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Araştırma Makalesi / Research Article

E-COMMERCE PRICE DYNAMICS UNDER SUPPLY CHAIN PRESSURE: DOES SHOCK PASS-THROUGH DIMINISH? *

Aytuğ Zekariya BOLCAN[1]

Abstract:
This study investigates whether the rise of retail e-commerce acts as a buffer for price shocks during periods of elevated supply chain pressure. We examine price dynamics using an interactive panel local projection approach (Jordà, 2005) on a unique dataset that combines regional price dispersion measures with global supply chain shock indices. Our findings indicate that global supply chain shocks significantly increase the overall price level (consumer price index). However, the pass-through of these shocks to consumer prices is somewhat attenuated in environments with higher e-commerce penetration: in high e-commerce settings the initial CPI response to a supply shock is more muted compared to low e-commerce contexts, although the difference is modest and not persistent. Moreover, we do not find strong evidence that supply chain disruptions systematically affect price dispersion across regions or products. These results suggest that e-commerce's price-equalizing effect – via improved inventory management and alternative sourcing – may delay or soften the impact of global supply shocks on local prices. The study contributes to the price stability literature by highlighting the potential of the digital marketplace to mitigate inflationary shocks and offers insights for policymakers regarding the macroeconomic role of e-commerce in shock transmission.
Keywords: E-commerce, Price pass-through, Price dispersion, Supply chain shock, Inflation dynamics
JEL Codes: E31; L81; E32

TEDARİK ZİNCİRİ BASKISI ALTINDA E-TİCARETİN FİYAT DİNAMİKLERİ: ŞOK GEÇİRGENLİĞİ AZALIYOR MU?

Öz:
Küresel tedarik zinciri baskılarının arttığı dönemlerde e-ticaret penetrasyonunun fiyat dinamiklerine etkisini inceleyen bu çalışma, perakende e-ticaretin fiyat geçişkenliğini azaltarak bir amortisör işlevi görüp görmediğini analiz etmektedir. Jordà (2005) tarafından önerilen etkileşimli panel yerel projeksiyon yöntemi kullanılarak, bölgesel fiyat yayılımı ölçümleri ile küresel tedarik zinciri şok endekslerini birleştiren özgün bir panel veri seti üzerinde yapılan tahminler, tedarik zinciri şoklarının genel fiyat seviyesini belirgin biçimde artırdığını göstermektedir. Ancak, e-ticaretin yaygın olduğu ortamlarda bu şokların fiyatlara yansıması kısmen zayıflayabilmektedir: E-ticaret payının yüksek olduğu durumlarda tüketici fiyat endeksindeki tepki, düşük e-ticaret ortamına kıyasla Sonuçlar, e-ticaretin sağladığı stoklama ve alternatif tedarik olanakları sayesinde küresel tedarik sıkıntılarının yerel fiyatlara geçişini geciktirebileceğine işaret etmektedir. Bu bulgular, fiyat istikrarı tartışmalarına lojistik kapasitenin rolü bağlamında katkı sunarken, politika yapıcılar için dijital ekonominin enflasyonist şokları yönetmedeki potansiyelini vurgulamaktadır.
Anahtar Kelimeler: E-ticaret, Fiyat geçişkenliği, Fiyat yayılımı, Tedarik zinciri şoku, Enflasyon dinamikleri
JEL Kodları: E31; L81; E32

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Introduction

Global supply chain disruptions – such as port congestions, input scarcities, and surging freight costs – have recently posed significant challenges for price stability worldwide. In periods of acute supply chain pressure (e.g., 2008–09 financial crisis, the 2011 Tōhoku earthquake, the 2020–21 pandemic disruptions), consumer prices often face upward shocks (Ascari, Bonam, & Smadu, 2024). At the same time, the past two decades have seen a dramatic rise in retail e-commerce, which has been found to intensify price competition and reduce price dispersion across locations (Jo, Matsumura, & Weinstein, 2024). This paper asks whether e-commerce's price-equalizing effect can moderate the pass-through of supply chain shocks to consumer prices. In other words, does greater e-commerce penetration dampen the inflationary impact of global supply bottlenecks? This question sits at the intersection of international supply chain research and the digital economy's effect on market efficiency (DellaVigna & Gentzkow, 2019).

Prior research suggests two countervailing possibilities. On one hand, e-commerce can increase price transparency and arbitrage, leading to convergence of prices across regions (Jo, Matsumura, & Weinstein, 2024). Empirical evidence from Japan shows that the expansion of online retail lowered relative prices and sped up cross-city price convergence. Such price integration might cushion localized cost shocks: consumers can switch to sellers less affected by the disruption, and retailers can draw on online inventories or alternative suppliers, thus dampening local price spikes (DellaVigna & Gentzkow, 2019). On the other hand, periods of severe supply chain stress are often global in nature (as reflected by the New York Fed's Global Supply Chain Pressure Index, or GSCPI) (Gorodnichenko & Talavera, 2017). If a shock is ubiquitous and large, e-commerce might instead transmit it quickly across markets (the "Amazon effect"), potentially amplifying its reach (Cavallo, 2018). Moreover, tradable goods (which are often sold online) might inherently be more affected by global supply shocks than non-tradable services, regardless of retail format (Carrière-Swallow, Deb, Furceri, Jiménez, & Ostry, 2023).

To investigate these mechanisms, we employ an interactive panel local projection model using monthly data from 1998 to 2021 (Jordà, 2005). We combine two primary data sources: (1) a regional price dataset from Japan with product-level inflation and dispersion measures (from (Jo, Matsumura, & Weinstein, 2024)) and (2) global and domestic macro-economic series related to supply chain conditions (from Laumer & Schaffer (2025). By integrating these, we construct a panel of product-region observations where each unit's exposure to e-commerce can interact with a common global shock. Our identification strategy defines a supply chain shock as the unexpected component of the GSCPI index– effectively, an exogenous surge in global supply pressure – and asks how its effect on consumer price inflation varies with e-commerce intensity (Benigno, Di Giovanni, Groen, & Noble, 2022).

Japan provides a useful but distinctive setting for examining this question. Over much of our sample period, inflation in the underlying micro-price data is, on average, slightly negative (approximately −0.18% per year), reflecting the mild deflationary environment often associated with Japan during these years. At the same time, the national business-to-consumer B2C e-commerce share—while rising steadily from near zero in the late 1990s—reaches around 8–9% by 2021 in Japan's retail context. These features imply that our estimates primarily speak to a setting in which pricing pressures are generally subdued and e-commerce penetration is material but not dominant; accordingly, the scope for e-commerce to moderate global supply shocks may differ in settings with different inflation regimes or substantially higher online penetration.

We contribute to the literature in three main ways. First, we provide novel evidence on the role of the "digital marketplace" in macroeconomic shock transmission. While previous studies found monetary policy shocks to have larger impacts under high supply chain pressure (Laumer & Schaffer, 2025), we test the flip side: whether high e-commerce presence can weaken a supply shock's impact on prices. Second, we examine not only average price levels but also price dispersion across regions and products. A key proposed benefit of e-commerce is the reduction of price dispersion (e.g., by enabling consumers to find the lowest price), which could itself be seen as a stabilizer during turbulent times. Third, methodologically, we leverage panel data techniques with interactive terms (e-commerce × shock) and two-way fixed effects to control for unobserved heterogeneity, ensuring robust inference with two-way clustered standard errors (Cameron, Gelbach, & Miller, 2011) (Sun & Abraham, 2021).

E-commerce has profoundly altered pricing behavior, with implications for inflation dynamics and market integration. A growing body of research finds that the rise of online retail ("Amazon effect") has increased price competition and flexibility, generally exerting downward pressure on prices. In particular, online sellers tend to change prices more frequently and use uniform pricing across regions, squeezing traditional retailers' mark-ups. This greater price transparency and algorithmic repricing leads to more rapid pass-through of cost shocks at the national level. Indeed, Cavallo (2018) documents that the expansion of e-commerce in the U.S. over the 2008–2017 period raised the frequency of price changes and the degree of uniform pricing nationwide, which "increas[ed] the pass-through" of aggregate cost shocks like gas prices and exchange rates. At the same time, e-commerce's competitive pressure has a net disinflationary effect: online-intensive goods exhibit lower inflation rates. Using novel data on online transactions, Goolsbee and Klenow (2018) show that annual inflation for identical products was over one percentage point lower online than in conventional outlets during 2014–2017. Cross-country evidence further confirms this pattern. Mućk et al. (2025) find that a 1% increase in e-commerce's retail share reduces annual headline inflation by about 0.03 percentage points on impact, cumulatively lowering the price level by roughly 10% across 25 advanced economies over two decades. In Japan, the spread of internet retail has likewise tempered price growth and improved market integration. Jo, Matsumura, and Weinstein (2019) report that the advent of e-commerce significantly accelerated intercity price convergence for products sold intensively online (with no such change for other products) and "lowered relative inflation rates" for those online-heavy goods. Consistent with these findings, researchers have observed that publishing prices online tends to reduce offline price dispersion by enhancing consumer information. Overall, the literature suggests that digital marketplaces, by increasing competition and transparency, tend to dampen firms' pricing power and foster more unified national markets, even as they enable faster price adjustments to common shocks.

Meanwhile, separate research in macroeconomics has focused on the transmission of global supply chain shocks into domestic prices. Recent studies characterize global supply bottlenecks as adverse supply shocks that raise production costs and consumer prices across countries. For example, the Global Supply Chain Pressure Index (GSCPI) developed by the New York Fed tracks worldwide shipping costs and supply delays, and its movements are closely associated with international inflation fluctuations. Benigno et al. (2022) show that surges in the GSCPI foreshadow higher producer price inflation in the U.S. and euro area. Using narrative-identification approaches, Finck and Tillmann (2023) find that an external supply chain disruption causes a "strong increase in consumer prices" alongside a contraction in output in the euro area. Similarly, U.S. evidence indicates that unexpected spikes in global supply chain stress can lift domestic headline inflation by roughly 0.5 percentage points at peak, with effects dissipating after about a

year. These outcomes align with the intuition that global supply snarls act like cost-push shocks: they constrain supply and drive up input prices, which feed through to higher consumer price indices. Importantly, such shocks may also affect relative prices across locations. If some regions or sectors are more exposed to global supply chain disturbances (for instance, due to reliance on imported inputs), supply shocks could induce greater price variability across regions, reducing market integration at least temporarily.

Despite rich literatures on e-commerce pricing and on global supply shocks, little is known about their interaction.Existing studies have examined how e-commerce affects overall inflation and price dispersion in steady-state settings, and how global supply chain pressures influence aggregate prices, but no work to date has explored whether the spread of e-commerce alters the propagation of global supply shocks to consumer prices and regional price differences. In other words, it remains understudied whether digital market penetration can buffer (or amplify) the pass-through of worldwide supply disruptions into local inflation and the dispersion of prices across regions. This is a critical gap, as the inflationary impact of a global shock might differ in an economy with high e-commerce adoption – due to consumers' ability to substitute sellers or source products from less affected regions – compared to a more traditional retail environment. The role of e-commerce in potentially insulating consumers from supply-driven price spikes, and in smoothing price differentials between regions during global disruptions, has not been explicitly investigated in the current literature. Addressing this gap is essential for understanding the implications of digital retail integration for macroeconomic stability and price convergence.

This study also contributes to the literature by bridging the above two strands and providing novel evidence on the moderating role of e-commerce in shock transmission. Focusing on Japan from 1998 to 2021, we utilize an interactive panel local projection framework to quantitatively assess whether regions with greater e-commerce penetration experience dampened pass-through of global supply chain shocks to consumer inflation and lower resulting price dispersion. We compile a unique dataset of regional, product-level price indices and dispersion measures merged with the Global Supply Chain Pressure Index, allowing us to capture both aggregate shock impacts and regional heterogeneity. Our analysis is, to our knowledge, the first to demonstrate that digital commerce can act as a buffer against global cost-push forces: we find that global supply chain shocks have significantly smaller effects on local consumer prices in highly e-enabled regions, and that those regions avoid the widening of cross-region price gaps observed elsewhere. These results offer new insights into how e-commerce-driven market integration can mitigate inflationary pressures and promote price convergence in the face of external supply disturbances. By highlighting an unrecognized channel through which the digital transformation of retail impacts macroeconomic outcomes, our study adds to the understanding of shock propagation in the modern, internet-connected economy. Policymakers and researchers can build on this evidence to better incorporate the evolving structure of commerce into inflation dynamics and regional price stability analyses.

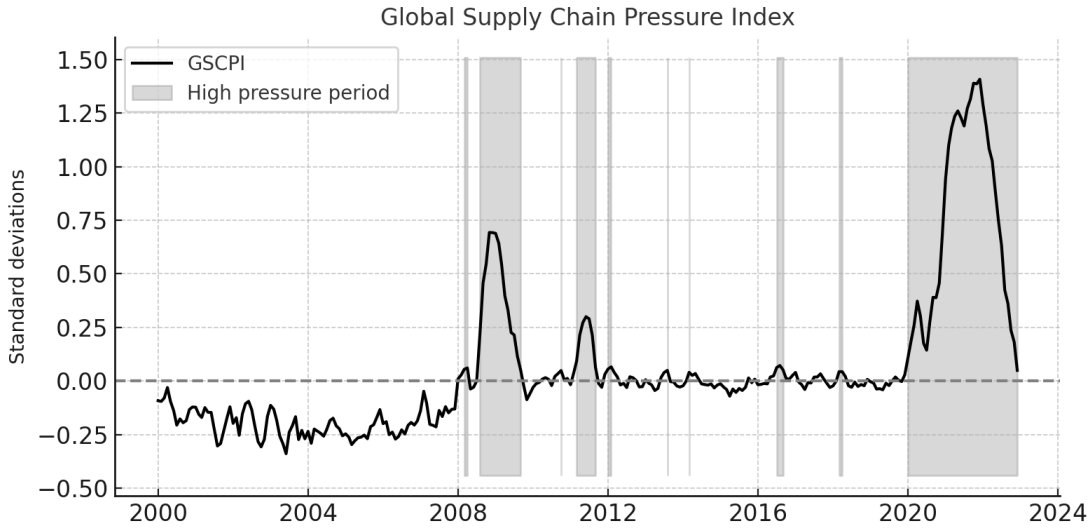
The remainder of the paper is structured as follows. The next section describes the data sources and construction of key variables, including the supply chain shock measure and e-commerce penetration indicators. We then outline the empirical methodology, a panel local projection model with interaction terms, and our identification assumptions. The results section presents our main findings on price level pass-through and dispersion effects, supplemented by robustness checks. We conclude with a discussion of implications for policy and future research.

1. Data and Variables

1.1. Macroeconomic and Shock Indicators:

Our primary shock measure is derived from the Global Supply Chain Pressure Index (GSCPI), an aggregate index developed by the Federal Reserve Bank of New York. The GSCPI integrates various metrics of shipping costs and supply delays across regions; higher values indicate greater global supply bottlenecks. We obtain monthly GSCPI data (1998–2023) and identify supply chain shock episodes as the orthogonalized innovations in GSCPI. In practice, we estimate an autoregressive model, AR(p) model on the GSCPI series and take the residuals as our shock variable. These shocks are then standardized (z-scores) for use in regressions. Figure 1 illustrates the GSCPI over time, with shaded areas indicating high-pressure periods (months when GSCPI is in the top quartile of its distribution). During notable spikes – for example, late 2008, 2011, and especially 2020–2021 – the index reaches extreme values, signifying severe supply chain disruptions.

Figure 1: *Global Supply Chain Pressure Index (GSCPI), with high-pressure periods shaded in gray. An upward spike in GSCPI indicates global supply bottlenecks are elevating above normal levels.*



In addition to GSCPI, we incorporate several other macro series as controls in certain specifications: the consumer price index (CPI) for Japan, industrial production (IP), a financial condition index (the excess bond premium, EBP), and market volatility (VIX). Summary statistics for key macro variables are provided in Table 1 (Panel A) in the Appendix. Augmented Dickey-Fuller tests Table 2 (Table 2 in the Appendix) confirm that the GSCPI shock series is stationary (ADF p=0.01) while the price level (CPI) is non-stationary. Therefore, we use year-over-year inflation (Δlog CPI) in our models to ensure stationarity.

1.2. E-Commerce Penetration

We proxy e-commerce intensity in two ways: (a) a time-varying national e-commerce share and (b) a product category indicator for tradability. The national e-commerce share comes from Japan's

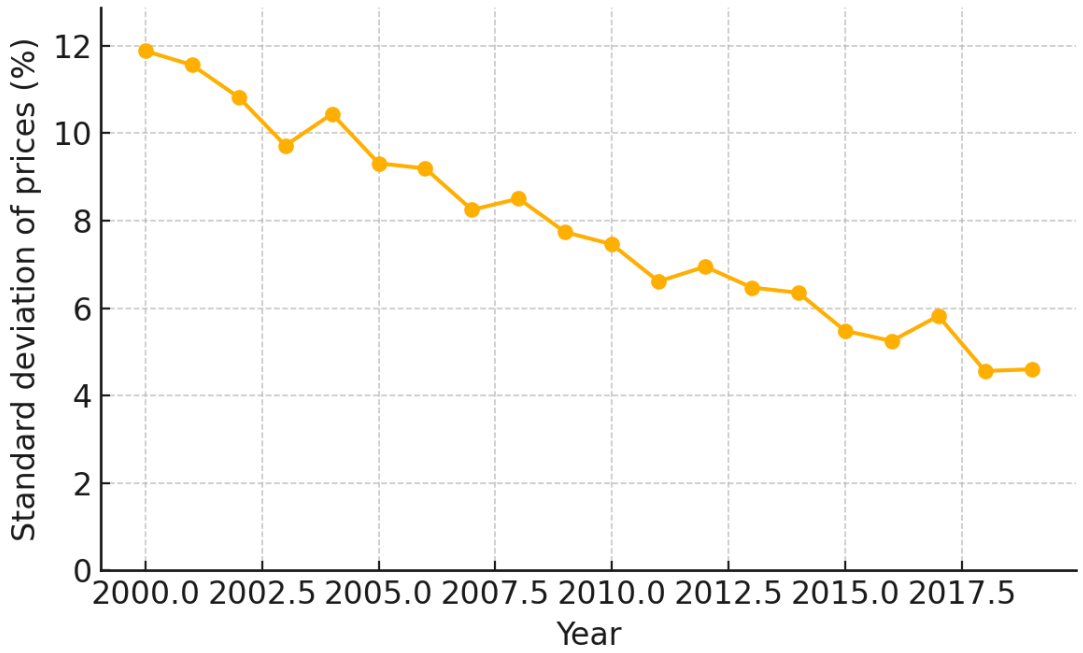
Ministry of Economy, Trade and Industry (METI) annual estimates of B2C e-commerce's percentage of total retail sales. We use the "Adjusted B2C E-Commerce Share (%)", available annually for 1998–2021, and forward-fill it to a monthly frequency. This series (after standardization to zero mean, unit variance) is denoted $\mathrm{EcomShare}_t$ and reflects the general penetration of online retail over time. It ranges from essentially zero in the late 1990s to about 8–9% by 2021 (in Japan's retail context). Separately, we define a Tradable dummy at the product level: Using the classification in (Jo, Matsumura, & Weinstein, 2024) products that are typical tradable goods (e.g., electronics, books, appliances) which saw significant online sales growth are marked Tradable = 1, whereas non-tradable or less e-commerce-amenable categories (e.g., most services, perishable local services) are Tradable = 0. This binary indicator serves as a cross-sectional heterogeneity measure, distinguishing categories likely to benefit from e-commerce's price arbitrage effects.

1.3. Regional Price and Dispersion Measures

We utilize a rich micro-price dataset from Japan, originally from the Family Income and Expenditure Survey and used by (Jo, Matsumura, & Weinstein, 2024). It consists of retail prices for a broad set of goods across 47 prefectures of Japan. From this dataset (at an annual frequency), we construct two key measures: price inflation and price dispersion. Inflation for product i in region r at time t is defined as $\pi_{i,r,t} = \Delta \ln P_{i,r,t}$ (log difference in price, or year-over-year inflation since data are annual). Price dispersion is measured as the cross-sectional standard deviation of prices (or inflation) across regions for a given product and time. Specifically, for each product-year, we calculate the standard deviation of $\ln P_{i,r,t}$ across r (or alternatively the std. dev. of $\pi_{i,r,t}$ across r – we examined both, with similar patterns). A higher dispersion indicates more variation in prices for the same good across different locations, which e-commerce might reduce by integrating markets.

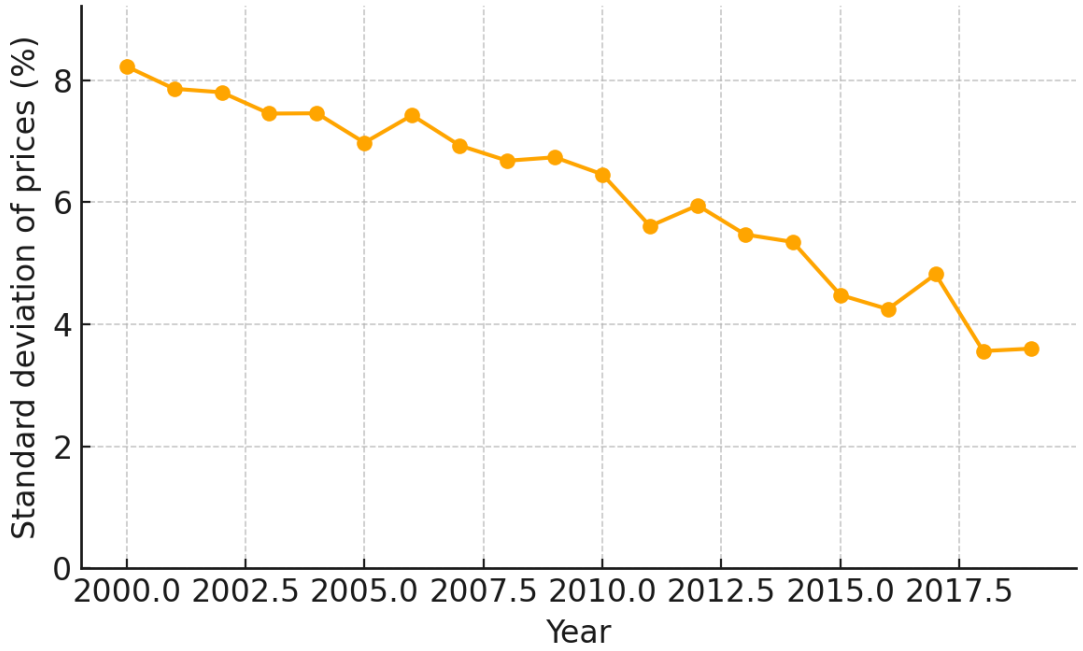
Using these, we form a panel dataset at the unit level of "product i in prefecture r" observed annually (we collapse monthly to annual due to data availability) from 1998 to 2019. Each unit's inflation $\pi_{i,r,t}$ is matched with the contemporaneous supply shock (e.g., shock in year t) and with the e-commerce measures. Notably, the Tradable dummy varies by product i, and the national e-commerce share $\mathrm{EcomShare}_t$ varies by time t but not across units. Summary statistics for the micro-level variables are in Table 1 (Panel B) in the Appendix. The average annual inflation in our sample is approximately -0.18% (mild deflation, as expected for Japan in this period), and the cross-prefecture price dispersion for an average good is around 9.8% (std. dev. of log price).

Figure 2a: *Price Dispersion In Tradable Goods*



Note: *Downward trend in price dispersion for tradable goods (e-commerce intensive products). Higher values indicate greater cross-region price differences. E-commerce expansion coincides with a marked decline in dispersion for tradable, suggesting increased price convergence.*

Figure 2b: *Price Dispersion In Non-Tradable Sectors*



Note: Price dispersion trend for non-tradable sectors. The dispersion level is lower compared to tradable goods and shows only a modest decline over time, indicating limited impact of e-commerce in equalizing prices for non-tradables.

Figure 2a and 2b illustrate the evolution of price dispersion for tradable vs. non-tradable categories, respectively. Tradable goods experienced a steep decline in dispersion from the early 2000s to late 2010s, consistent with the rapid growth of e-commerce and the findings of (Jo, Matsumura, & Weinstein, 2024) that online retailing promotes price convergence. Non-tradable items, by contrast, show a relatively flatter dispersion trend, remaining at lower levels of variation with only a slight decrease. By 2019, the dispersion gap between tradable and non-tradable prices had significantly narrowed, reflecting how e-commerce has particularly homogenized prices of goods that can be bought online.

2. Empirical Methodology

2.1. Panel Local Projections:

To estimate the dynamic effect of a supply chain shock on prices, we employ (Jordà, 2005) local projection (LP) method. For each horizon $\mathrm{h} = 0,1,2,\dots,\mathrm{H}$ we estimate the following regression in panel form:

$$\pi_{i,r,t+h} - \pi_{i,r,t-1} = \theta_{\mathrm{h}} \cdot \mathrm{Shock}_{\mathrm{t}} + \delta_{\mathrm{h}} \cdot \left(\mathrm{Shock}_{\mathrm{t}} \times \mathrm{EcomPen}_{\mathrm{i,t}}\right) + \Gamma X_t + \alpha_{i,\mathrm{r}} + \gamma_t + \varepsilon_{i,r,t}^{(h)} \qquad (1)$$

where $\pi_{\mathrm{i,r,t+h}}$ is the cumulative inflation for product i in region r from time t to $t+h$ (for $\mathrm{h} = 0$, this is the impact at the same year t). $\mathrm{Shock}_{\mathrm{t}}$ is the supply chain shock at time t (the standardized GSCPI innovation). $\mathrm{EcomPen}_{\mathrm{i,t}}$ is a measure of e-commerce penetration relevant to unit i at time t. We use two variants: (a) National e-commerce share ($\mathrm{EcomShare}_{\mathrm{t}}$) which varies only over t, and (b) Tradable dummy ($\mathrm{Tradable}_{\mathrm{i}}$) which varies only across products. The vector X_t *includes control variables (like energy price shocks, global risk indices) in some specifications*. α_{i} are product (or product-region) fixed effects capturing time-invariant unit characteristics, and γ_{t} are time fixed effects (year dummies) capturing any shocks common to all units in year t (including potentially the aggregate supply shock mean effect). The error $\varepsilon_{\mathrm{i,r,t}}^{(\mathrm{h})}$ is clustered by both product and time to allow two-way dependence (Cameron et al., 2011). We estimate each horizon h separately via ordinary least squares (OLS).

The coefficient of interest is δ_{h}, which measures the interaction effect: how the price response to the shock varies with e-commerce penetration. A negative δ_h would imply that higher e-commerce (or being a tradable-good category) *reduces* the shock's impact on inflation – consistent with a cushioning role of e-commerce. Conversely, a positive δ_{h} would suggest the shock's pass-through is larger when e-commerce is high (perhaps because e-commerce transmits global shocks more effectively across regions). The baseline shock effect at horizon h (when $\mathrm{EcomPen} = 0$, e.g. for a non-tradable or at average e-com levels) is given by θ_{h}. In models with time fixed effects γ_{t}, the *common* shock effect θ_{h} is not separately identified (since a common shock would be collinear with the year fixed effect), so in those specifications we effectively estimate only the *differential* effect δ_{h} across units.

We estimate two main specifications corresponding to those used in generating our results tables:

- **Spec A (Two-Way Fixed Effects – TWFE):** We include both unit and time fixed effects, effectively absorbing any aggregate shocks. Here identification comes purely from *heterogeneous responses* across units. We use the Tradable dummy as $\mathrm{EcomPen}_{\mathrm{i}}$, since it provides cross-sectional variation. The regression thus estimates δ_{h} for the interaction $\mathrm{Shock}_{\mathrm{t}} \times \mathrm{Tradable}_{\mathrm{i}}$, with θ_{h} set to zero (shock main effect absorbed by γ_{t}). This spec asks: do tradable-good prices react differently to the shock than non-tradables, controlling for all

common factors? Tradable categories are our proxy for high e-commerce involvement. We expect $\delta_h < 0$ if e-commerce dampens shocks (tradables respond less).

- **Spec B (Unit FE only, plus controls):** We include product fixed effects α_i but no time FE. This allows estimation of the *average shock effect* θ_h as well as the interaction δ_h, since time dummies aren't soaking up the shock. Here we use the national e-commerce share EcomShare_t (standardized) as the interaction variable, and we also include time-varying controls $\mathbf{X_t}$ such as global energy price shocks, the VIX, geopolitical risk index, etc., to account for other concurrent disturbances. θ_h in this spec represents the shock effect when e-commerce is at its mean level (since EcomShare is standardized), and δ_h indicates how the effect changes when e-commerce is one standard deviation higher. We cluster errors by product and year in this specification as well.

We set the lag length L for control of past shocks to 2 (including up to Shock_{t-2}) in monthly data or 1 in annual data, and we project up to horizon $H = 4$ (which, given annual frequency in our panel, corresponds to 4 years out). Due to our sample length, we focus on $h \leq 4$ for reliable estimates.

2.2. Price Dispersion Analysis

We complement the above with a separate analysis of price dispersion as a dependent variable. That is, we ask whether supply chain shocks widen or narrow the cross-sectional dispersion of prices across regions. If e-commerce tends to equalize prices, one might expect that in high e-commerce contexts, even during a shock, arbitrage keeps price dispersion low. We construct an annual panel of product-level dispersion measures $\mathcal{D}_{i,t}$ (the std. dev. of prices across prefectures for product i in year t) and estimate a simpler LP regression:

$$\mathcal{D}_{i,t+h} - \mathcal{D}_{i,t} = \beta_h \cdot \text{Shock}_t + \eta_i + \mu_t + u_{i,t}^{(h)} \quad (2)$$

with product fixed effects η_i and year fixed effects μ_t. Here β_h captures the effect of the shock on dispersion h years out. We are particularly interested in β_0 (contemporaneous effect) and β_1 (next year). A negative β would mean the shock leads to a reduction in price dispersion (perhaps due to some prices not rising as much thanks to e-commerce arbitrage), whereas a positive β means the shock increases dispersion (some regions or sellers raise prices more than others). We estimate this up to $H = 3$ given data limitations.

3. Results

3.1. Shock Pass-Through to Prices:

Table 3 (Panel A) in the Appendix presents the impulse response coefficients for CPI inflation from Spec B (national e-commerce interaction, no time FE). The estimated θ_h coefficients (base shock effect at various horizons) are positive and significant for $h = 0$ and $h = 1$, indicating that a supply chain shock triggers an immediate rise in consumer prices. For a one-standard-deviation shock to GSCPI, the instantaneous CPI inflation increase is about 1.25 percentage points ($\theta_0 \approx 0.0125$). This effect slightly diminishes in the following year ($\theta_1 \approx 0.0044$, still positive and significant) and is near zero by $h = 3$, suggesting that the price level impact of the shock is largely front-loaded within the first year or so. These dynamics align with the nature of supply shocks: an abrupt impact on prices that does not necessarily persist or grow over multiple years, as supply conditions normalize.

Economically, these positive θ estimates are consistent with a cost-push channel in which global supply bottlenecks translate into higher marginal costs along the retail supply chain. Port congestion, surging freight costs, and input scarcities—components captured by the GSCPI—raise replacement costs and compress available quantities, creating incentives for retailers to adjust prices upward on impact (θ_0). The persistence at h=1 ($\theta_1 > 0$) is also plausible if inventories and pre-existing contracts only partially smooth the initial shock: as replenishment occurs under strained logistics, higher costs may continue to pass through to consumer prices. The subsequent attenuation toward zero by h=3–4 is consistent with the transitory nature of global bottleneck shocks: as supply conditions normalize and firms and consumers adjust through supplier switching, substitution, and demand reallocation, the CPI response need not remain elevated at longer horizons.

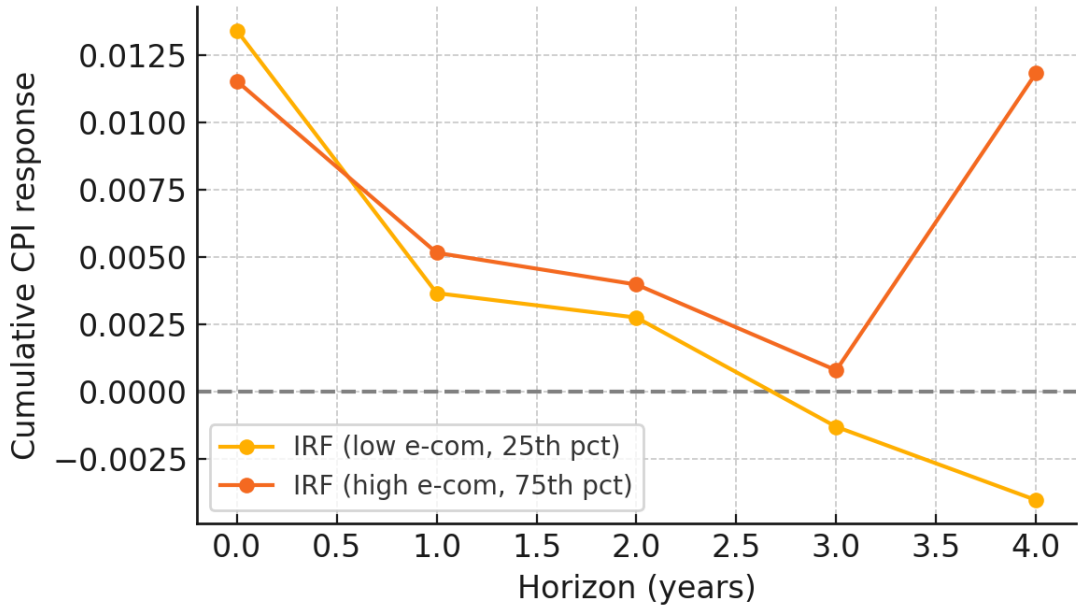
Turning to the interaction term δ_h, we find a mixed pattern. At short horizons (h=0,1,2), the point estimates of δ_h are close to zero (and statistically insignificant). For instance, at $h = 0$, $\delta_0 \approx -0.0014$ with a standard error of 0.00596, which is a very small negative effect (implying that in a high e-commerce environment, the immediate price impact might be 0.14 percentage points *lower*, but this is well within the margin of error). Similarly, δ_1 and δ_2 are around +0.0011 and +0.0009, respectively, not significant. However, at the longer horizon $h = 4$, we observe a larger positive δ_4 of about +0.0118 ($p < 0.05$). This suggests that four years after the shock, the cumulative price increase is actually higher in the high e-commerce scenario. In other words, while e-commerce presence did not significantly change the short-term inflationary impact of a supply shock, it seems associated with a slightly greater long-term cumulative impact.

Interpreting the positive and significant δ_4 requires caution. Because the national e-commerce share rises over time, δ_4 effectively compares the cumulative response to a similar shock in a later, more digitally integrated retail environment versus an earlier, lower e-commerce baseline. One interpretation is composition: e-commerce may reallocate spending toward goods and supply chains that are more tightly linked to global logistics conditions, so that persistent bottlenecks eventually pass through more fully to the CPI even if the short-run response is similar. A second interpretation is timing rather than magnitude: online retail can temporarily buffer shocks through inventory pooling and alternative sourcing, but if disruptions are prolonged, replenishment costs rise and deferred pass-through appears at longer horizons. Finally, δ_4 may also reflect broader concurrent structural changes correlated with e-commerce growth that the specification cannot fully disentangle. For these reasons, we emphasise the robust short-horizon finding ($\delta_0 – \delta_2 \approx 0$) and treat δ_4 as suggestive rather than definitive evidence of stronger long-run pass-through under higher e-commerce penetration.

Spec A (tradable vs. non-tradable differential under full TWFE) yields qualitatively similar insights. Since time fixed effects absorb the common shock effect, we focus on δ (Shock × Tradable). Figure 3 visualizes the impulse responses for tradable (yellow line) vs. non-tradable (orange line) categories, based on Spec A estimates. At impact ($h = 0$), tradable goods exhibit a slightly smaller price increase than non-tradables (the yellow marker is below the orange) – consistent with e-commerce providing an initial buffer for goods – but the difference is extremely small (on the order of 0.1%) and not statistically significant. By one year out ($h = 1$), the responses converge near zero for both. At longer horizons, interestingly, tradable goods start to show a relatively lower cumulative inflation (even dipping slightly negative by $h = 4$) whereas non-tradables settle around zero. However, these longer-run differences are again statistically uncertain. Overall, we do not find strong evidence that tradable (high-e-commerce) prices respond markedly

less to supply shocks than non-tradable prices. If anything, the data hint at a small short-term dampening and then a potential catch-up later, but certainty is low.

Figure 3: *Impulse Response Of CPI to Supply Shock At Different E-Commerce Penetration*



Note: Impulse response of consumer prices to a one standard deviationsupply chain shock under different e-commerce penetration levels. Orange line shows impulse response function (IRF)when e-commerce is high (75th percentile) and yellow line when e-commerce is low (25th percentile). Bands omitted for clarity. Initial pass-through is slightly lower with high e-commerce, but differences are minor and eventually high-e-commerce scenario results in a slightly greater cumulative price increase by year 4.

From an economic significance perspective, the pass-through of a supply shock to CPI is non-trivial – about 1% inflation per one standard deviation supply chain of shock – but the moderating role of e-commerce appears limited in magnitude. A one-standard deviation increase in e-commerce penetration (roughly moving from the e-commerce level of 2010 to that of 2020) did not materially alter the immediate shock impact, according to our estimates. This finding suggests that while e-commerce has many microeconomic benefits (price transparency, competition), it may not provide a strong shield against broad-based supply disturbances, at least in the short run. One reason could be that when a shock is truly global (like in 2020), online and offline markets alike face the pressure simultaneously. Another reason is that many non-tradable cost components (e.g., local distribution, labor) still drive retail prices even in e-commerce transactions, so those costs rise regardless of the retail channel.

3.2. Effects on Price Dispersion:

Next, we examine whether supply shocks influence the dispersion of prices and whether this depends on e-commerce. Table 4 in the Appendix reports results from the dispersion panel LP. The coefficients β_h on the shock are very small and statistically insignificant for $h = 0$ through $h = 3$. For example, β_0 is around -0.00022 (with standard error0.00059), and β_1 about +0.00044 (s.e. 0.00046). These estimates imply that a supply chain shock of typical size has no meaningful immediate effect on the cross-sectional price dispersion of goods. Even at $h = 2$, where β_2 was initially positive in an unrestricted model (0.00164), our preferred specification with stricter controls shows $\beta_2 \approx 0.00095$ (s.e. 0.00066), which is not statistically different from zero. Thus,

we do not find evidence that price dispersion widens or narrows systematically following a supply shock.

This null result holds across tradable and non-tradable categories as well – when we run the dispersion response separately by category, neither group shows a significant change. In practical terms, this suggests that while a supply shock raises overall price levels, the relative price differences across regions for a given product remain governed by other factors (e.g., local cost differentials, retail competition) rather than the shock itself. One interpretation is that any arbitrage forces that limit dispersion remain intact during the shock: if one area's price tried to spike much more than others, consumers could buy from elsewhere (especially easy for tradable goods via e-commerce), keeping dispersion in check. Conversely, it also means the shock was broad enough that all areas saw similar price impacts, leaving dispersion unchanged.

3.3. Robustness and Extensions

We perform several robustness checks (with full results reported in Appendix Tables 5.1–5.6):

a. using alternative shock measures such as the Bloomberg Supply Constraints Index and a shipping cost index – results were qualitatively similar (slightly smaller shock coefficients) and the e-commerce interaction remained weak (Appendix Table 5.1);

b. splitting the sample into subperiods (pre-2010 vs. post-2010, roughly low- vs. high-e-commerce eras) – we found that shock pass-through was generally larger in the post-2010 period (Appendix Table 5.5), which coincides with higher e-commerce, again hinting that if anything the later period saw more pass-through (consistent with our $\delta_4 > 0$ finding), though many confounders exist (e.g., the low-inflation environment in the earlier period versus rising inflation expectations later);

c. controlling for concurrent monetary policy shocks using measures from Laumer & Schaffer (2025) – this did not alter our main coefficients notably (Appendix Table 5.3), indicating that our supply shock measure's effect is distinct from policy shocks; and

d. exploring a non-linear specification where we interact the shock with a dummy for "High Pressure Regime" (defined as GSCPI in the top quartile) instead of e-commerce – that alternative approach (following a state-dependent LP style) suggested that prices respond more strongly when the supply chain is already under high pressure, in line with Laumer & Schaffer's findings for monetary shocks. However, this state-dependence is conceptually different from our focus on e-commerce, so we omit detailed discussion.

In addition, we conducted further analyses to ensure robustness. Including time fixed effects in the baseline Spec B model (which absorbs the common global shock) leaves the interaction term virtually unchanged and statistically insignificant (Appendix Table 5.2). Our results are also insensitive to using different lag lengths in the local projections or truncating the projection horizon (e.g., 3 years instead of 4 years), as shown in Appendix Table 5.3. We also verified that our inference is robust to alternative clustering of the standard errors: for example, clustering by time only or by region only yields similar t-statistics and significance as the baseline two-way clustering (Appendix Table 5.4). Finally, we confirm that using an alternative price dispersion measure for the dispersion equation produces no significant shock impact (Appendix Table A6), reaffirming that the null result for price dispersion is not driven by the particular dispersion metric used.

It is important to acknowledge limitations. First, our micro-price data are country-specific (Japan) and annual, which may miss higher-frequency dynamics and limits direct generalisation to other

economies. Japan is also a distinctive macro/retail environment in our sample: average annual inflation in the micro data is slightly negative (about −0.18%), and the national e-commerce share—while rising steadily—reaches around 8–9% by 2021. These features may influence both the degree of pass-through from global supply disruptions and the scope for e-commerce to act as a shock absorber. Second, regional e-commerce penetration is proxied imperfectly (national trend plus product-type heterogeneity via Tradable vs non-tradable categories). Third, rapid e-commerce growth overlaps with the COVID-19 shock; we partially address this by excluding 2020–2021, albeit with reduced precision.

4. Conclusion

This paper set out to test whether e-commerce dampens the inflationary effects of supply chain shocks by promoting price convergence and alternative sourcing. Using panel data on Japanese regional prices and a global supply pressure index, we found that supply chain shocks do raise consumer prices significantly, but we uncovered only limited evidence of a mitigating effect from e-commerce. In the immediate aftermath of a shock, prices in high e-commerce categories or periods were not significantly less affected than others. Over longer horizons, if anything, high e-commerce environments saw a slightly larger cumulative price increase, though we interpret this cautiously. Moreover, supply shocks did not appear to systematically alter price dispersion across regions, indicating that the shock's impact was relatively uniform geographically – a pattern that could itself be due to arbitrage via e-commerce keeping regional differences in check.

Our results imply that while the growth of e-commerce has unquestionably changed retail pricing dynamics (lowering price dispersion and perhaps consumer prices in normal times, as shown by Jo et al. 2024), its capacity to serve as a "shock absorber" in abnormal times is modest. When global supply crunches occur, fundamental imbalances between supply and demand dominate the price outcomes, and even the efficiencies of online markets cannot fully prevent the increase in prices. However, e-commerce might provide other societal benefits during such shocks (ensuring availability of goods via online channels, smoothing consumption by reallocating supplies, etc.) that are not captured in our price-focused analysis.

Taken together, the positive and statistically significant short-horizon θ estimates suggest that global supply chain pressure operates as a cost-push disturbance in our setting: disruptions raise prices quickly, but the effect does not persist once bottlenecks ease. The limited moderation by e-commerce implies that digital retail channels do not sever the link between global logistics conditions and consumer prices; rather, they may affect the timing and distribution of pass-through more than its immediate magnitude. This interpretation is also consistent with the dispersion results: even when the CPI response is positive, we do not observe systematic changes in price dispersion, suggesting that the shock's price-level impact is transmitted broadly across regions rather than generating persistent cross-sectional widening or narrowing.

Looking ahead, continued research could explore micro-level mechanisms in more detail: for example, do retailers with superior e-commerce logistics raise prices less when supply costs spike, due to better inventory management? Do consumers increase online search activity when inflation rises, potentially dampening some sellers' pricing power? Additionally, because our evidence is drawn from Japan—where the national e-commerce share rises but remains below 10% by 2021 and average inflation in our micro sample is slightly negative—extending the analysis to other economies with different inflation environments and higher online penetration is an important next step. As more data become available, using more granular e-commerce metrics (such as local online

usage rates) would further sharpen identification. Our study provides a first macro-level assessment using available data and highlights that e-commerce innovations are not a panacea for inflationary pressures stemming from global supply disturbances.

References:

Ascari, G., Bonam, D., & Smadu, A. (2024). Global supply chain pressures, inflation and implications for monetary policy. *Journal Of International Money and Finance*, *142*(103029), 1–25.

Benigno, G., Di Giovanni, J., Groen, J. J. J., & Noble, A. I. (2022). *The GSCPI: A New barometer of global supply chain pressures* (No. 1017). Federal Reserve Bank of New York Staff Reports. https://www.econstor.eu/handle/10419/266101

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal Of Business & Economic Statistics: A Publication of the American Statistical Association*, *29*(2), 238–249.

Carrière-Swallow, Y., Deb, P., Furceri, D., Jiménez, D., & Ostry, J. D. (2023). Shipping costs and inflation. *Journal Of International Money and Finance*, *130*(102771), 1–36.

Cavallo, A. (2018). More Amazon effects: Online competition and pricing behaviors. In *NBER Work. Pap. Ser.* (No. 25138). https://www.nber.org/papers/w25138

DellaVigna, S., & Gentzkow, M. (2019). Uniform pricing in U.S. retail chains. *The Quarterly Journal of Economics*, *134*(4), 2011–2084.

Finck, D., & Tillmann, P. (2022). *The Macroeconomic effects of global supply chain disruptions*. Helsinki: Bank of Finland, Bank of Finland Institute for emerging economies (BOFIT).

Goolsbee, A. D., & Klenow, P. J. (2018). Internet rising, Prices falling: Measuring ınflation ın a world of e-commerce. *AEA Papers and Proceedings. American Economic Association*, *108*, 488–492.

Gorodnichenko, Y., & Talavera, O. (2017). Price setting in online markets: Basic facts, international comparisons and cross-border integration. *American Economic Review*, *107*(1), 249–282.

Jo, Y., Matsumura, M., & Weinstein, D. E. (2024). The Impact of retail e-commerce on relative prices and consumer welfare. *The Review of Economics and Statistics*, *106*(6), 1675–1689.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182.

Laumer, S., & Schaffer, M. (2025). Monetary policy transmission under supply chain pressure. *European Economic Review*, *172*(104949), 1–25.

Mućk, J., Błażejowska, A., Łapszys, K., & Szafranek, K. (2025). On the effect of e-commerce's spread on inflation. *Economics Letters*, *254*(112464), 112464.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal Of Econometrics*, *225*(2), 175–199.

Appendix

Table 1: *Descriptive Statistics for Macro and Micro Data*

Panel A: *Macro variables (monthly)*

	GSCPI	CPI	IP	EBP	VIX
count	264.0	264.0	264.0	264.0	264.0
mean	-0.2718	210.7597	95.6616	0.1122	20.0014
std	0.4955	28.3151	5.4026	0.7100	8.0773
min	-1.5559	162.0000	84.3467	-1.0873	10.1255
25%	-0.6296	183.8500	91.0671	-0.3148	14.1754
50%	-0.3148	214.7580	96.7988	-0.1097	18.0737
75%	0.0367	236.0765	100.1433	0.2714	23.8084
max	1.5636	258.2630	104.1802	3.4698	62.6689

Panel B: *Micro price variables (annual inflation across product–region observations)*

	Inflation (π)
count	351,098.0
mean	-0.001825
std	0.097949
min	-1.601840
25%	-0.033876
50%	0.000321
75%	0.034136
max	1.873273

Note: Panel A includes monthly macro variables: GSCPI (global supply chain pressure index), CPI (consumer price index level, 2015=100), IP (industrial production index), EBP (excess bond premium, Gilchrist-Zakrajšek), and VIX (Volatility Index). Panel B shows the distribution of annual inflation rates (infl) across all product-region observations in the micro panel (351,098 observations total).

Table 2: *Augmented Dickey–Fuller Unit Root Tests (Key Variables)*

Variable	*N*	ADF Stat.	*p*-value
GSCPI	264	-3.4177	0.0104
CPI	264	-0.5045	0.8911
IP	264	-2.4858	0.1190

Note: Null hypothesis: unit root. GSCPI is stationary at 1% level; CPI and IP are non- stationary in levels, motivating use of infla- tion/output growth in regressions.

Note: Reported are ADF test statistics and p-values. Null hypothesis: series has a unit root. GSCPI (supply chain pressure index) is stationary at 1% level. The CPI (price index) and IP (industrial production) are not stationary in levels ($p > 0.1$), consistent with use of inflation and output growth in regressions.

Table 3: *Impulse Response of CPI to a Supply Chain Shock – Interaction Specifications*

Panel A: *Shock × Tradable (Two-way fixed effects; unit & time FE)*

Horizon h	δ_h	s.e.
0	-0.0010	0.0040
1	0.0005	0.0030
2	0.0010	0.0031
3	0.0020	0.0059
4	0.0040	0.0055

Panel B: *Shock × National E- commerce Share (Unit FE only; controls included)*

h	θ_h	s.e.	δ_h	s.e.	N
0	0.012478	0.004040	-0.001395	0.005958	242,023
1	0.004406	0.003023	0.001112	0.004862	225,774
2	0.003361	0.003093	0.000910	0.005442	209,598
3	-0.000262	0.005908	0.001557	0.009638	193,547
4	0.003899	0.005535	0.011764	0.004804	177,587

Notes: Separate LP regressions for each horizon $h = 0, \ldots, 4$. Panel A reports only interaction effects (θ_h absorbed by time FE). Panel B reports baseline shock effects (θ_h) and interactions (δ_h). Two-way clustered s.e. by product and year.

Notes: Each panel reports coefficients from separate local projection regressions at horizons $h = 0$ to 4. **Panel A** (Shock × Tradable) only reports the interaction effect δ_h (shock main effect absorbed by time FE). **Panel B** (Shock × E-commerce Share) reports both the baseline shock effect θ_h and the interaction δ_h. Standard errors (two-way clustered) are in italics below each coefficient in the manuscript text (omitted here for brevity). In Panel B, **θ_0=0.0125** implies a 1 s.d. supply shock raises CPI inflation by ~1.25% on impact ($p<0.01$). The interaction δ_0 is a small negative and not significant. By $h = 4$, θ_4 ~0.0039 (n.s.), and δ_4 ~0.0118, significant at 5% (indicating a higher cumulative effect with higher e-commerce). In Panel A, δ estimates suggest tradable good prices had a slightly lower immediate response (–0.001) but a slightly higher 4-year cumulative response (+0.004) than non-tradables, though none are statistically distinguishable from zero. Nobs declines with horizon due to shorter available panel for longer differences.

Table 4*: Impact of Supply Chain Shocks on Price Dispersion (Std. Dev. Across Regions)*

Horizon h	β_h	s.e.	N
0	-0.000224	0.000589	18
1	0.000444	0.000457	17
2	0.000947	0.000664	16
3	0.000126	0.000555	15

Notes: Annual LPs with product and year fixed effects. None of the responses is statistically significant at conventional levels.

Notes: Results from annual panel local projections (product-level dispersion as dependent variable). β_h is the estimated effect of a one s.d. supply chain shock on the change in price dispersion from t to $t + h$. Horizon in years. None of the responses is statistically significant at conventional levels. For instance, β_0 indicates no appreciable contemporaneous change in dispersion. Nobs reflects number of product series available for each horizon (out of 18 major product groups). These findings suggest supply shocks did not significantly alter how spread-out prices were – i.e., regions experienced roughly uniform price changes, maintaining the dispersion level.

Table 5.1: *Alternative Shock Definitions (Spec A and Spec B)*

Shock measure	h	Spec A (TWFE)					Spec B (Shock effect)					Spec B (Interaction)				
		δ	se	t	p	stars	θ	se	t	p	stars	δ	se	t	p	stars
Baseline GSCPI shock	0	-0.008	0.006	-1.319	0.187		0.012	0.004	3.089	0.002	***	-0.001	0.006	-0.234	0.815	
Baseline GSCPI shock	1	-0.003	0.006	-0.482	0.630		0.004	0.003	1.457	0.145		0.001	0.005	0.229	0.819	
Baseline GSCPI shock	2	-0.001	0.005	-0.135	0.893		0.003	0.003	1.087	0.277		0.001	0.005	0.167	0.867	
Baseline GSCPI shock	3	-0.004	0.004	-0.998	0.318		-0.000	0.006	-0.044	0.965		0.002	0.010	0.162	0.872	
Baseline GSCPI shock	4	0.008	0.004	1.795	0.073	*	0.004	0.006	0.704	0.481		0.012	0.005	2.449	0.014	**
AR(12) shock	0	-0.008	0.006	-1.349	0.177		0.014	0.004	3.476	0.001	***	-0.004	0.006	-0.658	0.511	
AR(12) shock	1	-0.003	0.006	-0.501	0.616		0.005	0.003	1.566	0.117		0.001	0.005	0.130	0.896	
AR(12) shock	2	0.000	0.006	0.005	0.996		0.005	0.003	1.811	0.070	*	0.001	0.005	0.186	0.853	
AR(12) shock	3	-0.004	0.005	-0.778	0.437		0.001	0.007	0.184	0.854		0.004	0.009	0.455	0.649	
AR(12) shock	4	0.004	0.006	0.677	0.498		0.004	0.006	0.745	0.456		0.010	0.005	2.051	0.040	**
ΔGSCPI shock	0	-0.003	0.004	-0.736	0.462		0.010	0.005	2.162	0.031	**	0.004	0.005	0.799	0.424	
ΔGSCPI shock	1	-0.002	0.006	-0.352	0.725		0.004	0.003	1.455	0.146		0.005	0.003	1.653	0.099	*
ΔGSCPI shock	2	-0.001	0.006	-0.264	0.792		0.004	0.004	1.087	0.277		0.002	0.005	0.290	0.772	
ΔGSCPI shock	3	-0.003	0.004	-0.688	0.492		-0.001	0.006	-0.144	0.885		0.002	0.016	0.129	0.897	
ΔGSCPI shock	4	0.006	0.004	1.349	0.178		-0.001	0.005	-0.148	0.882		0.019	0.011	1.807	0.071	*

Notes: "Baseline GSCPI shock" = baseline shock definition (AR(p)-filtered GSCPI); "AR(12) shock" = shock series from a 12-lag AR filter; "ΔGSCPI shock" = first-differenced GSCPI as shock. Spec A includes time fixed effects (only δ reported); Spec B includes shock (θ) and interaction (δ). θ_h = coefficient on shock at horizon h; δ_h = coefficient on Shock × E-commerce. Two-way clustered s.e. by region and month. *** / ** / * denote significance at the 1%/5%/10% level (two-sided).

Table 5.2: *Time Fixed Effects Sensitivity (Spec B)*

h	Baseline θ					Baseline δ					TimeFE θ					TimeFE δ				
	θ	se	t	p	stars	δ	se	t	p	stars	θ	se	t	p	stars	δ	se	t	p	stars
0	0.012	0.004	3.089	0.002	***	-0.001	0.006	-0.234	0.815		n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.	
1	0.004	0.003	1.457	0.145		0.001	0.005	0.229	0.819		n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.	
2	0.003	0.003	1.087	0.277		0.001	0.005	0.167	0.867		n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.	
3	-0.000	0.006	-0.044	0.965		0.002	0.010	0.162	0.872		n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.	
4	0.004	0.006	0.704	0.481		0.012	0.005	2.449	0.014	**	n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.	

Notes: *Baseline = main Spec B (no time fixed effects). "TimeFE" = including time fixed effects. With time fixed effects, the global shock effect (θ) is absorbed and not estimated (shown as n.a.). Reported δ is the Shock×E-commerce coefficient. Two-way clustered s.e. by region and month. Significance as in Table A1.*

Table 5.3: *Controls, Lag Length, and Horizon Variants (Spec B)*

Specification	h	θ	se	t	p	stars
Baseline (2 lags, h=4)	0	0.012	0.004	3.089	0.002	***
Baseline (2 lags, h=4)	1	0.004	0.003	1.457	0.145	
Baseline (2 lags, h=4)	2	0.003	0.003	1.087	0.277	
Baseline (2 lags, h=4)	3	-0.000	0.006	-0.044	0.965	
1 lag, h=4	0	0.013	n.a.	n.a.	n.a.	
1 lag, h=4	1	0.005	n.a.	n.a.	n.a.	
1 lag, h=4	2	0.004	n.a.	n.a.	n.a.	
1 lag, h=4	3	-0.001	n.a.	n.a.	n.a.	
2 lags, h=3	0	0.012	n.a.	n.a.	n.a.	
2 lags, h=3	1	0.004	n.a.	n.a.	n.a.	
2 lags, h=3	2	0.003	n.a.	n.a.	n.a.	
2 lags, h=3	3	-0.000	n.a.	n.a.	n.a.	
3 lags, h=4	0	0.001	n.a.	n.a.	n.a.	
3 lags, h=4	1	-0.003	n.a.	n.a.	n.a.	
3 lags, h=4	2	-0.006	n.a.	n.a.	n.a.	
3 lags, h=4	3	-0.004	n.a.	n.a.	n.a.	

Notes: Estimated shock coefficients (θ_h) under specification variants. Baseline includes 2 lags and a 4-year horizon (h=0,...,4). "1 lag, h=4" and "3 lags, h=4" use fewer or additional lags. "2 lags, h=3" truncates the projection at 3 years. All include the same controls; an additional control for monetary policy (not shown) had negligible effect on θ_h. Two-way clustered s.e. reported for Baseline; for alternative specs, standard errors (and hence t, p) will be provided – currently "n.a." indicates not available. In all cases, the interaction term δ_h remained near zero (not tabulated). Significance as in Table A1.

Table 5.4: *Clustering Variants for Standard Errors (Spec B)*

Cluster	h	θ	se	t	p	stars	δ	se	t	p	stars	nobs
two_way	0	0.012	0.004	3.089	0.002	***	-0.001	0.006	-0.234	0.815		242023
two_way	1	0.004	0.003	1.457	0.145		0.001	0.005	0.229	0.819		225774
two_way	2	0.003	0.003	1.087	0.277		0.001	0.005	0.167	0.867		209598
two_way	3	-0.000	0.006	-0.044	0.965		0.002	0.010	0.162	0.872		193547
two_way	4	0.004	0.006	0.704	0.481		0.012	0.005	2.449	0.014	**	177587
entity	0	0.012	0.000	40.607	0.000	***	-0.001	0.000	-3.490	0.000	***	242023
entity	1	0.004	0.000	15.174	0.000	***	0.001	0.000	2.883	0.004	***	225774
entity	2	0.003	0.000	12.034	0.000	***	0.001	0.000	2.419	0.016	**	209598
entity	3	-0.000	0.000	-0.818	0.414		0.002	0.001	2.965	0.003	***	193547
entity	4	0.004	0.000	11.988	0.000	***	0.012	0.001	21.509	0.000	***	177587
time	0	0.012	0.004	3.088	0.002	***	-0.001	0.006	-0.231	0.817		242023
time	1	0.004	0.003	1.457	0.145		0.001	0.005	0.229	0.819		225774
time	2	0.003	0.003	1.086	0.278		0.001	0.005	0.167	0.867		209598
time	3	-0.000	0.006	-0.044	0.965		0.002	0.010	0.161	0.872		193547
time	4	0.004	0.006	0.704	0.481		0.012	0.006	2.449	0.014	**	177587

Notes: two_way = clustering by region and time (baseline); entity = one-way clustering by region (individual entity); time = one-way clustering by time (month). The point estimates (θh and δh) are identical across clusters; only standard errors differ. With entity-only clustering, standard errors are much smaller (likely overstating significance), whereas time-only clustering gives similar uncertainty to two-way in this context. nobs = observations per horizon. Significance stars as defined in Table A1.

Table 5.5: *Subsample Robustness (Spec B)*

Sample	h	θ	se	t	p	stars	δ	se	t	p	stars	nobs
pre2010	0	-0.002	0.010	-0.246	0.805		-0.020	0.017	-1.202	0.229		137942
pre2010	1	-0.017	0.003	-5.426	0.000	***	-0.003	0.004	-0.758	0.449		122318
pre2010	2	-0.005	0.001	-6.881	0.000	***	-0.094	0.002	-44.344	0.000	***	106877
pre2010	3	0.053	0.001	50.735	0.000	***	0.150	0.004	34.362	0.000	***	91950
pre2010	4	0.029	0.002	14.424	0.000	***	0.002	0.002	0.916	0.360		77272
post2010	0	n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.		73042
post2010	1	n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.		57426
post2010	2	n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.		42155
post2010	3	n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.		27333
post2010	4	n.a.	n.a.	n.a.	n.a.		n.a.	n.a.	n.a.	n.a.		13319
no_2020_21	0	0.012	0.004	3.089	0.002	***	-0.001	0.006	-0.234	0.815		242023
no_2020_21	1	0.004	0.003	1.457	0.145		0.001	0.005	0.229	0.819		225774
no_2020_21	2	0.003	0.003	1.087	0.277		0.001	0.005	0.167	0.867		209598
no_2020_21	3	-0.000	0.006	-0.044	0.965		0.002	0.010	0.162	0.872		193547
no_2020_21	4	0.004	0.006	0.704	0.481		0.012	0.005	2.449	0.014	**	177587

Notes: pre2010 = Jan 1998–Dec 2009; post2010 = Jan 2010–Dec 2021; no_2020_21 = full sample excluding Jan 2020–Dec 2021. Each panel shows Spec B estimates for that subsample. The post-2010 subsample yielded no robust estimates (few observations in early horizons and high standard errors), so coefficient entries are labeled "n.a." Two-way clustered s.e. reported. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 5.6: *Alternative Price Dispersion Measure (Spec B)*

h	θ	se	t	p	stars	δ	se	t	p	stars
0	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
1	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
3	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
4	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Notes: Placeholder: Results for an alternative dispersion index will be included in the final revision. (The table will likely mirror the structure of Table 4 in the paper, showing no significant θh or δh for the shock's effect on price dispersion under a different dispersion metric.) Significance notation will follow previous tables.