend aligns with the relationship-capital interpretation documented post-shock. I note this as a caveat for the upstream buyer-retention result specifically.

Taken together, the pre-trend analysis supports three conclusions. The direct exposure design is cleanly identified, with no economically meaningful pre-trends in either baseline or interaction specifications. For network exposure, some baseline pre-trends persist even after reweighting, reflecting the structural tendency of network-embedded firms to grow faster—a compositional feature rather than an identification failure. The post-shock estimates for these margins should be interpreted as conservative lower bounds on the true causal effect, since the wildfires reversed a pre-existing upward trajectory. Most importantly for this paper's contribution, the trade credit interaction pre-trends are largely insignificant for the real outcomes (sales, employment, purchases) where post-shock buffering is documented. The few significant interaction pre-trends concern either different outcomes from those driving the main results or carry opposite signs, reinforcing rather than undermining the post-shock interpretation. This pattern isolates the value of trade credit to the post-disaster period and supports a causal reading of the heterogeneous buffering effects.

The horizon-by-horizon impulse responses reported in the next subsection provide visual confirmation of these patterns. For the TC^P interactions, the pre-shock trajectories of high- and low-trade-credit firms are largely indistinguishable across the six months preceding treatment. In the direct exposure panels, the two groups track each other closely for all outcomes, with the divergence emerging only after impact. For downstream exposure, the sales and employment IRFs show flat, overlapping pre-shock paths that separate sharply at $h = 0$, while the purchases IRF exhibits a mild pre-shock gap consistent with the significant pre-trend coefficient flagged above. For upstream exposure, the sales and employment pre-shock paths overlap cleanly before diverging progressively in the post-shock window; the purchases IRF shows both groups converging to zero at $h = -1$ before the characteristic emergency procurement spike at impact. The TC^R impulse responses display even cleaner pre-trends: across all three exposure types, the paths for high- and low-receivables firms are nearly superimposed throughout the pre-shock window, with any separation emerging exclusively after the wildfire event. This visual evidence corroborates the formal pre-trend tests and reinforces the conclusion that the documented heterogeneity in post-shock outcomes reflects the causal role of trade credit positions rather than pre-existing differential trends.

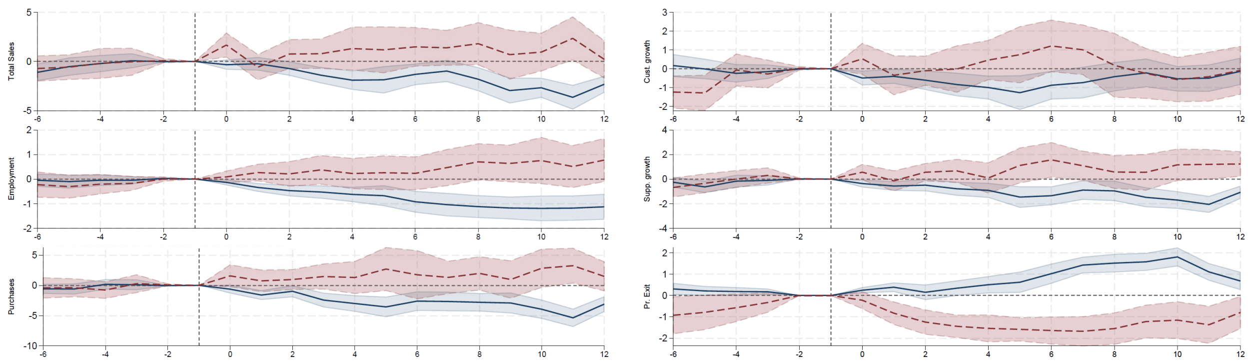
Table 7: Pre-Trends: Coefficients on Key Variables of Interest

VARIABLES	(1) ΔSales	(2) Purchases	(3) Employment	(4) Pr. Exit	(5) # Sellers	(6) # Buyers
Panel A: Direct Exposure						
Baseline Model:						
Treatment	-0.415	-0.489	-0.123	-0.221***	-0.265	-0.0781
	(0.417)	(0.386)	(0.0834)	(0.0792)	(0.196)	(0.224)
Heterogeneity TC^P*:*						
Treatment	-0.414	-0.549	-0.124	-0.224***	-0.277	0.000666
	(0.436)	(0.393)	(0.0889)	(0.0806)	(0.203)	(0.220)
Treatment × TC^P	-0.00388	0.444	0.00466	0.0203	0.105	-0.525*
	(0.601)	(0.697)	(0.169)	(0.128)	(0.286)	(0.297)
Heterogeneity TC^R*:*						
Treatment	-0.278	-0.455	-0.00996	-0.181**	-0.243	0.0109
	(0.442)	(0.416)	(0.0900)	(0.0833)	(0.200)	(0.267)
Treatment × TC^R	-0.523	-0.128	-0.433***	-0.151*	-0.0859	-0.281
	(0.546)	(0.574)	(0.153)	(0.0897)	(0.233)	(0.401)
Panel B: Downstream Exposure						
Baseline Model:						
Treatment	0.0977	-0.333*	0.0766	-0.106***	-0.173**	0.376***
	(0.149)	(0.200)	(0.0563)	(0.0274)	(0.0853)	(0.0953)
Heterogeneity TC^P*:*						
Treatment	0.0970	-0.576***	0.0938	-0.104***	-0.244**	0.443***
	(0.164)	(0.222)	(0.0618)	(0.0299)	(0.0951)	(0.105)
Treatment × TC^P	0.0116	1.309***	-0.0972	-0.0173	0.401**	-0.374*
	(0.317)	(0.436)	(0.126)	(0.0577)	(0.183)	(0.225)
Heterogeneity TC^R*:*						
Treatment	0.0589	-0.442*	0.0876	-0.0826***	-0.217**	0.343***
	(0.176)	(0.232)	(0.0678)	(0.0319)	(0.100)	(0.114)
Treatment × TC^R	0.112	0.338	-0.0335	-0.0643	0.136	0.0850
	(0.301)	(0.415)	(0.114)	(0.0538)	(0.178)	(0.198)
Panel C: Upstream Exposure						
Baseline Model:						
Treatment	0.167	1.485***	-0.0104	-0.0890***	0.546***	-0.389***
	(0.118)	(0.153)	(0.0456)	(0.0222)	(0.0681)	(0.0916)
Heterogeneity TC^P*:*						
Treatment	0.107	1.382***	-0.0213	-0.0919***	0.502***	-0.310***
	(0.128)	(0.165)	(0.0495)	(0.0241)	(0.0737)	(0.101)
Treatment × TC^P	0.409	0.676	0.0749	0.0198	0.305**	-0.416**
	(0.383)	(0.356)	(0.106)	(0.0489)	(0.153)	(0.206)
Heterogeneity TC^R*:*						
Treatment	0.192	1.441***	-0.00255	-0.0444*	0.562***	-0.523***
	(0.132)	(0.169)	(0.0512)	(0.0248)	(0.0759)	(0.108)
Treatment × TC^R	-0.0998	0.174	-0.0310	-0.177***	-0.0690	0.447**
	(0.264)	(0.332)	(0.0991)	(0.0447)	(0.145)	(0.185)
Fixed Effects	Firm, Month–Region, Month–Sector					

Notes: This table reports pre-trend coefficients from three separate specifications for each exposure type. "Baseline Model" reports the coefficient on the Treatment dummy. "Heterogeneity Models" report the coefficients on the interaction terms $Treatment \times TC^P$ (Trade Credit Received) and $Treatment \times TC^S$ (Trade Credit Supplied). Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Impulse Response Function from LP - Heterogeneity by Trade Credit Received (TC^P and Supplied TC^R)

Figure 5: Dynamic Effects of Direct Exposure on Firm Outcomes - $Treatment \times TC^P$

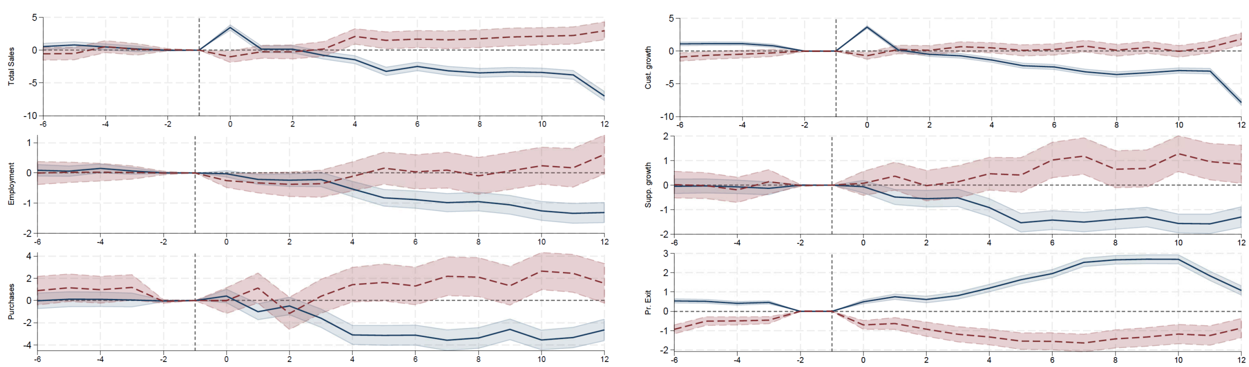


(a) Real Effects

(b) Network Stability

Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the firm level.

Figure 6: Dynamic Effects of Downstream Exposure on Firm Outcomes- $Treatment \times TC^P$

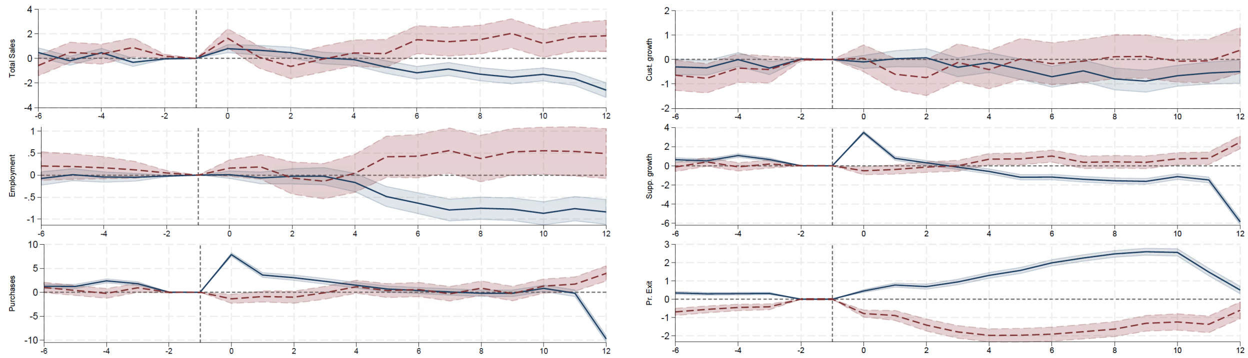


(a) Real Effects

(b) Network Stability

Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the firm level.

Figure 7: Dynamic Effects of Upstream Exposure on Firm Outcomes $Treatment \times TC^P$

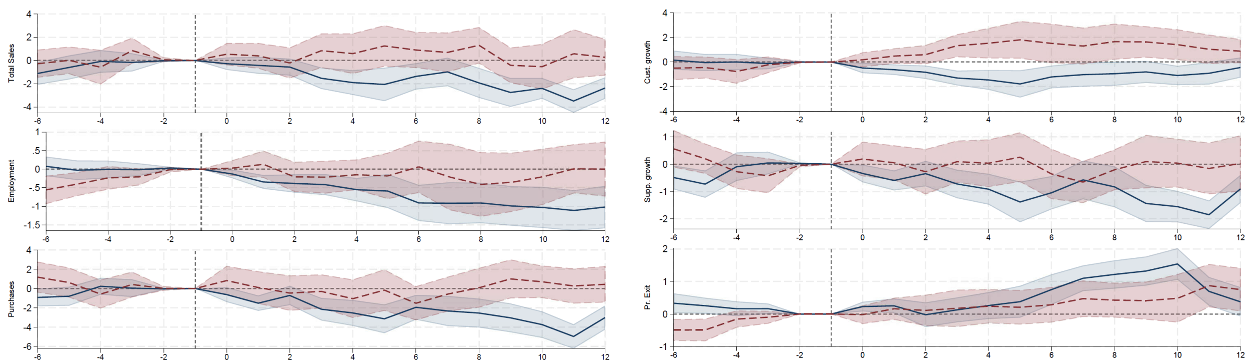


(a) Real Effects

(b) Network Stability

Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the firm level.

Figure 8: Dynamic Effects of Direct Exposure on Firm Outcomes - $Treatment \times TC^R$

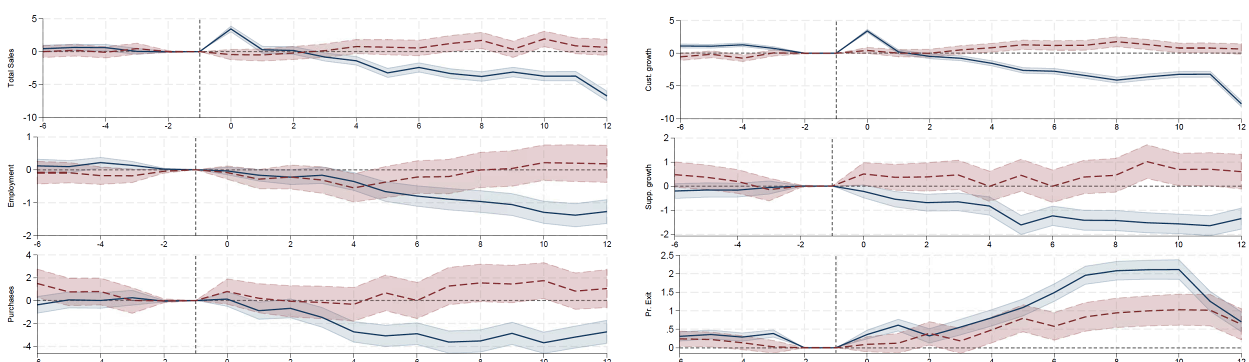


(a) Real Effects

(b) Network Stability

Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the firm level.

Figure 9: Dynamic Effects of Downstream Exposure on Firm Outcomes - $Treatment \times TC^R$

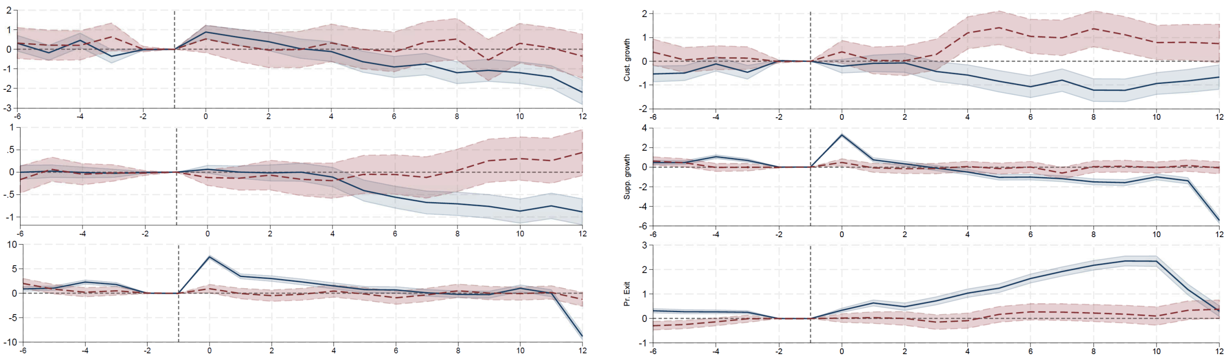


(a) Real Effects

(b) Network Stability

Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the firm level.

Figure 10: Dynamic Effects of Upstream Exposure on Firm Outcomes - $Treatment \times TC^R$



(a) Real Effects

(b) Network Stability

Note: Horizontal axis represents months relative to the wildfire event. Vertical axis in %. CI 95% . SE are clustered at the firm level.

E Pooled LP - Heterogeneity by Size and Sector

Robustness Checks Alternative Exposure Measures

Table 15: Direct Exposure: Alternative Burned Area Cutoffs

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Direct Exposure (≥500 ha)						
Direct	-0.618*	-0.821*	-0.253**	0.113	-0.174	-0.0902
	(0.362)	(0.429)	(0.121)	(0.165)	(0.224)	(0.239)
Observations	13,895,553	13,215,994	13,895,553	20,530,537	13,215,994	8,004,095
Panel B. Direct Exposure (≥200 ha)						
Direct	-0.564**	-0.691*	-0.212**	0.00585	-0.283**	-0.0469
	(0.269)	(0.361)	(0.0882)	(0.155)	(0.142)	(0.215)
Observations	13,239,597	12,586,092	13,239,597	19,624,203	12,586,092	7,628,831

Firm FE, Month-Region FE, Month-Sector FE and lagged outcomes included in all regressions. SE clustered at the firm-level-

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Pooled LP: Direct, Downstream, and Upstream Exposure – Small Firms

Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Direct Exposure						
A1. Baseline						
Direct	-0.834***	-1.491***	-0.463***	0.185*	-0.534***	-0.402**
	(0.241)	(0.429)	(0.114)	(0.110)	(0.204)	(0.190)
N	6,671,582	6,423,825	6,671,582	9,639,540	6,423,825	3,814,266
A2. With Trade Credit Received $TC^{\{P\}}$						
Direct	-0.937***	-1.653***	-0.519***	0.200*	-0.583***	-0.423**
	(0.261)	(0.461)	(0.117)	(0.117)	(0.219)	(0.193)
Direct × $TC^{\{P\}}$	1.050*	1.600**	0.568***	-0.153	0.494	0.216
	(0.558)	(0.803)	(0.200)	(0.291)	(0.360)	(0.326)
N	6,671,582	6,423,825	6,671,582	9,639,540	6,423,825	3,814,266
A3. With Trade Credit Supplied $TC^{\{R\}}$						
Direct	-0.992***	-1.591***	-0.472***	0.0674	-0.572***	-0.750***
	(0.237)	(0.424)	(0.135)	(0.116)	(0.213)	(0.211)
Direct × $TC^{\{R\}}$	0.522	0.344	0.0336	0.403**	0.130	0.958***
	(0.413)	(0.536)	(0.174)	(0.175)	(0.251)	(0.291)
N	6,671,582	6,423,825	6,671,582	9,639,540	6,423,825	3,814,266
Panel B. Downstream Exposure						
B1. Baseline						
Down	-0.375**	-1.021***	-0.372***	0.376***	-0.509***	-0.503***
	(0.172)	(0.244)	(0.0862)	(0.0796)	(0.105)	(0.110)
N	4,611,947	4,379,622	4,611,947	6,226,082	4,379,622	3,528,082
B2. With Trade Credit Received $TC^{\{P\}}$						
Down	-0.442**	-1.211***	-0.368***	0.431***	-0.570***	-0.516***
	(0.184)	(0.261)	(0.0920)	(0.0836)	(0.113)	(0.116)
Down × $TC^{\{P\}}$	0.578	1.599***	-0.0304	-0.479**	0.494*	0.118
	(0.401)	(0.583)	(0.214)	(0.224)	(0.255)	(0.292)
N	4,611,947	4,379,622	4,611,947	6,226,082	4,379,622	3,528,082
B3. With Trade Credit Supplied $TC^{\{R\}}$						
Down	-0.258	-1.076***	-0.241**	0.233**	-0.593***	-0.713***
	(0.208)	(0.290)	(0.105)	(0.0984)	(0.126)	(0.135)
Down × $TC^{\{R\}}$	-0.306	0.142	-0.344**	0.350**	0.219	0.596***
	(0.320)	(0.468)	(0.163)	(0.150)	(0.202)	(0.202)
N	4,611,947	4,379,622	4,611,947	6,226,082	4,379,622	3,528,082
Panel C. Upstream Exposure						
C1. Baseline						
Up	0.0309	2.159***	-0.260***	0.614***	0.266***	-0.0333
	(0.132)	(0.180)	(0.0669)	(0.0595)	(0.0799)	(0.110)
N	5,916,017	5,744,526	5,916,017	8,879,833	5,744,526	3,383,200
C2. With Trade Credit Received $TC^{\{P\}}$						
Up	-0.113	2.020***	-0.329***	0.642***	0.196**	-0.0424
	(0.141)	(0.190)	(0.0712)	(0.0624)	(0.0845)	(0.118)
Up × $TC^{\{P\}}$	1.323***	1.284***	0.637***	-0.241	0.618***	0.0888
	(0.332)	(0.457)	(0.166)	(0.166)	(0.209)	(0.290)
N	5,916,017	5,744,526	5,916,017	8,879,833	5,744,526	3,383,200
C3. With Trade Credit Supplied $TC^{\{R\}}$						
Up	-0.0762	2.228***	-0.248***	0.614***	0.260***	-0.201
	(0.148)	(0.198)	(0.0755)	(0.0671)	(0.0897)	(0.134)
Up × $TC^{\{R\}}$	0.376	-0.249	-0.0445	-0.00177	0.0205	0.513**
	(0.273)	(0.365)	(0.138)	(0.122)	(0.162)	(0.205)
N	5,916,017	5,744,526	5,916,017	8,879,833	5,744, 526	3,383,200

Firm FE, Month-Region FE, and Month-Sector FE included in all regressions. Include lagged outcomes in levels. Panel A SE clustered at the municipality-level; Panels B and C at the firm-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Pooled LP: Direct, Downstream, and Upstream Exposure – Medium Firms

Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Direct Exposure						
A1. Baseline						
Direct	-1.373***	-1.031*	-0.262	0.282	-0.277	0.441
	(0.431)	(0.561)	(0.188)	(0.196)	(0.301)	(0.274)
N	1,601,539	1,587,386	1,601,539	2,003,246	1,587,386	1,180,219
A2. With Trade Credit Received $TC^{\{P\}}$						
Direct	-1.946***	-1.338*	-0.338	0.361	-0.439	0.350
	(0.480)	(0.690)	(0.215)	(0.226)	(0.345)	(0.318)
Direct × $TC^{\{P\}}$	2.387***	1.228	0.314	-0.320	0.673	0.374
	(0.646)	(1.144)	(0.308)	(0.452)	(0.473)	(0.497)
N	1,601,539	1,587,386	1,601,539	2,003,246	1,587,386	1,180,219
A3. With Trade Credit Supplied $TC^{\{R\}}$						
Direct	-0.818	-0.976	-0.192	0.139	-0.307	0.368
	(0.532)	(0.696)	(0.264)	(0.240)	(0.334)	(0.299)
Direct × $TC^{\{R\}}$	-1.877*	-0.182	-0.232	0.483	0.106	0.267
	(0.969)	(1.236)	(0.495)	(0.314)	(0.467)	(0.598)
N	1,601,539	1,587,386	1,601,539	2,003,246	1,587,386	1,180,219
Panel B. Downstream Exposure						
B1. Baseline						
Down	-0.651**	-0.548	-0.613***	0.215	-0.290*	-0.616***
	(0.272)	(0.380)	(0.133)	(0.145)	(0.154)	(0.174)
N	1,217,364	1,204,038	1,217,364	1,458,645	1,204,038	1,029,194
B2. With Trade Credit Received $TC^{\{P\}}$						
Down	-0.791**	-0.669	-0.597***	0.275*	-0.324*	-0.694***
	(0.314)	(0.441)	(0.154)	(0.163)	(0.178)	(0.199)
Down × $TC^{\{P\}}$	0.553	0.489	-0.0600	-0.235	0.135	0.313
	(0.507)	(0.713)	(0.255)	(0.295)	(0.294)	(0.337)
N	1,217,364	1,204,038	1,217,364	1,458,645	1,204,038	1,029,194
B3. With Trade Credit Supplied $TC^{\{R\}}$						
Down	-0.312	-0.359	-0.451***	0.103	-0.228	-0.752***
	(0.309)	(0.428)	(0.148)	(0.166)	(0.171)	(0.196)
Down × $TC^{\{R\}}$	-1.179**	-0.661	-0.562**	0.362	-0.212	0.537
	(0.538)	(0.790)	(0.275)	(0.290)	(0.323)	(0.355)
N	1,217,364	1,204,038	1,217,364	1,458,645	1,204,038	1,029,194
Panel C. Upstream Exposure						
C1. Baseline						
Up	-0.0462	2.126***	-0.267**	0.376***	0.0785	-0.143
	(0.259)	(0.342)	(0.121)	(0.122)	(0.138)	(0.174)
N	1,325,718	1,315,706	1,325,718	1,719,846	1,315,706	973,931
C2. With Trade Credit Received $TC^{\{P\}}$						
Up	-0.640**	1.795***	-0.434***	0.365***	-0.183	-0.236
	(0.294)	(0.389)	(0.140)	(0.136)	(0.157)	(0.199)
Up × $TC^{\{P\}}$	2.429***	1.373**	0.681***	0.0413	1.065***	0.385
	(0.496)	(0.623)	(0.231)	(0.240)	(0.259)	(0.336)
N	1,325,718	1,315,706	1,325,718	1,719,846	1,315,706	973,931
C3. With Trade Credit Supplied $TC^{\{R\}}$						
Up	0.152	2.509***	-0.226*	0.382***	0.202	-0.235
	(0.291)	(0.377)	(0.134)	(0.135)	(0.153)	(0.196)
Up × $TC^{\{R\}}$	-0.720	-1.395**	-0.151	-0.0211	-0.448	0.355
	(0.528)	(0.691)	(0.254)	(0.242)	(0.280)	(0.352)
N	1,325,718	1,315,706	1,325,718	1,719,846	1,315,706	973,931

Firm FE, Month-Region FE, and Month-Sector FE included in all regressions. Include lagged outcomes in levels. Panel A SE clustered at the municipality-level; Panels B and C at the firm-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Pooled LP: Direct, Downstream, and Upstream Exposure – Large Firms

Variables	Δ Sales	Purchases	Employment	Pr. Exit	Number of Sellers	Number of Buyers
Panel A. Direct Exposure						
A1. Baseline						
Direct	-1.085**	-0.958	-0.350	-0.0714	-0.325	0.215
	(0.424)	(0.597)	(0.267)	(0.228)	(0.288)	(0.271)
N	824,811	823,017	824,811	993,570	823,017	688,682
A2. With Trade Credit Received $TC^{\{P\}}$						
Direct	-1.251***	-1.713***	-0.284	0.0973	-0.475	-0.0101
	(0.435)	(0.616)	(0.311)	(0.272)	(0.341)	(0.317)
Direct × $TC^{\{P\}}$	0.493	-2.210**	-0.189	-0.488	0.439	0.647
	(0.740)	(0.921)	(0.413)	(0.449)	(0.390)	(0.449)
N	824,811	823,017	824,811	993,570	823,017	688,682
A3. With Trade Credit Supplied $TC^{\{R\}}$						
Direct	-0.580	-0.811	-0.155	-0.275	-0.274	0.0746
	(0.484)	(0.627)	(0.309)	(0.229)	(0.244)	(0.273)
Direct × $TC^{\{R\}}$	-2.948**	-0.853	-1.138*	1.134**	-0.295	0.882
	(1.139)	(1.115)	(0.624)	(0.497)	(0.586)	(0.621)
N	824,811	823,017	824,811	993,570	823,017	688,682
Panel B. Downstream Exposure						
B1. Baseline						
Down	-0.293	-0.120	-0.164	0.450***	-0.114	-0.705***
	(0.294)	(0.383)	(0.148)	(0.148)	(0.147)	(0.194)
N	605,064	603,362	605,064	737,065	603,362	558,129
B2. With Trade Credit Received $TC^{\{P\}}$						
Down	-0.505	-0.389	-0.0601	0.532***	-0.250	-0.733***
	(0.354)	(0.458)	(0.174)	(0.175)	(0.178)	(0.228)
Down × $TC^{\{P\}}$	0.610	0.777	-0.302	-0.232	0.391	0.0827
	(0.522)	(0.699)	(0.270)	(0.274)	(0.271)	(0.335)
N	605,064	603,362	605,064	737,065	603,362	558,129
B3. With Trade Credit Supplied $TC^{\{R\}}$						
Down	-0.0240	0.223	-0.0846	0.257*	-0.0136	-0.740***
	(0.308)	(0.396)	(0.158)	(0.153)	(0.154)	(0.204)
Down × $TC^{\{R\}}$	-1.672**	-2.146**	-0.492	1.141***	-0.625	0.244
	(0.778)	(1.067)	(0.376)	(0.402)	(0.408)	(0.501)
N	605,064	603,362	605,064	737,065	603,362	558,129
Panel C. Upstream Exposure						
C1. Baseline						
Up	0.0415	1.577***	-0.188	0.00908	-0.295**	-0.258
	(0.292)	(0.372)	(0.144)	(0.138)	(0.141)	(0.192)
N	625,278	624,180	625,278	789,225	624,180	516,912
C2. With Trade Credit Received $TC^{\{P\}}$						
Up	0.0263	1.375***	-0.219	0.202	-0.350**	-0.223
	(0.340)	(0.434)	(0.170)	(0.157)	(0.162)	(0.223)
Up × $TC^{\{P\}}$	-0.0492	0.611	0.0950	-0.563**	0.168	-0.105
	(0.533)	(0.634)	(0.266)	(0.241)	(0.252)	(0.353)
N	625,278	624,180	625,278	789,225	624,180	516,912
C3. With Trade Credit Supplied $TC^{\{R\}}$						
Up	0.241	1.862***	-0.184	-0.0742	-0.231	-0.264
	(0.303)	(0.386)	(0.150)	(0.143)	(0.148)	(0.202)
Up × $TC^{\{R\}}$	-1.179	-1.716*	6.68e-05	0.478	-0.372	-0.0865
	(0.775)	(0.921)	(0.373)	(0.329)	(0.353)	(0.487)
N	625,278	624,180	625,278	789,225	624,180	516,912

Firm FE, Month-Region FE, and Month-Sector FE included in all regressions. Include lagged outcomes in levels. Panel A SE clustered at the municipality-level; Panels B and C at the firm-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Pooled LP: Direct, Downstream, and Upstream Exposure – Primary Sector

Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Direct Exposure						
A1. Baseline						
Direct	-0.404	0.085	-0.377	1.049***	-0.295	-0.299
	(0.423)	(0.564)	(0.231)	(0.318)	(0.252)	(0.343)
A2. With Trade Credit Received $TC^{\{P\}}$						
Direct	-0.355	0.388	-0.371	1.346***	-0.262	-0.477
	(0.459)	(0.616)	(0.245)	(0.341)	(0.264)	(0.355)
Direct × $TC^{\{P\}}$	-0.288	-1.799	-0.0476	-1.835***	-0.182	1.076*
	(0.882)	(1.225)	(0.447)	(0.665)	(0.438)	(0.641)
A3. With Trade Credit Supplied $TC^{\{R\}}$						
Direct	-0.807	-0.252	-0.197	1.225***	-0.238	-0.803*
	(0.544)	(0.649)	(0.262)	(0.331)	(0.280)	(0.425)
Direct × $TC^{\{R\}}$	1.213	1.039	-0.543	-0.517	-0.178	1.439***
	(0.811)	(0.976)	(0.409)	(0.612)	(0.412)	(0.537)
N	481,522	446,150	481,522	1,104,770	446,150	280,870
Panel B. Downstream Exposure						
B1. Baseline						
Down	-1.910***	-1.476***	-0.697***	2.089***	-0.689***	-1.760***
	(0.386)	(0.522)	(0.220)	(0.253)	(0.227)	(0.268)
B2. With Trade Credit Received $TC^{\{P\}}$						
Down	-2.176***	-1.992***	-0.737***	2.263***	-0.908***	-1.872***
	(0.428)	(0.585)	(0.243)	(0.277)	(0.252)	(0.294)
Down × $TC^{\{P\}}$	1.488*	2.707**	0.234	-1.026*	1.118**	0.617
	(0.855)	(1.092)	(0.479)	(0.602)	(0.485)	(0.571)
B3. With Trade Credit Supplied $TC^{\{R\}}$						
Down	-1.964***	-1.388**	-0.373	2.124***	-0.703***	-2.396***
	(0.471)	(0.617)	(0.263)	(0.310)	(0.265)	(0.323)
Down × $TC^{\{R\}}$	0.140	-0.257	-0.905**	-0.0723	0.0409	1.961***
	(0.719)	(1.010)	(0.420)	(0.483)	(0.437)	(0.476)
N	396,408	363,358	396,408	811,507	363,358	252,372
Panel C. Upstream Exposure						
C1. Baseline						
Up	-0.247	1.898***	-0.0289	1.873***	0.0772	-0.314
	(0.339)	(0.477)	(0.193)	(0.229)	(0.205)	(0.275)
C2. With Trade Credit Received $TC^{\{P\}}$						
Up	-0.491	1.797***	-0.120	2.177***	-0.004	-0.350
	(0.378)	(0.535)	(0.216)	(0.252)	(0.229)	(0.299)
Up × $TC^{\{P\}}$	1.210*	0.536	0.455	-1.542***	0.373	0.178
	(0.688)	(0.909)	(0.386)	(0.502)	(0.400)	(0.592)
C3. With Trade Credit Supplied $TC^{\{R\}}$						
Up	-0.417	2.052***	0.212	1.860***	0.257	-0.696**
	(0.407)	(0.549)	(0.226)	(0.271)	(0.238)	(0.328)
Up × $TC^{\{R\}}$	0.498	-0.526	-0.759**	0.0417	-0.547	1.088**
	(0.602)	(0.855)	(0.355)	(0.431)	(0.374)	(0.475)
N	382,954	351,963	382,954	970,092	351,963	219,388

Firm FE, Month-Region FE, and Month-Sector FE included in all regressions. Include lagged outcomes in levels. Panel A SE clustered at the municipality-level; Panels B and C at the firm-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 16: Downstream Exposure: Alternative Cutoffs

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Downstream Exposure ($E^D > 10\%$)						
Downstream	-0.725***	-1.054***	-0.479***	0.355***	-0.499***	-0.361***
	(0.141)	(0.191)	(0.0678)	(0.0544)	(0.0827)	(0.0849)
Observations	8,691,718	8,110,183	8,691,718	12,041,428	8,110,183	6,822,123
Panel B. Downstream Exposure ($E^D > 0\%$)						
Downstream	-1.408***	-1.699***	-0.675***	0.409***	-0.779***	-1.069***
	(0.158)	(0.225)	(0.0650)	(0.0511)	(0.0827)	(0.106)
Observations	6,782, 339	6,247, 731	6,782, 339	9,993, 709	6,247, 731	5,009,854

Firm FE, Month-Region FE, Month-Sector FE and lagged outcomes included in all regressions. SE clustered at the firm-level- *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Pooled LP: Direct, Downstream, and Upstream Exposure – Industry Sector

Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Direct Exposure						
A1. Baseline						
Direct	-1.415***	-0.990*	-0.476**	1.154***	-0.225	-0.524*
	(0.355)	(0.510)	(0.216)	(0.203)	(0.210)	(0.307)
A2. With Trade Credit Received $TC^{\{P\}}$						
Direct	-1.349***	-1.014**	-0.539**	1.267***	-0.323	-0.514
	(0.373)	(0.510)	(0.227)	(0.209)	(0.219)	(0.314)
Direct × $TC^{\{P\}}$	-0.520	0.111	0.466	-1.092*	0.718*	-0.0758
	(0.679)	(0.669)	(0.437)	(0.611)	(0.422)	(0.515)
A3. With Trade Credit Supplied $TC^{\{R\}}$						
Direct	-1.129***	-0.732**	-0.570***	2.168***	-0.588***	-1.388***
	(0.248)	(0.334)	(0.156)	(0.169)	(0.150)	(0.172)
Direct × $TC^{\{P\}}$	0.278	-0.786	-0.0248	-0.886**	0.341	-0.317
	(0.486)	(0.657)	(0.314)	(0.378)	(0.291)	(0.358)
N	1,576,966	1,473,229	1,576,966	3,257,680	1,473,229	1,014,669
Panel B. Downstream Exposure						
B1. Baseline						
Down	-1.180***	-0.883***	-9.574***	2.032***	-0.523***	-1.451***
	(0.222)	(0.299)	(0.141)	(0.155)	(0.134)	(0.156)
B2. With Trade Credit Received $TC^{\{P\}}$						
Down	-1.129***	-0.732**	-0.570***	2.168***	-0.588***	-1.388***
	(0.248)	(0.334)	(0.156)	(0.169)	(0.150)	(0.172)
Down × $TC^{\{P\}}$	0.278	-0.786	-0.0248	-0.886**	0.341	-0.317
	(0.486)	(0.657)	(0.314)	(0.378)	(0.291)	(0.358)
B3. With Trade Credit Supplied $TC^{\{R\}}$						
Down	-1.351***	-0.867**	-0.527***	1.571***	-0.473***	-1.585***
	(0.256)	(0.338)	(0.162)	(0.181)	(0.153)	(0.182)
Down × $TC^{\{R\}}$	0.523	-0.0502	0.286	1.249***	-0.158	0.505
	(0.448)	(0.624)	(0.286)	(0.313)	(0.279)	(0.312)
N	1,528,437	1,418,008	1,528,437	2,695,385	1,418,008	1,075,864
Panel C. Upstream Exposure						
C1. Baseline						
Up	-0.335*	0.525**	-0.419***	2.308***	-0.299**	-0.531***
	(0.194)	(0.262)	(0.127)	(0.136)	(0.119)	(0.156)
C2. With Trade Credit Received $TC^{\{P\}}$						
Up	-0.379*	0.549**	-0.481***	2.370***	-0.429***	-0.541***
	(0.213)	(0.283)	(0.138)	(0.148)	(0.130)	(0.174)
Up × $TC^{\{P\}}$	0.281	-0.0884	0.381	-0.445	0.761***	0.0648
	(0.460)	(0.626)	(0.302)	(0.342)	(0.272)	(0.354)
C3. With Trade Credit Supplied $TC^{\{R\}}$						
Up	-0.204	1.143***	-0.344**	2.289***	-0.00908	-0.659***
	(0.221)	(0.290)	(0.143)	(0.158)	(0.133)	(0.184)
Up × $TC^{\{R\}}$	-0.433	-2.069***	-0.246	0.0602	-0.970***	-0.469
	(0.404)	(0.543)	(0.264)	(0.278)	(0.246)	(0.307)
N	1,887,893	1,770,191	1,887,893	3,606,373	1,770,191	1,211,274

Firm FE, Month-Region FE, and Month-Sector FE included in all regressions. Include lagged outcomes in levels. Panel A SE clustered at the municipality-level; Panels B and C at the firm-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 17: Upstream Exposure: Alternative Cutoffs

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Upstream Exposure ($E^U > 10\%$)						
Upstream	0.180	1.988***	-0.167***	0.534***	0.422***	-0.0718
	(0.112)	(0.144)	(0.0542)	(0.0442)	(0.0645)	(0.0874)
Observations	11,623,063	11,215,409	11,623,063	17,939,673	11,215, 409	6,630, 643
Panel B. Upstream Exposure ($E^U > 0\%$)						
Upstream	-0.658***	-1.117***	-0.489***	0.639***	-0.430***	-0.415***
	(0.108)	(0.164)	(0.0549)	(0.0451)	(0.0787)	(0.0760)
Observations	7,641,357	7,258,095	7,641,357	13,470,986	7,258,095	4,156,087

Firm FE, Month-Region FE, Month-Sector FE and lagged outcomes included in all regressions. SE clustered at the firm-level-

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Pooled LP: Direct, Downstream, and Upstream Exposure – Commerce Sector

Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Direct Exposure						
A1. Baseline						
Direct	-1.363***	-1.475***	-0.410**	1.226***	-0.485*	-0.323
	(0.337)	(0.449)	(0.189)	(0.217)	(0.249)	(0.315)
A2. With Trade Credit Received $TC^{\{P\}}$						
Direct	-1.537***	-1.726***	-0.480**	1.386***	-0.602**	-0.556
	(0.361)	(0.511)	(0.198)	(0.213)	(0.263)	(0.337)
Direct × $TC^{\{P\}}$	0.956*	1.345*	0.384	-1.090***	0.623**	1.039
	(0.567)	(0.723)	(0.267)	(0.394)	(0.288)	(0.637)
A3. With Trade Credit Supplied $TC^{\{R\}}$						
Direct	-1.330***	-1.386***	-0.458**	1.139***	-0.385*	-0.671**
	(0.328)	(0.447)	(0.206)	(0.234)	(0.223)	(0.330)
Direct × $TC^{\{R\}}$	-0.164	-0.477	0.273	0.486	-0.545	1.589***
	(0.555)	(0.737)	(0.261)	(0.316)	(0.400)	(0.529)
N	2,096,527	1,989,565	2,096,527	4,015,299	1,989,565	1,100,259
Panel B. Downstream Exposure						
B1. Baseline						
Down	-1.422***	-1.718***	-0.344***	2.388***	-0.931***	-1.762***
	(0.188)	(0.272)	(0.112)	(0.143)	(0.119)	(0.151)
B2. With Trade Credit Received $TC^{\{P\}}$						
Down	-1.743***	-1.999***	-0.355***	2.648***	-1.160***	-1.969***
	(0.216)	(0.311)	(0.127)	(0.160)	(0.136)	(0.170)
Down × $TC^{\{P\}}$	1.417***	1.196**	0.0515	-1.294***	0.960***	0.897***
	(0.361)	(0.532)	(0.223)	(0.306)	(0.231)	(0.301)
B3. With Trade Credit Supplied $TC^{\{R\}}$						
Down	-1.524***	-1.815***	-0.392***	2.140***	-1.010***	-1.866***
	(0.213)	(0.303)	(0.127)	(0.162)	(0.133)	(0.167)
Down × $TC^{\{R\}}$	0.385	0.379	0.184	0.834***	0.305	0.483
	(0.392)	(0.589)	(0.232)	(0.306)	(0.253)	(0.326)
N	1,653,735	1,537,368	1,653,735	2,599,333	1,537,368	1,114,370
Panel C. Upstream Exposure						
C1. Baseline						
Up	0.167	0.553***	-0.272***	2.537***	-0.710***	0.195
	(0.143)	(0.208)	(0.0896)	(0.115)	(0.0949)	(0.150)
C2. With Trade Credit Received $TC^{\{P\}}$						
Up	0.107	0.490**	-0.269***	2.665***	-0.774***	0.0851
	(0.162)	(0.233)	(0.100)	(0.127)	(0.106)	(0.173)
Up × $TC^{\{P\}}$	0.302	0.323	-0.00908	-0.733***	0.306	0.457
	(0.300)	(0.445)	(0.197)	(0.261)	(0.204)	(0.313)
C3. With Trade Credit Supplied $TC^{\{R\}}$						
Up	0.306*	0.781***	-0.275***	2.501***	-0.641***	0.158
	(0.157)	(0.221)	(0.0989)	(0.127)	(0.102)	(0.168)
Up × $TC^{\{R\}}$	-0.677**	-1.125**	-0.00498	0.173	-0.345	0.168
	(0.343)	(0.52)	(0.218)	(0.272)	(0.229)	(0.336)
N	2,567,786	2,434,711	2,567,786	4,529,948	2,434,711	1,357,230

Firm FE, Month-Region FE, and Month-Sector FE included in all regressions. Include lagged outcomes in levels. Panel A SE clustered at the municipality-level; Panels B and C at the firm-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14: Pooled LP: Direct, Downstream, and Upstream Exposure – Service Sector

Variables	Δ% Sales	Δ% Purchases	Δ% Employment	Pr. Exit	Δ% Sellers	Δ% Buyers
Panel A. Direct Exposure						
A1. Baseline						
Direct	-0.289	-0.699	-0.225	1.126***	-0.714*	-0.0191
	(0.313)	(0.466)	(0.210)	(0.229)	(0.393)	(0.412)
A2. With Trade Credit Received $TC^{\{P\}}$						
Direct	-0.396	-1.010**	-0.277	1.129***	-0.831**	0.00425
	(0.313)	(0.466)	(0.210)	(0.229)	(0.393)	(0.412)
Direct × $TC^{\{P\}}$	1.118*	3.107**	0.549	-0.00516	1.181**	-0.303
	(0.661)	(1.406)	(0.375)	(0.581)	(0.590)	(0.671)
A3. With Trade Credit Supplied $TC^{\{R\}}$						
Direct	-0.605*	-0.774	-0.245	0.913***	-0.754*	-0.815
	(0.366)	(0.612)	(0.266)	(0.257)	(0.417)	(0.582)
Direct × $TC^{\{R\}}$	0.894	0.231	0.0560	0.685	0.121	1.559***
	(0.765)	(1.089)	(0.411)	(0.476)	(0.423)	(0.505)
Panel B. Downstream Exposure						
B1. Baseline						
Down	-1.780***	-1.903***	-0.885***	3.108***	-0.926***	-2.039***
	(0.272)	(0.419)	(0.162)	(0.194)	(0.188)	(0.192)
B2. With Trade Credit Received $TC^{\{P\}}$						
Down	-1.678***	-1.909***	-0.865***	3.131***	-0.896***	-2.011***
	(0.286)	(0.441)	(0.172)	(0.204)	(0.200)	(0.200)
Down × $TC^{\{P\}}$	-0.945	0.114	-0.187	-0.271	-0.264	-0.258
	(0.817)	(1.242)	(0.461)	(0.597)	(0.551)	(0.604)
B3. With Trade Credit Supplied $TC^{\{R\}}$						
Down	-2.583***	-2.422***	-0.988***	2.742***	-1.455***	-2.732***
	(0.387)	(0.556)	(0.224)	(0.266)	(0.252)	(0.265)
Down × $TC^{\{R\}}$	1.597***	1.063	0.203	0.697*	1.081***	1.454***
	(0.512)	(0.792)	(0.305)	(0.368)	(0.355)	(0.354)
N	1,113,308	931,902	1,113,308	1,981,166	931,902	765,612
Panel C. Upstream Exposure						
C1. Baseline						
Up	-0.436*	0.740*	-0.376**	1.555***	-0.670***	-0.570***
	(0.262)	(0.381)	(0.172)	(0.246)	(0.150)	(0.209)
C2. With Trade Credit Received $TC^{\{P\}}$						
Up	-0.242	0.766*	-0.332	1.710***	-0.706***	-0.681***
	(0.306)	(0.448)	(0.205)	(0.287)	(0.177)	(0.245)
Up × $TC^{\{P\}}$	-0.557	-0.077	-0.124	-0.442	0.105	0.317
	(0.493)	(0.703)	(0.325)	(0.455)	(0.278)	(0.392)
C3. With Trade Credit Supplied $TC^{\{R\}}$						
Up	-0.322	0.781**	-0.369**	1.297***	-0.668***	-0.535**
	(0.277)	(0.393)	(0.182)	(0.261)	(0.158)	(0.221)
Up × $TC^{\{R\}}$	-0.559	-0.165	-0.001	1.415**	0.030	-0.161
	(0.639)	(0.982)	(0.441)	(0.605)	(0.375)	(0.535)
N	413,223	412,120	413,223	576,426	412,120	334,312

Firm FE, Month-Region FE, and Month-Sector FE included in all regressions. Include lagged outcomes in levels. Panel A SE clustered at the municipality-level; Panels B and C at the firm-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

F Emergency Procurement

Upstream disruptions can force firms to replace missing inputs on short notice, often by shifting spending toward suppliers with whom they have no recent transaction history. To test this mechanism, Table 18 focuses on procurement from *new sellers*, defined as sellers that appear in month t but were not part of the firm's seller set in the prior 12 months. The dependent variable is the YoY growth rate from new sellers. The key explanatory variable is upstream exposure E^U_{it}, measured as the share of the firm's input base tied to suppliers that become affected, and the table reports specifications that differ only in how exposure is operationalized: column (1) uses the continuous share, while columns (2)–(4) replace it with indicators for any exposure and for exposure exceeding 5% and 10%, respectively. I also include the firm's *new-seller share*, the fraction of sellers in month t that are new, and its interaction with lagged exposure. The new-seller share captures supplier rotation on the extensive margin, while the interaction isolates whether exposure increases the intensity with which firms rely on new partners when rotation occurs. All specifications include firm fixed effects, month-by-region fixed effects, and month-by-sector fixed effects, and standard errors are clustered at the firm level.

The estimates in Table 18 point to an adjustment margin that is consistent with emergency procurement, but one that operates through a mix of contraction and reallocation. Lagged upstream exposure enters with a negative coefficient across specifications, suggesting that higher exposure is associated with lower purchases from new sellers on average, conditional on fixed effects and the other controls. This pattern fits an environment in which upstream disruptions are costly to navigate: even if firms attempt to substitute, they still face frictions in re-sourcing and may partially scale down procurement while relationships with alternative suppliers are formed.

At the same time, the new-seller share is strongly positive, which confirms that periods of supplier rotation coincide with substantially higher spending on newly added partners. This is not merely mechanical. It indicates that the rotation measure is capturing reorganization of the supplier set rather than transitory reporting noise, and it provides a clean way to distinguish whether upstream exposure changes procurement behavior on the intensive margin once switching is occurring.

The key evidence for emergency procurement comes from the interaction term. The positive, precisely estimated coefficient for lagged exposure interacting with the new seller share implies that upstream exposure steepens the relationship between supplier rotation and purchases from new sellers. In other words, when firms add new sellers, those facing greater upstream exposure allocate disproportionately more spending toward these new partners. This is the signature of active substitution under binding disruptions: exposure does not only correlate with switching; it predicts a stronger reallocation of procurement expenditure toward newly formed relationships precisely in the months when firms are reorganizing their sourcing.

The positive interaction implies that exposure amplifies the proportional increase in purchases from new sellers associated with supplier rotation. This supports the broader interpretation from the upstream results: when disruptions become sufficiently salient, firms not only passively contract, but actively re-optimize their sourcing strategy by reallocating procurement toward newly added suppliers, consistent with emergency procurement under short-run input scarcity.

Table 18: $Y=$ Internannual Δ Purchases from New Sellers (Emergency Procurement)

VARIABLES	(1) E_{it}^{U}	(2) $E_{it}^{U} > 0$	(3) $E_{it}^{U} > 5\%$	(4) $E_{it}^{U} > 10$
Lag Exposure	-0.655***	-0.187***	-0.152***	-0.159***
	(0.0197)	(0.00333)	(0.00456)	(0.00573)
$\%NewSeller$	2.499***	2.484***	2.499***	2.502***
	(0.00399)	(0.00339)	(0.00399)	(0.00339)
Lag Exposure $\times$% New Seller	0.964***	0.348***	0.267***	0.261***
	(0.0309)	(0.00544)	(0.00738)	(0.00919)
Δ Total Purchase	1.091***	1.091***	1.091***	1.091***
	(0.000560)	(0.000550)	(0.000560)	(0.000560)
Observations	13,927,852	13,927,852	13,927,852	13,927,852
R-squared	0.644	0.644	0.644	0.644
Firm FE	Yes	Yes	Yes	Yes
Month-Region FE	Yes	Yes	Yes	Yes
Month-Sector FE	Yes	Yes	Yes	Yes

Standard errors clustered at the firm-level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1