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Understanding China's 2024-25 Frontloading from the Lens of Product-Level Export Baskets

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January 2026

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WORKING PAPERS

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Understanding China's 2024–25 Frontloading from the Lens of Product-Level Export Baskets

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Abstract

A striking feature of US-China trade tensions in mid-2025 is China's acceleration of exports to the US ahead of new tariff increases, a phenomenon we term export frontloading. To understand how this was achieved, we develop a factor model analytical framework to characterize China's product-level exports, across time and destinations, according to a set of latent export baskets. Applying this to data from China's General Administration of Customs, we document the channels behind the 2024-25 episode and compare them with the 2018 US-China trade tensions. Our analysis points to broad-based adjustments across multiple dimensions in a manner not observed in 2018: (i) shipments to the US accelerated in the second half of 2024, possibly supported by the retention of intermediate inputs that facilitated a ramp-up in domestic production; (ii) from January 2025, domestic production slowed and shipments of intermediate inputs to Vietnam and other ASEAN economies accelerated, consistent with the relocation of export-oriented manufacturing following US tariffs; (iii) exporters prioritized shipments to the US through March 2025, reallocating flows away from third destinations with similar export profiles; and (iv) as shipments to the US fell sharply in April-May amid the escalation of reciprocal tariffs, the decline was offset by increased shipments to third destinations consistent with fulfilling previously deferred orders.

Keywords: Export Frontloading, Trade Tariffs, Production Relocation, Intertemporal Reallocation

1 Introduction

China's exports to the United States (US) have faced a renewed wave of tariff increases since early 2025, with the possibility of these increases anticipated by firms and other market participants. In principle, higher tariffs reduce the competitiveness of Chinese goods in the US market, leading to a decline in exports to the US and, by extension, weaker domestic production in China. In practice,

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these adverse effects can be temporarily mitigated by export frontloading to the US before the implementation of new tariffs.

Export frontloading was evident in aggregate trade data showing a marked increase in Chinese exports to the US during the final months of 2024. Nominal export flows in December 2024 were 6.6 billion USD higher than a year earlier, an increase of 15.6 percent, and a notable acceleration relative to the average annual growth rate of 5.6 percent observed during the ten-year period ending in 2023. The magnitude of this adjustment was largely unanticipated by contemporary analysts.

The objective of this paper is to understand how frontloading was achieved by identifying the channels that facilitated this adjustment over multiple months, and to contrast these dynamics with those observed during the 2018 US-China trade tensions. In particular, our goal is to disentangle the underlying mechanisms of export frontloading, rather than to quantify its macroeconomic impacts, which lie beyond the scope of this analysis.

At the core of our analysis is the novel application of factor models to identify latent export baskets at the product level to capture the dynamics of China's export flows over time and across destinations. At a practical level, the factor model provides a means of dimensionality reduction, collapsing variation at the product level into a small number of export baskets. At a conceptual level, our approach differs fundamentally from pre-defined mappings of product categories to end uses, as it endogenously identifies latent groupings of products that co-move across destinations, allowing the data to reveal economically meaningful export structures.

Specifically, our framework represents the panel of export flows across product categories and destinations at each point in time using a factor model, where each factor corresponds to a latent product-level export basket. For each factor, the loadings describe the composition of the corresponding export basket, that is, the specific weights across all product categories in the basket,[1] while the factor realizations capture the scaling, namely the total value of each basket exported to each destination.

Our representation of the export flows thus far consists of a few latent export baskets, each with specific weights across product categories, and the value of each basket that each destination receives in every period. At any given point in time, the value of exports from a specific basket to a particular destination can be alternatively expressed as the product of two components: (i) the total value of exports of that basket to all destinations, defined as the sum of its exports across destinations, and (ii) the allocation share of that basket assigned to each destination, with the allocation shares summing to one by construction. This decomposition provides a snapshot of how the total exports of each basket are distributed across destinations in a given period.

Leveraging this representation, we decompose the dynamics in each basket's exports across destinations over time into two components: changes in the total amount of exports of a specific basket to the world, which we define as changes along the *extensive margin*, and changes in a destination's allocation share of that basket's total exports over time, which we define as changes

[1] Empirically, the basket compositions capture the main directions of comovement across the space of product-level shipments, analogous to the loading structure in principal component analysis.

along the *intensive margin*.[2]

Applying this analytical framework to monthly Chinese customs data at the Harmonized System 2-digit (HS2) classification level, we find that a three-factor specification explains the bulk of the cross-sectional variation in exports across HS2 categories.

Among these three baskets, the first two account for the majority of China's total export value and dynamics, while the third basket has relatively low and stable total value and allocation shares. In particular, the first two baskets may be broadly characterized as:

- **Basket 1**, China's general export basket, has the highest concentration of consumer and final goods, shipped to major advanced economies such as the US, EU, and Japan.

- **Basket 2**, China's secondary export basket, has the highest concentration of industrial supplies and intermediate goods used in manufacturing, primarily shipped to Vietnam, Korea, Japan, and other ASEAN economies.

Using our framework, we summarize the 2024-25 frontloading episode by the following timeline of events. In the second half of 2024, shipments of basket 2 declined relative to the first half of the year, while shipments of basket 1 accelerated. This shift coincided with a ramp-up in domestic production, and possibly at the expense of third destinations which share a similar demand for intermediate inputs. In contrast, Vietnam saw an increase in allocations of basket 2, largely offsetting the overall decline in intermediate exports along the extensive margin. During this period, exporters also began prioritizing shipments of basket 1 to the US. This US prioritization along the intensive margin persisted through March 2025, despite the initial phases of US-China tariff rate increases.

In January 2025, total shipment value of basket 1 declined sharply. This timing is consistent with the typical duration of sea-freight shipments, as exports departing in January would no longer reach the US before the start of the new administration. At the same time, shipments of basket 2 accelerated to Vietnam and, to a lesser extent, other ASEAN economies. Supposing that shipments of the basket 2 reflect inputs used in manufacturing, this pattern indicates a relocation of production activity from China to Vietnam and more broadly across ASEAN.

Notably, a similar adjustment was not observed during the 2018 episode, either in the ramp-up of domestic production or in the subsequent redirection of intermediate inputs to ASEAN economies. Given that such adjustments likely require significant logistical preparation, this difference may reflect a lack of anticipation for the US-China tariff escalation in 2018. In that context, our findings suggest that producers and exporters learned from their experience in 2018 and invested in strategies to relocate production in the event of a renewed escalation in trade tensions.

Following the sharp escalation of reciprocal tariffs in April, allocations of basket 1 to the US dropped steeply, while allocations to other destinations rose, offsetting much of the shortfall. Specif-

[2]Our notions of intensive and extensive margins differ from their standard context in the trade literature, where the intensive margin refers to changes in quantities within a given product and the extensive margin refers to changes across products. In our setting, the notions of intensive and extensive margins are instead closely analogous to the within–between framework of Olley & Pakes (1992), in which aggregate changes are separated into shifts in shares and shifts in levels.

ically, we see that the ability for non-US destinations to absorb the decrease in US allocations is related to the deficits accumulated during the frontloading phase. In particular, the largest increases in allocations occurred in destinations whose import profiles from China closely resembled that of the US and that had experienced reduced allocations during the frontloading period.

This evidence points to a *backloading* of exports to third destinations that complemented the initial frontloading to the US and later facilitated the absorption of exports during the tariff implementation period. We may understand this pattern as a mechanism for *cross-destination intertemporal reallocation* in export shipments, which, to the best of our knowledge, we are the first to document. Our finding for the 2024–25 episode also stands in contrast to the 2018 experience, when frontloading to the US was short-lived and confined to the intensive margin. This mechanism, in turn, may explain why the frontloading payback in 2025 was generally smaller than expected.

Moreover, our observations on the adjustment in basket 2 shipments suggest an acceleration of Chinese investment and manufacturing relocation toward ASEAN production hubs. The existing research literature has identified this production relocation phenomenon as an ongoing trend since 2019, therefore beginning after the 2018 US-China trade tensions. While our methodology cannot directly speak to these shifts in production and supply chains, our findings have several implications in that context.

First, prior studies have shown that this relocation of production has been concentrated in sectors that benefit disproportionately from lower labor costs. The emergence of a tariff-rate wedge between China and ASEAN economies provided additional cost-saving incentives and may explain the accelerated pace of relocation observed in our analysis. Second, our findings highlight the capacity of China's supply chains to adapt and rapidly reconfigure in response to changing economic conditions. In particular, our analysis points to the role of China's vertical integration along the value-added chain, which may have facilitated the reallocation of intermediate goods to support domestic production in late 2024. Third, our findings also underscore the potential role of horizontal integration across economies in mitigating trade tariffs. Because investment in external production capacity typically require multiple years to fully materialize, firms have an incentive to invest preemptively as a hedge against future trade policy risk.

Looking ahead, questions arise about the sustainability of China's exports to Asia in the event the US imposes a tariff specifically targeting transshipments. In this context, we emphasize that our production relocation hypothesis is economically distinct from simple transshipment or re-exporting. While production relocation and transshipment can represent similarly in aggregate trade data, these hypotheses can be disentangled using product-level export flows. In the final part of this paper, we present additional evidence in support of the production relocation hypothesis, which taken together, suggest that the recent increase in exports to Asia is likely to be sustained over the medium term.

The structure of the remainder of the paper is as follows. Section 2 gives a review of the related literature. Section 3 describes our modeling framework and contrasts our empirical methodology with existing approaches. Section 4 documents the recent frontloading episode across multiple dimensions and compares it with the 2018 episode. Section 5 examines our identification strategy using higher-granularity export flows to evaluate the alternative transshipment narrative for the recent export strength to Vietnam, and presents our evidence against this explanation. The final section concludes with a summary of findings and directions for future research.

2 Related Literature

This paper contributes to several strands of literature at the intersection of international trade and supply chains, anticipatory behavior under policy uncertainty, and high-dimensional empirical methods.

A growing body of research has examined the immediate impacts of the 2018 US-China trade tensions, with a particular focus on price pass-through and the effects on trade volumes. Using aggregate and sectoral data, Amiti et al. (2019) document full tariff pass-through to US import prices and a sizable reduction in real income, while P. D. Fajgelbaum et al. (2020) similarly find that tariffs were fully reflected in duty-inclusive prices, with substantial welfare losses for US consumers but only modest aggregate GDP effects. Microdata evidence from Cavallo et al. (2021) confirms high border pass-through but muted effects at the retail level, suggesting adjustment through margins. Beyond import prices, recent work emphasizes trade volume responses. Handley et al. (2025) show that supply-chain linkages amplified the impact of tariffs on US exports, while Jiao et al. (2024) provide firm-level evidence that Chinese exporters did not absorb tariffs via lower prices, instead reducing exports to the U.S. and diverting modestly to the EU. Overall, while these studies reveal significant price effects and a hit to trade volumes, they report little evidence of systematic export frontloading during the 2018 episode.

Several studies provide evidence of export frontloading in response to anticipated tariff changes. Alessandria et al. (2010) show how delivery lags and inventory frictions can generate anticipatory import dynamics, while Alessandria et al. (2021) emphasize that firm-level investment in reducing export costs over time leads to gradual adjustment and short-run frontloading behavior. Similarly, Khan & Khederlarian (2021) exploit the staged tariff reductions under NAFTA to document sizable anticipatory slumps and liberalization bumps in imports, highlighting how forward-looking behavior biases conventional estimates of trade elasticities. Finally, Alessandria et al. (2024) identify US frontloading relative to a counterfactual of other exporters during the annual MFN renewal votes prior to China's WTO accession. In our case, however, such a counterfactual is not appropriate, since reallocation effects simultaneously influenced exports to third destinations. Taken together, these studies illustrate the desired intertemporal response to anticipated trade policy changes, but the relatively modest scale of frontloading meant that it did not necessitate the same degree of coordination between producers and exporters at the national level.

The incentive for export frontloading also relates to a broader literature documenting how households shift consumption in anticipation of future changes in prices or tax rates. For instance, Burke & Ozdagli (2023) show that US households raised durable goods spending when expecting higher inflation, while Cashin & Unayama (2016) exploit Japan's preannounced VAT increase to estimate intertemporal substitution in consumption. Similarly, Baker et al. (2021) find strong evidence of stockpiling and cross-border shopping in response to local sales tax changes, and Agarwal et al. (2017) document sharp increases in spending during temporary sales tax holidays. These studies highlight a common mechanism: when faced with anticipated price or tax changes, households and firms advance (or delay) purchases to lower costs, paralleling the anticipatory dynamics observed in international trade. In the case of consumption frontloading, this also requires logistics and coordination to ensure sufficient inventories are available, for example, during holiday shopping seasons, but the scale of coordination at the level of retailers is smaller well understood.

The 2018 US-China trade tensions triggered a broad restructuring of production and supply chains across Asia, with evidence pointing to both trade diversion and deeper relocation of production and supply chains. Choi & Nguyen (2023) and Alfaro & Chor (2023) document sharp increases in US imports from Vietnam and Mexico, while Freund et al. (2024) emphasize that even as China's direct share of US imports fell, many "replacement" exporters became more integrated into China's supply chains. Luo et al. (2023), Graziano et al. (2024), and Grossman et al. (2024) further illustrate how tariffs reshaped global supply chains, while P. Fajgelbaum et al. (2024) identify how economy-specific tariff elasticities determined which bystander economies benefited most from new export opportunities. More broadly, Gopinath et al. (2025) show that these changes in supply chain patterns fit into a wider picture of fragmentation along geopolitical lines, with emerging "connector" economies serving as bridges between rival blocs.

Several studies highlight Vietnam as a key beneficiary of this reallocation. Schulze & Xin (2024) distinguish genuine production reallocation from simple transshipment and find evidence of increased domestic content in Vietnam's exports, partly driven by Chinese FDI. Rotunno et al. (2024) show that this expansion created new jobs, while Mayr-Dorn et al. (2023) and Nguyen & Lim (2023) provide evidence that tariff exposure accelerated Vietnam's labor market transformation, boosting formal manufacturing employment. Taken together, this literature shows that while US tariffs reduced bilateral trade with China, they triggered broader adjustments in trade routes and supply chains, with Vietnam and other ASEAN economies emerging as the primary destinations for relocated Chinese manufacturing.

High-dimensional approaches to modeling trade flows are most commonly based on gravity models, which provide structural and parametric frameworks for quantifying the impact of trade policy on bilateral flows.[3] Classic applications such as Romalis (2007) and Caliendo & Parro (2015) use detailed tariff and trade data to identify trade elasticities and welfare effects of NAFTA, while more recent work such as Gopinath et al. (2025) employs gravity estimates to document the fragmentation of trade and investment along geopolitical lines. While these models are powerful for capturing global trade patterns, they are less well-suited for analyzing the short-run dynamics of trade flows in response to anticipated shocks. An important exception is Khan & Khederlarian (2021), who introduce dynamics into a gravity model framework by incorporating structural breaks between the phased rollout of tariffs under NAFTA. This approach assumes that trade flows between breaks reflect a stable equilibrium, making it unsuited for the rapid and evolving dynamics observed

[3]In the context of nowcasting, Centorrino et al. (2025) use dynamic factor models to monitor the impact of trade policy developments across 197 countries/territories.

in the recent frontloading episode. This underscores the limitations of conventional gravity models in capturing general trade flow dynamics and motivates the development of nonparametric, data-driven methods for modeling trade patterns.

3 Data and Empirical Methodology

3.1 Data Source

Our analysis relies on high-frequency trade data published by China's General Administration of Customs (GACC), which provides monthly export and import values disaggregated by HS2 product categories and destination economies. This dataset offers a valuable combination of timeliness and cross-sectional breadth, allowing us to monitor trade flows across sectors and trade partners with minimal delay.

More detailed product-level export flows from GACC are also available, but they are typically released with substantial publication delays, at lower frequencies, or only for a subset of major trading partners. As a result, a full balanced panel of higher-granularity trade flows becomes available only with a significantly longer delay. Global trade databases such as UN Comtrade or the World Bank's WITS platform offer broader coverage and harmonized classifications, but are likewise subject to considerable delays.

This observation highlights the trade-off between granularity and timeliness, and motivates our data choice. The most detailed data are not available in real time, while the most timely data are limited to aggregates. The monthly HS2 dataset offers a useful middle ground, as it is released about 15 days after the reference month while still providing meaningful detail across product categories and destinations. Although HS2 data cannot fully resolve within-category distinctions, their monthly frequency makes them well suited for tracking the fast-moving frontloading dynamics that are central to our analysis.

3.2 Model Framework

The monthly Chinese customs export data is reported at the HS2 commodity classification level, disaggregated by export destination, which covers 92 HS2 product categories and 42 export destinations. This results in a panel of dimension $H \times N \times T$, where H denotes the number of product categories, N the number of destinations, and T the number of time periods.

To address the high dimensionality of the panel, we implement a factor model that summarizes variation across HS2 categories using a limited number of latent export "baskets". The aim is to capture the extent to which cross-destination variation in HS2-level exports can be explained by a small set of common export profiles. Implicit in this approach is the assumption that both changes in export flows over time for a given destination and differences in export profiles across destinations can be expressed as combinations of these baskets.

In principle, grouping HS exports into latent baskets serves a purpose similar to mapping HS categories into Broad Economic Categories (BEC) or International Standard Industrial Classification (ISIC) classifications, as both approaches aim to reduce the dimensionality of trade data by aggregating across a large number of product codes.

However, approaches based on pre-defined mappings can suffer from a few potential limitations. First, many product categories at the HS2 level are context-dependent, and they may function as either intermediate or final goods depending on the destination, stage of processing, or specific end use. A fixed mapping treats each HS2 code in a static manner and therefore cannot capture this context, meanwhile our basket-based approach is tailored to explaining China's export structure and is not restricted in the same way. Second, our approach does not classify each HS category in isolation but instead infers latent groupings by analyzing the full profile of exports across destinations and their patterns of comovement. As a result, even if a particular HS category appears ambiguous on its own, its role can be clarified by the context in which it is exported, that is, by the relative proportions in which it is shipped alongside other categories. In this way, the basket approach differs fundamentally from pre-defined mappings, as it leverages the entire cross-sectional composition of export flows.

Formally, our model is specified as:

$$X_t = \Lambda_t F_t + \varepsilon_t, \tag{1}$$

where X_t is an $H \times N$ matrix of exports across HS2 categories and destinations at time t, Λ_t is an $H \times P$ matrix of basket loadings that maps HS2 categories into P latent export baskets, F_t is a $P \times N$ matrix of basket-level export quantities across destinations, and ε_t is an $H \times N$ matrix of idiosyncratic residuals.

As we show in Section 5, the latent baskets recover the same broad distinctions that emerge from more granular HS4-BEC classifications, indicating that the factor model preserves the essential structure of the underlying data while providing a more parsimonious representation.

3.3 Estimation Procedure

Estimation of Basket Compositions. To estimate the model at a given point in time, we first apply Non-negative Matrix Factorization (NMF),[4] to the 12-month rolling average of the export-flow matrix at time t. The 12-month rolling average of the export-flow matrix as

$$\bar{X}_t = \frac{1}{12} \sum_{i=0}^{11} X_{t-i}, \tag{2}$$

which smooths out monthly volatility and residual seasonality, allowing us to capture stable and robust patterns in the composition of exports. The Non-negative Matrix Factorization (NMF)

[4] NMF solves a constrained least-squares reconstruction problem with non-negativity restrictions on the factors and loadings, see Lee & Seung (1999). In our implementation, we use the `NMF` routine from the `scikit-learn` package. PCA also solves a least-squares approximation problem, but without non-negativity restrictions and instead imposing orthogonality of the components together with a rank-k constraint.

estimator of $\hat{\Lambda}_t$ is defined as

$$\boxed{\hat{\Lambda}_t = \mathrm{NMF}_P(\bar{X}_t),} \tag{3}$$

where $\mathrm{NMF}_P(\cdot)$ denotes the Non-negative Matrix Factorization operator applied to $\bar{X}_t$ conditional on P latent baskets (factors). This decomposition satisfies

$$\bar{X}_t \approx \hat{\Lambda}_t \bar{F}_t', \tag{4}$$

where $\hat{\Lambda}_t$ represents the estimated basket loadings (the contribution of each HS category to each basket) and $\bar{F}_t$ denotes the corresponding basket intensities associated with the 12-month rolling average of exports at time t.

Estimation of Basket Intensities. In the second step, we recover the monthly export intensities of each basket by applying Non-Negative Regression (NNR).[5] Specifically, we regress the current-period export matrix X_t on the estimated basket loadings from the previous step, $\hat{\Lambda}_t$, while imposing non-negativity constraints to ensure interpretability. Formally, the estimated basket intensities are defined as

$$\boxed{\hat{F}_t = \mathrm{NNR}(X_t \mid \hat{\Lambda}_t),} \tag{5}$$

where $\mathrm{NNR}(\cdot)$ denotes the Non-negative Regression operator that minimizes the reconstruction error of X_t given $\hat{\Lambda}_t$. This estimation satisfies

$$X_t \approx \hat{\Lambda}_t \hat{F}_t' + e_t, \tag{6}$$

where $\hat{F}_t$ captures the estimated monthly export intensities for each basket across destinations at time t, and e_t is the matrix of model errors.

While the use of NMF and NNR imposes non-negativity constraints on both $\hat{\Lambda}_t$ and $\hat{F}_t$, our main findings are robust to the choice of factor model. Replicating our analysis using standard Principal Components Analysis (PCA), we find that both methods recover a similar structure of export baskets and adjustments during the recent frontloading episode. That is to say, both NMF and PCA span the same subspace of variation in the HS2-destination panel. However, because PCA allows for negative weights, this complicates the economic interpretation of the resulting baskets. In contrast, the non-negativity of NMF ensures that each export basket can be interpreted as a physically plausible grouping of HS2 flows that move together across destinations.

Decomposition of Basket Intensities. In the final step, we decompose the estimated basket intensities $\hat{F}_t$ into two components: a vector of total basket shipments, $\hat{q}_t$, and a matrix of normalized destination profiles, $\hat{\Theta}_t$. This decomposition follows

$$\hat{F}_t = \mathrm{diag}(\hat{q}_t)\, \hat{\Theta}_t, \tag{7}$$

[5] NNR solves the OLS least-squares problem subject to non-negativity constraints on the coefficients, see Lawson & Hanson (1995). We implement NNR using the `nnls` solver from the `scipy.optimize` module.

where $\hat{q}_t$ captures the scale of each basket's total export intensity, and $\hat{\Theta}_t$ represents the normalized composition of basket *allocation shares* across destinations.

Specifically, we define the scale vector $\hat{q}_t$ as the column-wise sum of $\hat{F}_t$,

$$\boxed{\hat{q}_t = \hat{F}_t'\mathbf{1},} \tag{8}$$

where $\mathbf{1}$ is a column vector of ones. The corresponding allocation shares are then obtained as

$$\boxed{\hat{\Theta}_t = \mathrm{diag}(\hat{q}_t)^{-1}\hat{F}_t,} \tag{9}$$

which ensures that the elements of each column of $\hat{\Theta}_t$ sum to one.

This decomposition separates the overall magnitude of each basket's exports from their distribution across shipment destinations. Specifically, the vector $\hat{q}_t$ captures the total scale of exports in each basket, representing the *extensive margin*, while the matrix $\hat{\Theta}_t$ describes how those exports are distributed across destinations, representing the *intensive margin*.

3.4 Baseline Estimation

We first present the baseline estimation for June 2024, a period just prior to the onset of the main frontloading phase. The overall R^2 of the factor model, averaged across HS2 categories and destinations, is 0.79, leaving 21 percent of the variation unexplained. The estimation results reveal three distinct export baskets with stable structures across time. In particular, three baskets was sufficient to explain the majority of the variation in our sample, but the general analytical framework can readily accommodate more or fewer baskets depending on the context and application.

Figure 1 shows the normalized HS2 weights of the three export baskets, but the full table of basket weights by HS2 code and category is also provided in Appendix A. The normalization standardizes the cross-destination variation in export flows within each HS2 category so that the estimated weights range from zero to one, with higher values indicating a stronger association between a product category and a given export basket.

Figure 2 displays the amount of each export basket shipped to each destination. The US is the largest recipient of basket 1, followed by other advanced economies: Germany, the United Kingdom, Japan, and the Netherlands in that order. Vietnam is the largest recipient of basket 2, with other ASEAN economies also receiving a significant share. Basket 3 is shipped overwhelmingly to Hong Kong SAR, with Singapore a distant second.

Table 1 reports the average BEC composition associated with each export basket by mapping HS2 categories to BEC categories.[6] Accordingly, basket 1 captures China's general export basket, with the highest relative share of consumer goods, shipped primarily to the advanced economies.

[6]The HS2–BEC mapping is based on the HS6-to-BEC correspondence from the WITS concordance tables (https://wits.worldbank.org/product_concordance.html). HS6-level BEC codes are aggregated to HS2, averaged within each HS2 category, and then combined with the estimated basket weights using a weighted average across HS2 categories.

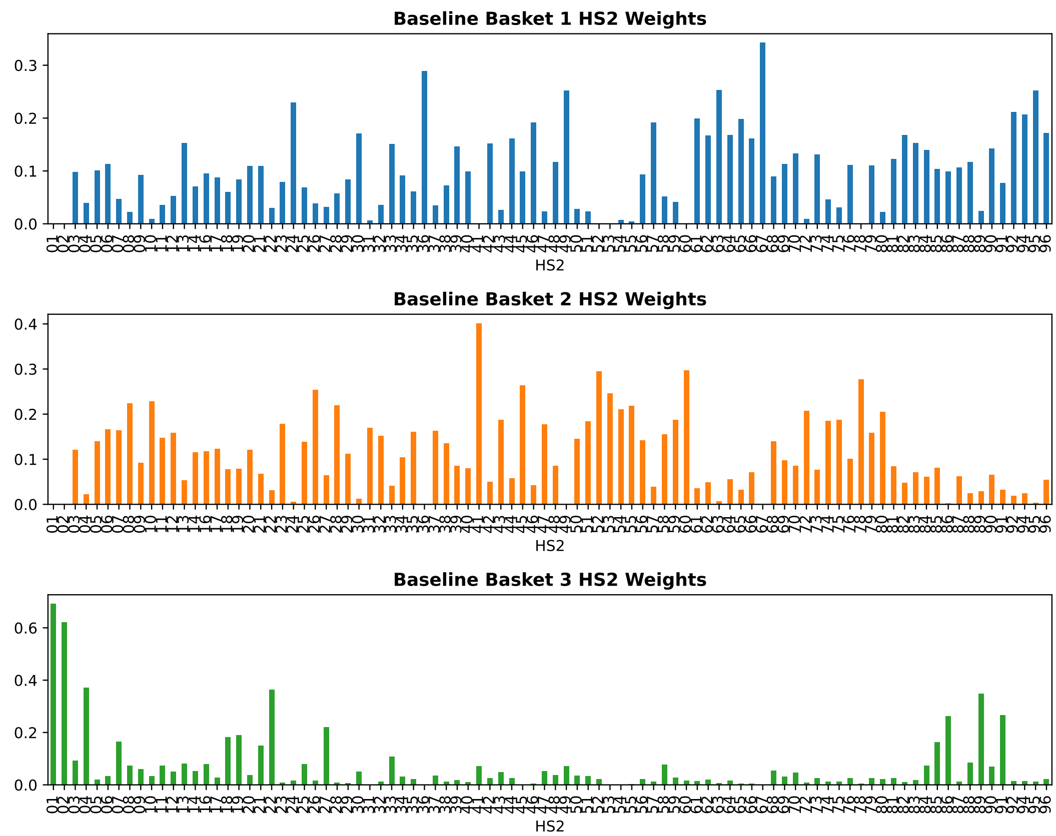

Figure 1: Normalized Basket Weights Across HS2 Categories

Table 1: BEC Composition of Export Baskets

BEC Category	Basket 1	Basket 2	Basket 3
Food & beverages	0.110	0.160	0.490
Industrial supplies	0.420	0.710	0.250
Fuels & lubricants	0.004	0.005	0.019
Capital goods	0.060	0.030	0.060
Transport equipment	0.040	0.010	0.090
Consumer goods	0.370	0.080	0.090
Goods n.e.s.	0.004	0.001	0.012

Basket 2 corresponds to China's secondary export basket, which places greater weight on materials and components used in manufacturing and is shipped primarily to ASEAN economies. Basket 3 has the highest relative weight in food and beverages, fuels and lubricants, and transport equipment, and reflects goods typically shipped to Hong Kong SAR.

Figure 3 shows the baseline export basket decomposition for China's top 10 export destinations. We see that the composition of the three baskets broadly resembles the profile of exports to the US, Vietnam, and Hong Kong SAR.[7]

[7] Note, this resemblance is neither imposed by the model nor a necessary feature. Accordingly, some model residual

Figure 2: Baseline Export Intensities by Basket Across Destinations

Figure 4 reports the goodness-of-fit of the factor model across individual HS2 product categories. Explanatory power is high across most HS2 categories, with only a few exceptions concentrated in low-value export segments. For instance, HS2 category 43 (Furskins and artificial fur; manufactures thereof) shows relatively lower model fit, yet it represents only 0.03% of China's total export value.

3.5 Full-Sample Estimation

We now present the results of our estimation over the full sample period, spanning 2016 through May 2025. Figure 5 shows the top five destinations by allocation share for each export basket, which captures the full-sample variation along intensive margins.

The allocation shares capture secular shifts in the geographic distribution of exports across baskets. The US remains the dominant destination for the first basket: its share fell with the onset of the first US–China trade tensions in 2018, rebounded temporarily in 2021–2022, and has trended downward again since 2023. While the dataset disaggregates the EU into individual member economies, the EU's combined allocation share is comparable in scale to that of the US.

The allocation shares of basket 2 are more evenly distributed across destination economies. A

remains when fitting the export profiles of the US, Vietnam, and Hong Kong SAR, as the estimation adjusts the composition of the baskets to simultaneously explain the profiles of exports to other destinations.

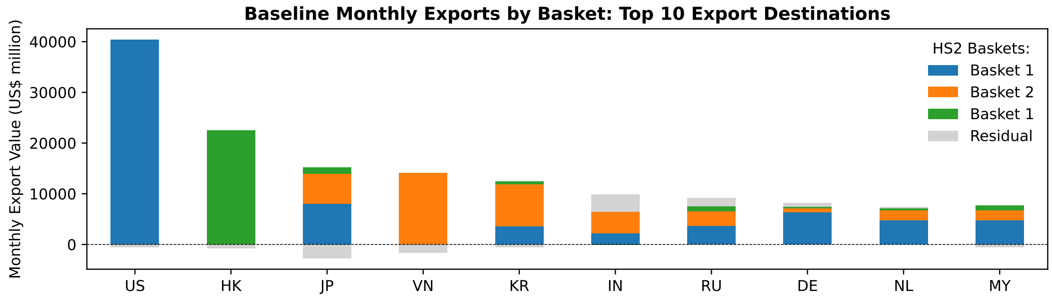

Figure 3: Export Basket Composition by Destination

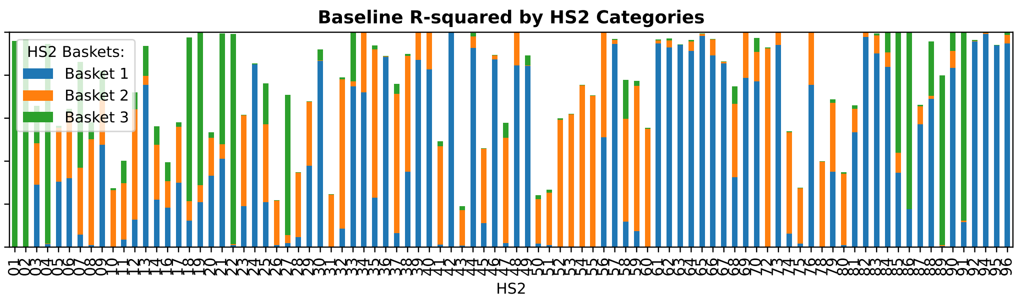

Figure 4: Model Fit Across HS2 Categories

notable trend is the sustained increase in Vietnam's, consistent with the literature documenting the relocation of Chinese manufacturing activities to Vietnam since 2018.

The allocation share of basket 3 remains heavily concentrated in Hong Kong SAR, although it has declined steadily since 2020 following the US decision to reclassify Hong Kong SAR as part of the same customs entity as the Chinese Mainland. Over the same period, Singapore has received an increasing share of basket 3 while it expanded its role as a re-routing export hub. Nonetheless, the magnitude of these shifts is modest compared with the adjustments observed in the first two baskets.

Figure 6 presents the total export value of each basket over the same period, capturing full-sample variation along extensive margins. From this, we highlight a few key observations. First, basket 1 remains the dominant component of China's export flows, accounting for the largest share of total exports and was the principal driver of China's export growth in 2024. Its high-frequency dynamics exhibit positive comovement with domestic production indicators, for example industrial production growth (see right panel of Figure 7).

Second, basket 2 has accounted for an increasing share of export growth since 2018, a trend that accelerated during the COVID-19 period when domestic production contracted. Notably, we observe some degree of negative monthly comovement between shipments of basket 1 and basket 2 (see left panel of Figure 7). This is consistent with the input allocation hypothesis, under which an increase in intermediate goods exports leaves fewer inputs available for domestic production, leading to a deceleration in final goods shipments. At the same time, exports and external demand account

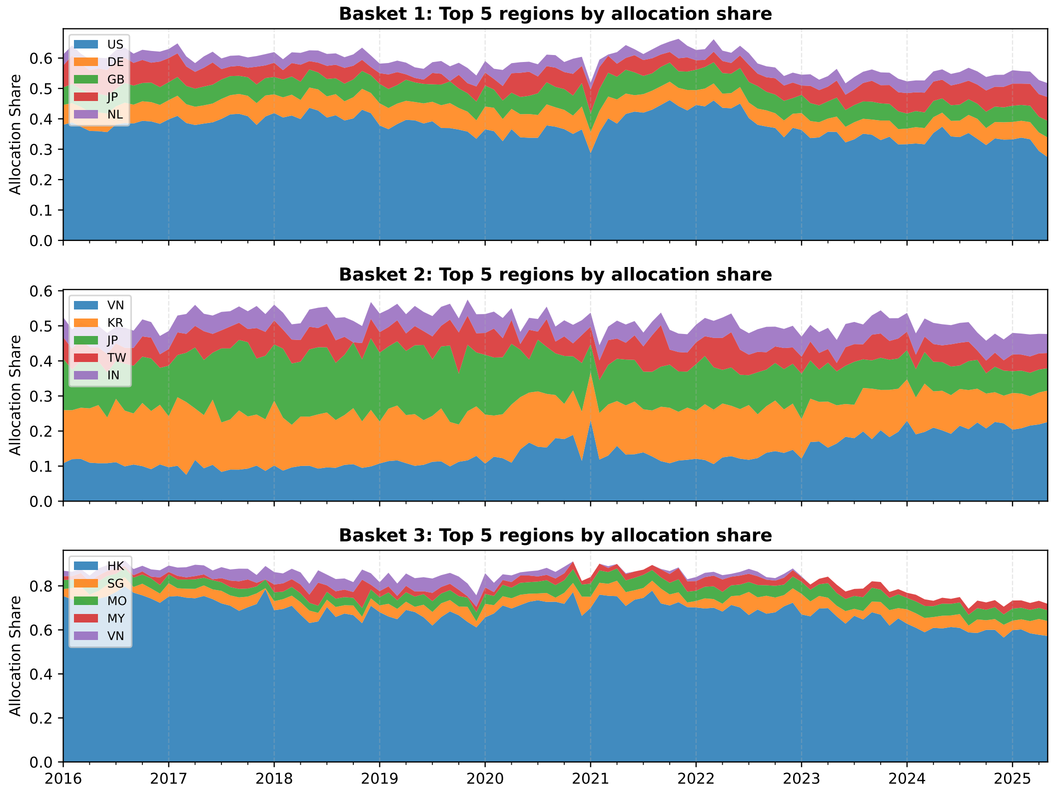

Figure 5: Cumulative Export Allocation Shares by Basket

for only a portion of China's domestic production, which is more generally driven by fluctuations in domestic demand.

Third, while basket 3 is important for capturing the distinct profile of exports to Hong Kong SAR, its total nominal value remained relatively stable over time and has not been a major driver of export growth in recent years.

4 The Anatomy of Frontloading

We next use the full-sample estimation results to analyze how export adjustments unfolded across destinations during the 2024–25 frontloading episode. We focus on the dynamics of basket 1 and basket 2, as these account for the bulk of the variation in export intensities over time and across destinations. By contrast, basket 3 is smaller in value and has remained relatively stable in both export intensity and allocation shares, so we omit a discussion of its dynamics for the remainder of this section.

We examine deviations in export intensities for the baskets 1 and 2 across destination economies relative to a baseline:

$$\Delta F_t = F_t - \bar{F},$$

where $\bar{F}$ is the pre-frontloading baseline given by the 12-month average ending in June 2024.

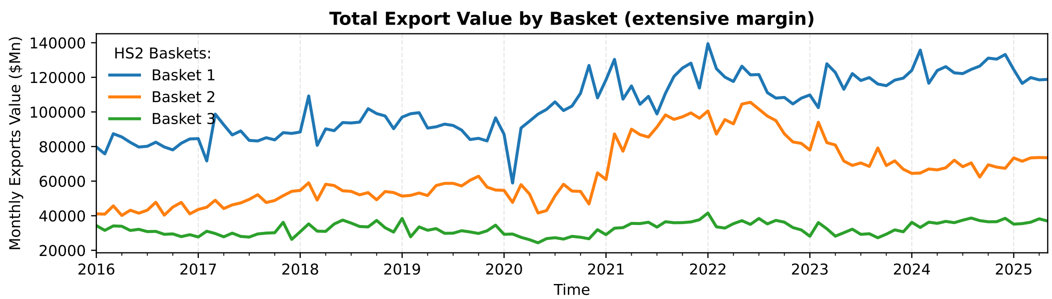

Figure 6: Total Export Value by Basket from 01-2016 to 05-2025.

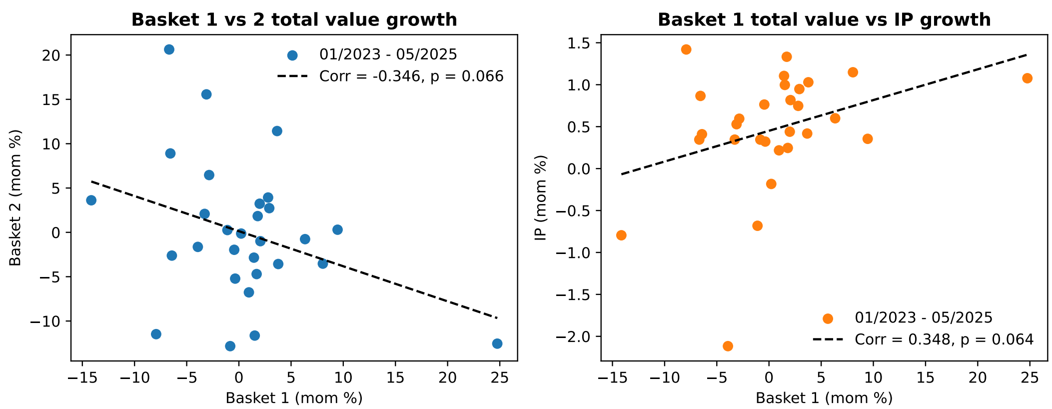

Figure 7: Basket 1 and Basket 2 Total Value Growth and China's Industrial Production Growth

Note that because we compare deviations in export intensities and allocation shares relative to a fixed baseline, the following analysis does not disentangle frontloading effects from other confounding influences during the same period, such as changes in regional demand or broader secular trends in allocation shares. However, we can expect the impact of such underlying trends to be relatively small over this short time window, given their generally slow-moving nature.

We further decompose the change in export intensities into three components: the *extensive margin*, the *intensive margin*, and an *interaction term*. The *extensive margin* captures changes in destination export values driven purely by variation in the total value exported for each basket, holding the allocation shares constant. The *intensive margin* reflects changes arising from the reallocation of trade across destinations, conditional on fixed basket export values. The *interaction term* captures second-order effects resulting from simultaneous changes in both basket sizes and allocation shares.

Formally, the margin decomposition is given by:

$$\begin{aligned}
\text{ExtMargin}_t &= \operatorname{diag}(q_t - \bar{q})\,\bar{\theta}, \\
\text{IntMargin}_t &= \operatorname{diag}(\bar{q})\,(\theta_t - \bar{\theta}), \\
\text{Interaction}_t &= \operatorname{diag}(q_t - \bar{q})\,(\theta_t - \bar{\theta}),
\end{aligned}$$

where q_t is the vector of total export values by basket at time t, θ_t is the matrix of allocation shares across destinations, and $\bar{q}$ and $\bar{\theta}$ denote their respective baseline values over the reference period.

For the remainder of this discussion, we omit the interaction term, as it is of second-order relevance. In our application, the average absolute contribution of each margin relative to the total change is roughly 70 percent for the intensive margin, 27 percent for the extensive margin, and only 2 percent for the interaction term. Focusing on first-order effects, we therefore use the following approximate decomposition:

$$\Delta F_t \approx \text{ExtMargin}_t + \text{IntMargin}_t. \tag{10}$$

We begin by applying this decomposition to analyze the variation in exports by destination and basket, focusing first on the extensive margin.

4.1 Adjustment Along the Extensive Margin

Figure 8 shows the evolution of export values along the extensive margin for baskets 1 and 2, reflecting changes in the total nominal value of export shipments. From the third quarter of 2024, shipments of the general export basket exhibit a sustained acceleration, peaking in December before reversing in early 2025.[8] By contrast, shipments of basket 2 show a sharp contraction in September 2024, followed by a recovery in late 2024 and a surge in early 2025. The timing of this surge coincides with the decline in total shipments of the general basket, which is consistent with the input allocation hypothesis, whereby changes in production location are reflected in shifts between basket 1 and basket 2 exports.

The extensive-margin frontloading phase ends in January 2025. A sharp decline follows in February, coinciding with both the start of the new US administration and the Lunar New Year. Extensive-margin exports of basket 1 then recover gradually through May, despite the escalation of reciprocal tariffs between the US and China. This recovery in extensive margin basket 1 shipments may also reflect underlying trend growth in exports, or the fading of the initial tariff impact from February.

For basket 2, shipments along the extensive margin decline sharply in September 2024. The broader weakness in basket 2 shipments during the second half of 2024, alongside accelerating basket 1 shipments, mirrors the pattern observed during the 2021–22 pandemic period, when basket 2 shipments surged while basket 1 shipments declined.

These dynamics are consistent with a deceleration in Chinese domestic production and a reallocation of production toward external manufacturing hubs in Vietnam and other ASEAN economies. Taken together, these extensive-margin adjustments suggest a narrative of rapidly adapting supply chains during China's export frontloading.

[8] Note that although the third quarter of 2024 predates the outcome of the 2024 US election, this pattern may reflect precautionary frontloading behavior in anticipation of a potential tariff escalation.

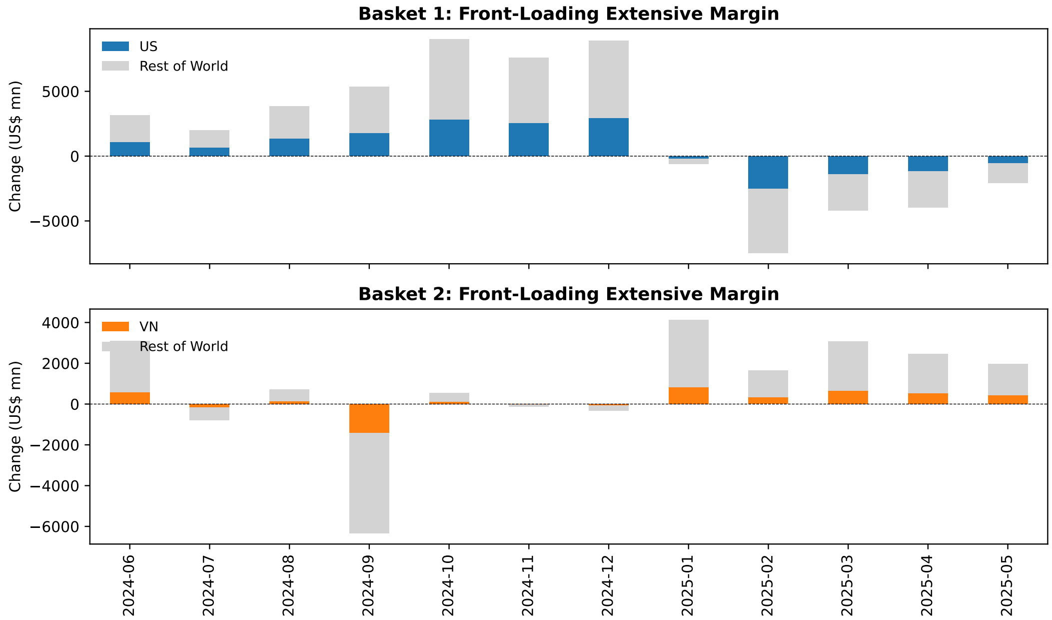

Figure 8: Frontloading Along the Extensive Margin

4.2 Adjustment Along the Intensive Margin

Figure 9 displays the adjustments along the intensive margin driven by changes in allocation shares. The figure highlights the prioritization of US-bound shipments for basket 1 throughout the second half of 2024, and the reallocation of basket 2 toward Vietnam.

We observe a similar turning point along the intensive margin beginning in the third quarter of 2024 for basket 1. There, the allocation shares begin to shift decisively toward the United States in July, consistent with a deliberate effort to prioritize US-bound shipments ahead of the anticipated tariff increases.

Notably, US-bound shipments remained a priority during the initial phases of tariff escalation. Reallocation along the intensive margin largely offset the decline in US shipments on the extensive margin during this period. By April, however, the effects of tariff escalation are fully evident: allocation shares for US-bound shipments in the general export basket drop sharply. At the same time, Vietnam's share of intermediate goods exports rises further, indicating an intensification of production across all channels of Chinese supply chains.

In basket 2, reallocation becomes evident in September. Allocation shares shift toward Vietnam, indicating a broader reconfiguration of China's export supply chains toward external production hubs. This trend continues through November and December, with Vietnam steadily gaining allocation share. The pace of reallocation slows in January and February, aligning with the initial implementation of tariff increases, but accelerates again from March onward amid rising concerns over trade tensions and the escalation of reciprocal tariffs.

These intensive margin adjustments underscore the potential flexibility of China's exporters and producers to dynamically reallocate shipments in response to shifting trade policy expectations. In

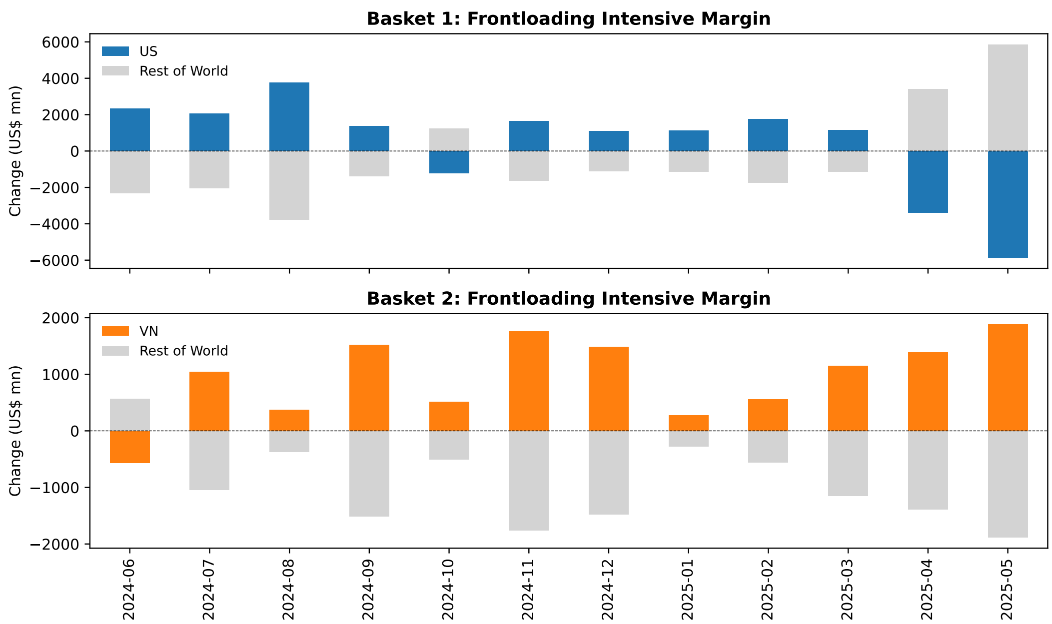

Figure 9: Frontloading Along the Intensive Margin

particular, the ability to prioritize US-bound exports helped offset the decline in values along the extensive margin in the first three months of 2025. We next investigate how this flexibility was achieved.

4.3 Cross-Destination Intertemporal Reallocation of Shipments

Next, we turn to the mechanism of cross-destination intertemporal reallocation between the initial frontloading phase and the post-tariff phase. Specifically, we focus on deviations in allocation shares relative to a linear trend estimated from the sample starting in 2023. Figure 10 displays these deviations by for the general and intermediate good baskets, across destination economies, comparing the pre-tariff frontloading phase (10/2024–12/2024) with the post-tariff phase (01/2025–05/2025).

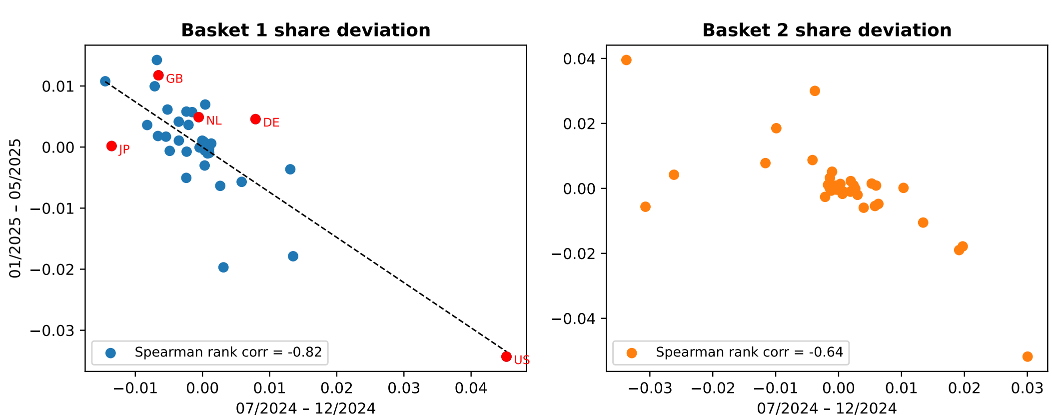

Figure 10: Deviation from Linear Trend in Allocation Shares Across Frontloading Phases

We observe a strong negative relationship between deviations in allocation shares of basket 1 in the pre-tariff frontloading phase and the post-tariff period from January to May 2025. In particular, the US received larger allocation shares in the pre-tariff phase but experienced correspondingly lower shares in the post-tariff period, especially in April and May.

Additionally, our analysis reveals a pervasive and robust negative relationship across destinations, reflected in a strongly negative Spearman rank correlation.[9] This pattern suggests a broader cross-destination adjustment: economies facilitate US frontloading by receiving a lower allocation share during the pre-tariff phase, and then, following tariff implementation, they receive a higher allocation share to replenish depleted inventories and absorb excess capacity arising from reduced US demand.

Specifically, the next four economies with the largest allocation shares of the general export basket, Germany, the United Kingdom, Japan, and the Netherlands, each exhibited the opposite adjustment to that of the United States.[10] Together, this evidence is consistent with frontloading facilitated by cross-destination intertemporal reallocation. While exports to the US were frontloaded, third destinations experienced the opposite adjustment—namely, a backloading of exports.[11] This mechanism enables greater frontloading to the US by diverting goods there in advance, while simultaneously reducing the magnitude of the subsequent payback, as backloading from third destinations helps absorb the loss in export share to the US.

Beyond basket 1, we do not observe the same cross-destination intertemporal pattern. This is reflected in a lower Spearman rank correlation between allocation share deviations across phases and a generally less robust negative relationship. These results suggest that the buffer mechanism is primarily relevant for the basket of final goods. By contrast, intermediate goods are more likely to be processed immediately, leaving less scope for intertemporal reallocation, or they may face stronger international competition from alternative suppliers.

For frontloading to serve as an effective form of tariff mitigation, there must be capacity for earlier shipments to be retained and used later, that is, some buffer that smooths fluctuations between inflows and outflows. Prior work by Alessandria et al. (2010), Alessandria et al. (2021), Alessandria et al. (2024), among others, documents how commercial inventory stocks can facilitate this buffering mechanism, though similar effects may also arise from household-level inventory accumulation or from models distinguishing between durable and non-durable consumption. Regardless of the

[9] The Spearman rank correlation coefficient is defined as the Pearson correlation between the ranked values of two variables. It measures the strength and direction of a monotonic relationship and is more robust to outliers and non-normality than the Pearson correlation.

[10] The reciprocal shift was also evident in the net exports component of national accounts data. For example, Japan saw a boost to 24Q4 GDP growth due to weaker imports from China, followed by a drag on 25Q1 GDP growth as imports rebounded. With accurate inventory data, one would expect a counteracting adjustment in inventory accumulation, lowering growth in 24Q4 but raising it in 25Q1, but this dynamic was not captured in the national accounts data.

[11] For reallocation to be necessary, there must be limited slack in China's manufacturing capacity. Data on China's manufacturing capacity utilization show an increase from 74.5 percent in 24H1 to 75.8 percent in 24H2, before easing to 74.2 percent in 25H1. These movements indicate that manufacturing slack decreased during the period most relevant for export frontloading, consistent with our intertemporal reallocation hypothesis, although it is notable that overall manufacturing utilization remained below its peak of 78.2 percent in 21H1.

specific channel, we provide indirect evidence that such buffers enabled additional flexibility to support the frontloading of exports to the US. A deeper investigation of cross-destination inventory dynamics, however, lies beyond the scope of this analysis and is therefore left for future research.

4.4 Comparison with the 2018 Episode

To contrast the recent frontloading episode with the 2018 US–China trade tensions, Figure 11 plots basket-level adjustments along the intensive margin during 2018. Frontloading is evident only in May and June. Although the magnitude of this adjustment was comparable, its duration was much shorter than in the recent episode. Moreover, there is no evidence of anticipatory frontloading: trade tensions had already escalated by May and June, and the observed frontloading responded directly to the announced US tariff increases scheduled for July, August, and September. Notably, in 2018 Japan was the largest recipient of basket 2 shipments, whereas Vietnam did not become the leading destination until mid-2020. Taking Japan as the primary counterpart, we do not observe the negative comovement between intensive margin adjustments of the general basket and the intermediate basket that characterizes the recent episode.

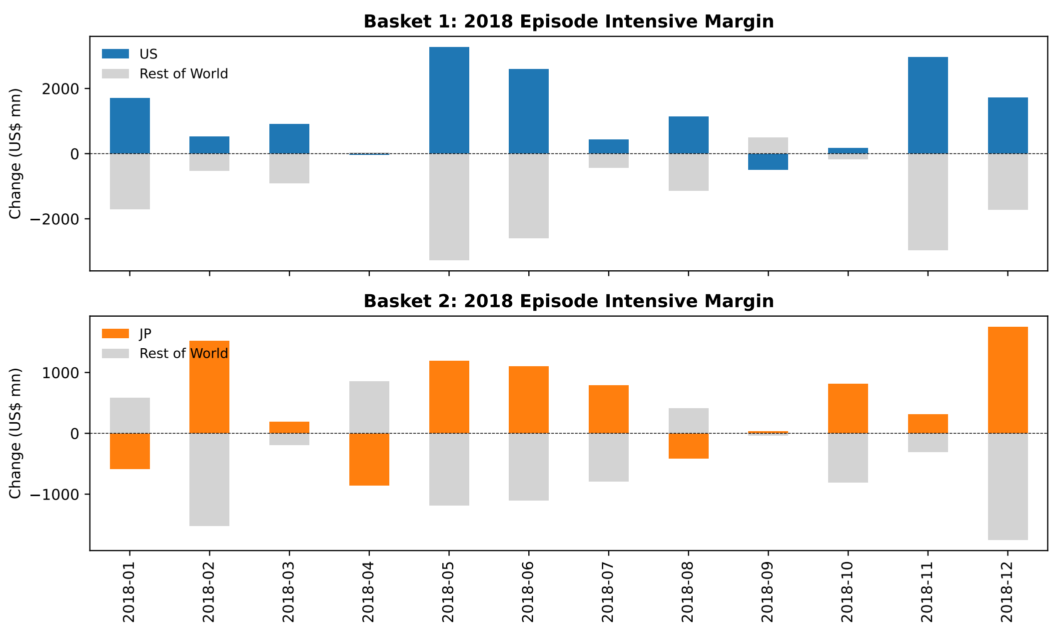

Figure 11: 2018 Episode Along the Intensive Margin

Figure 12 plots the adjustments by basket along the extensive margin throughout 2018. Most notably, we do not see any evidence of a production ramp-up preceding the tariff escalations.[12] Similarly, we observe no coordination between extensive-margin shipments of baskets 1 and 2. In fact, the extensive-margin adjustment for basket 1 was negligible, while that for basket 2 was consistently negative throughout most of 2018.

[12]The peak and trough of shipments in the general basket in February and March 2018 are attributable to residual seasonality from the Lunar New Year, and are not indicative of a broad-based pickup in domestic production.

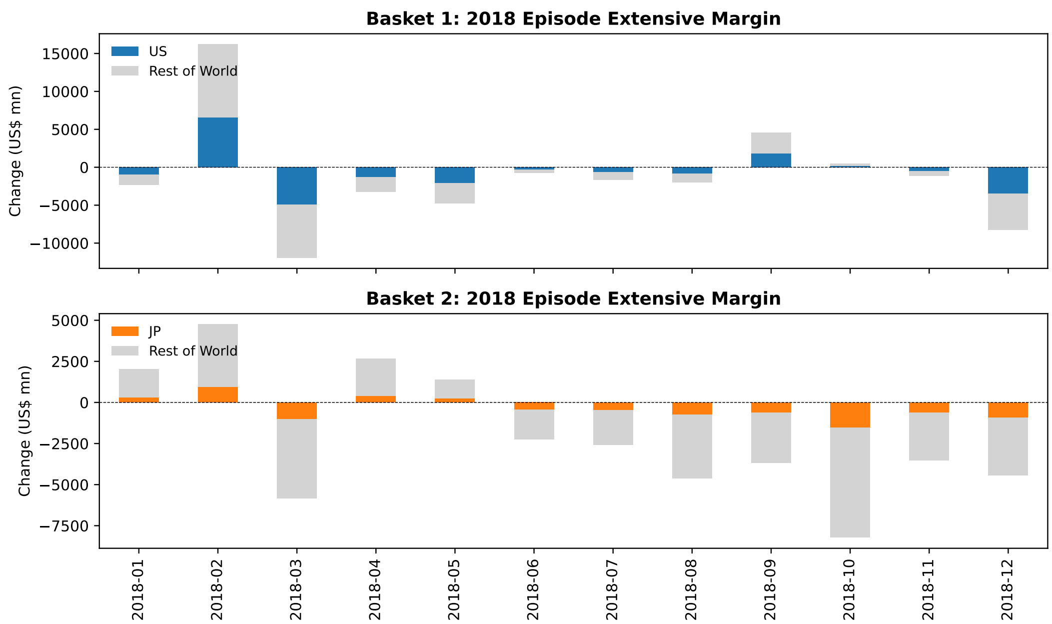

Figure 12: 2018 Episode Along the Extensive Margin

Overall, the combined intensive- and extensive-margin frontloading adjustments in 2018 were significantly smaller than in the recent episode. The adjustment was meaningfully positive only in May and June, and it was confined to the intensive margin. Moreover, there is no evidence of supply chain adjustments through Vietnam or other ASEAN economies.

We next examine deviations in allocation shares relative to a linear trend, estimated over the 2017–2018 sample. Figure 13 plots these deviations by basket across destination economies, comparing the three months preceding and following the tariff escalation in July 2018.

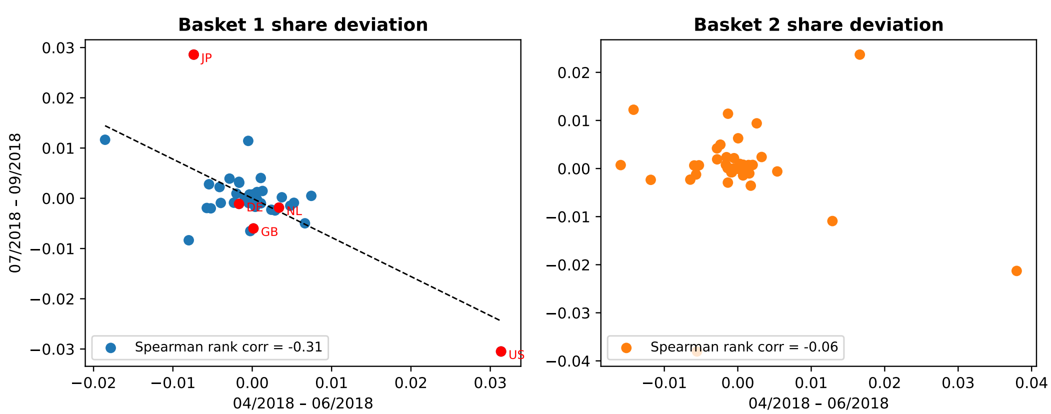

Figure 13: Deviation from Linear Trend in Allocation Shares in the 2018 Episode

Intensive-margin frontloading to the US in May/June is reflected in a higher allocation share in the frontloading phase, followed by a lower allocation share between July and September. As with the recent episode, we do not observe a comparable frontloading adjustment in basket 2.

Unlike the current episode, the negative relationship in 2018 was far pervasive across destinations, as indicated by a lower Spearman rank correlation. The comovement across destinations is driven largely by Japan and the US, as Germany, the UK, and the Netherlands showed virtually no change in allocation shares across phases. This suggests that the cross-destination intertemporal reallocation channel of frontloading was limited in the 2018 episode. Moreover, since the Japanese economy entered recession in the second half of 2018, it is possible that the observed adjustments in allocation shares were influenced instead by domestic demand conditions in Japan than by trade reallocation.

5 Understanding the 2025H1 Export Surge to Vietnam

There has been a recent debate about the drivers of China's export strength since the start of 2025, particularly the sharp increase in total shipments to Vietnam, which rose by 22.0% year-on-year in May 2025. Our basket-based decomposition of Chinese export flows shows that the recent surge is driven by basket 2, reflective of intermediate goods, with no contribution from baskets 1 and 3. Taken at face value, this suggests an acceleration of production relocation from China to Vietnam since the start of 2025, one that leverages newly established infrastructure and logistics since 2018-19.

In contrast, the transshipment (or re-exporting) narrative suggests that goods are rerouted through Vietnam with little or no transformation. Evidence often cited in support of this view is that as exports from China to Vietnam increased, Vietnam's exports rose only to the US and not to other destinations. However, this pattern is equally consistent with the redirection of supply chains to exploit lower tariffs on Vietnamese exports. The key distinction lies in value added: transshipment implies that no meaningful processing occurs in Vietnam, whereas production relocation entails at least some degree of domestic manufacturing activity.

The existing literature has examined the rise in exports to Vietnam since 2018 and generally finds evidence of value added consistent with production relocation; see, for example, Schulze & Xin (2024), Rotunno et al. (2024), Mayr-Dorn et al. (2023), and Nguyen & Lim (2023). However, these studies cover data only through 2022, leaving open the question of whether the renewed increase in exports is attributable to relocation or to transshipments.

In the remainder of this section, we present additional evidence *suggestive* of the production relocation hypothesis over the transshipment narrative. The contrast between these two explanations also serves as a useful test of our empirical framework and provides broader insights into the evolving structure of China's export dynamics.

5.1 HS2 Granularity and Basket-Level Identification

The HS2-level granularity of export flows is not always sufficient to capture the underlying economic drivers of trade dynamics. Some HS2 categories have well-defined use cases—for instance, raw hides and skins (HS2=41) fall clearly within the intermediate goods basket—while others are more ambiguous. Electronics (HS2=85) is the most prominent example: it is the largest category by value, contains both components and finished goods, and appears meaningfully in all three baskets. While our framework points to production relocation as the primary driver of the surge in exports to Vietnam, we next examine the robustness of this conclusion from several perspectives. Although HS2 data cannot fully separate transshipment from relocation, the evidence presented below consistently points to relocation as the likely primary mechanism.

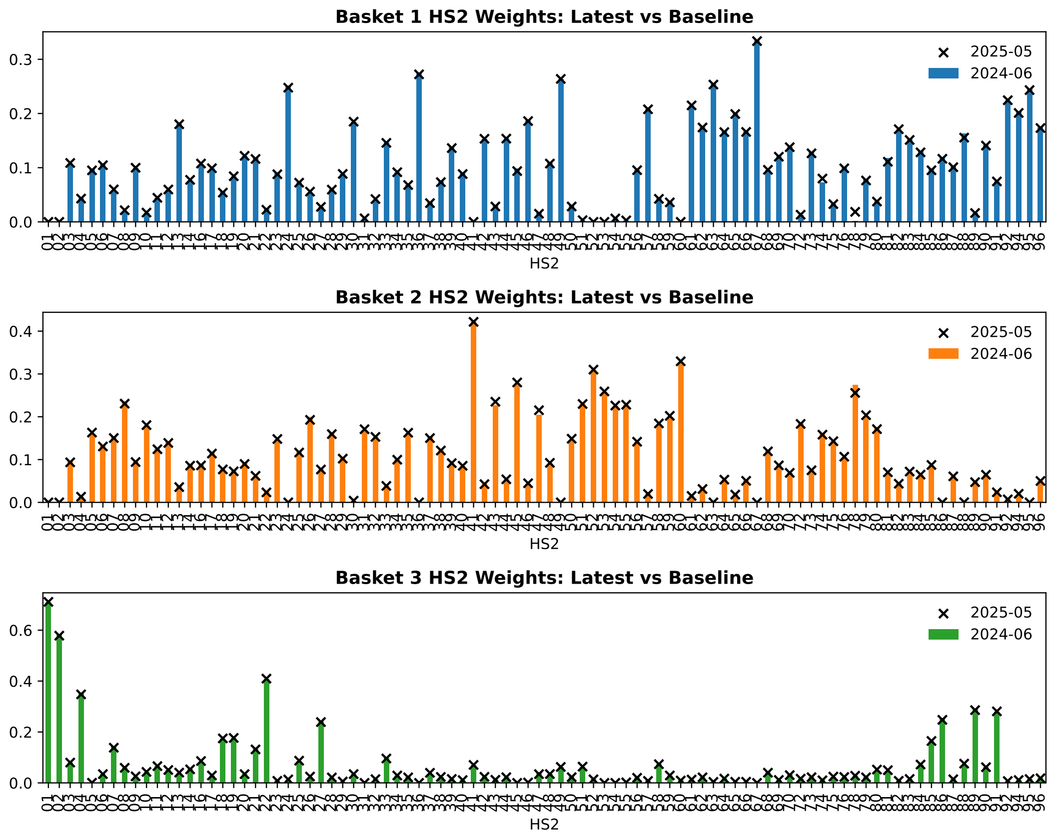

Figure 14: Change in Normalized Basket Weights Across HS2 Categories

Figure 14 displays the change in normalized basket weights by HS2 category between the latest data (May 2025) and the baseline month (June 2024). Consider the hypothesis that the recent export strength reflects transshipment activity. Under this view, we would expect a shift in the composition of exports to Vietnam, particularly an increase in goods typically exported to the US. Instead, the composition of the intermediate basket shows virtually no change.

Data through May 2025 indicate that electronic shipments from China to Vietnam and from Vietnam to the US rose by approximately equal margins. Despite this, the relative weight of electronics (HS2 = 85) within the intermediate basket remains stable. If this entire increase were driven solely by transshipment, it would imply a simultaneous and offsetting decline in end-stage electronic manufacturing in Vietnam, with no corresponding adjustments in other sectors or categories, which we view as generally unlikely.

All of this highlights the core identification assumption underlying our framework: that the drivers of trade flows give rise to changes in export flows across HS2 categories in relatively stable proportions. By identifying these proportions, we can infer the underlying drivers of export flows, even when certain categories, like electronics, are ambiguous in isolation. Comparing the latest data to the baseline period reveals no discernible shift toward a transshipment-heavy profile in exports to Vietnam.

Nonetheless, this raises a natural question: to what extent did our methodology accurately distinguish between subcomponents and final goods when both fall under the same HS2 code, such as electronics (HS2=85)? To evaluate this, we turn to additional data sources for evidence.

5.2 Evidence from 2024 Annual HS4-Level Exports

We next examine higher-granularity trade data to better understand the end-use of electronic shipments to the US and Vietnam. Table 2 reports China's 2024 annual HS4-level electronics exports to Vietnam and the US, mapped to Broad Economic Categories (BEC).[13]

Table 2: US versus Vietnam Electronic Export Shares (HS2=85) by BEC Category.

BEC Category	**US Share**	**VN Share**	**VN – US**
22: Processed industrial supplies	0.051	0.021	-0.031
41: Capital goods (ex. Transport)	0.483	0.282	-0.201
42: Parts/accessories of capital goods (ex. Transport)	0.180	0.436	0.257
53: Parts/accessories of transport equipment	0.120	0.062	-0.058
61: Durable consumption goods	0.136	0.055	-0.081
62: Semi-durable consumption goods	0.028	0.143	0.116
63: Non-durable consumption goods	0.003	0.001	-0.002

From this, we see that electronic exports to Vietnam are more heavily concentrated in intermediate goods and subcomponents, consistent with the production relocation hypothesis. By contrast, electronic exports to the US include a larger share of final capital and consumer goods. This provides independent validation of our empirical methodology using trade patterns through the end of 2024. Notably, the decomposition relies exclusively on the relative proportions of HS2-level export flows across destinations and does not incorporate any HS4-level detail. The fact that the BEC-based classification derived independently from HS4-level mappings aligns with these results supports the robustness of our approach.

It remains possible that the underlying composition of exports to Vietnam shifted dramatically at the start of 2025, thereby rendering the evidence from 2024 exports redundant. However, such an abrupt transformation would constitute a structural break, one for which we find no evidence

[13] HS4-level export data are sourced from the UN Comtrade database (https://comtradeplus.un.org/TradeFlow). The mapping from product codes to BEC categories is based on the HS6-to-BEC concordance provided by the World Bank's WITS platform (https://wits.worldbank.org/product_concordance.html). To match our HS4-level export data, we aggregate the HS6-to-BEC mapping to the HS4 level by taking the unweighted average of BEC shares across all HS6 codes nested within each HS4 category.

in the HS2-level composition of the intermediate basket.

5.3 Value Added, Tariff Mitigation Incentives, and Policy Implications

Lastly, we turn to measures of aggregate exports, imports, and manufacturing value added. While these do not provide direct evidence of transformation in Vietnam, they are again suggestive of the production relocation hypothesis.

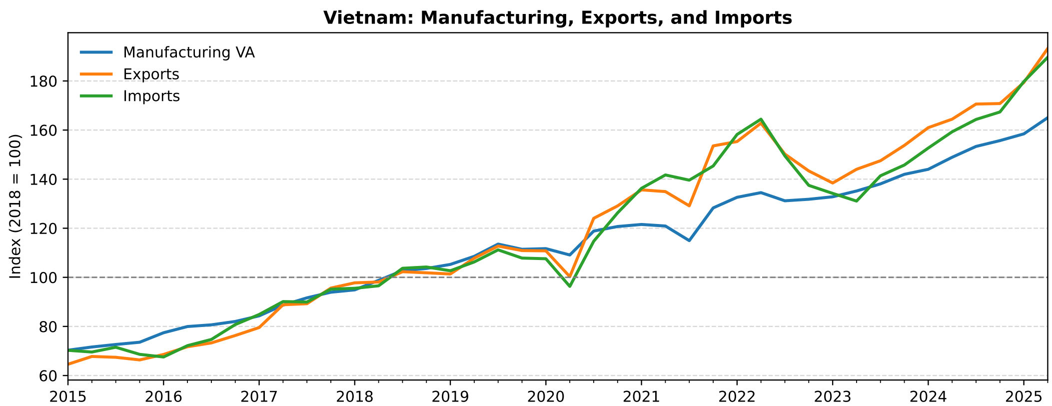

Figure 15: Seasonally adjusted manufacturing value added, exports, and imports for Vietnam.

Figure 15 shows seasonally adjusted indices of Vietnam's manufacturing value added, exports, and imports, each normalized to 100 in 2018. From this, we see a marked acceleration in Vietnam's manufacturing value added in the first half of 2025, with growth reaching 20% on a quarter-on-quarter annualized basis. Moreover, we observe robust positive comovement between exports and manufacturing value added, both historically and in recent quarters. This pattern is inconsistent with the transshipment narrative as that would imply no impact on domestic value added.

It is important to recognize that value added lies along a continuum between conventional end-stage manufacturing, typically around one-fifth of the final value, and zero value-added transshipment. In theory, outsourced manufacturing can fall anywhere along this spectrum. In practice, when the share of value added is too low, the cost savings are unlikely to justify the investment in infrastructure required to relocate production to Vietnam.

The opening of a tariff rate wedge between Vietnam and China additionally incentivizes the relocation of manufacturing activities. In particular, this wedge lowers the profitability threshold, as manufacturing activities that were previously too low-margin to justify outsourcing may now become profitable to relocate to Vietnam. As a result, we should expect an expansion of Vietnam's end-stage manufacturing, especially at the margin of lower value-added activities.

While exports and imports have increased proportionally since 2018, manufacturing value added has grown by a smaller margin. This suggests a decline in the marginal domestic value added per unit of exports, consistent with the nature of outsourced end-stage manufacturing relocated to Vietnam. Moreover, this trend appears to have accelerated in the first half of 2025, as export and import growth outpaced the strong increase in manufacturing value added.

Fundamentally, both production relocation and transshipment respond to tariff rate differentials, and many of their empirical predictions therefore overlap. Our key takeaway is that the underlying trend of production relocation appears well established and ongoing, and that a widening tariff differential is likely to accelerate this process.

The distinction between transshipment and production relocation has important implications for the future path of export flows. If the recent strength of exports to Vietnam were primarily driven by transshipment, a US tariff specifically targeting such activity could trigger a sharp reversal. In that case, exports from China to Vietnam could fall abruptly as the tariff wedge is eliminated or narrowed. We view this outcome as unlikely, however, given the evidence pointing to meaningful product transformation in Vietnam.

In summary, our analysis provides tentative evidence that the increase in shipments from China to Vietnam in 2025 reflects an acceleration of production relocation rather than a surge in transshipment, though further work is needed to draw more definitive conclusions.

6 Conclusion

This paper examines the anatomy of China's export frontloading in response to anticipated tariff increases in 2025. At the core of our analysis is the novel application of a factor models to identify export baskets that capture the dynamics and cross-destination differences in the profile of exports from China.

Applying this framework allows us to leverage China's product-level export flows to examine adjustments in export shipments and uncover underlying changes in supply chains. We find evidence of coherent adjustments along multiple margins. Shipments to the US accelerated in the second half of 2024, possibly supported by the retention of intermediate inputs that facilitated a ramp-up in domestic production. Beginning in January 2025, domestic output decelerated while shipments to Vietnam and other ASEAN economies increased, consistent with the relocation of export-oriented manufacturing following US tariffs. Exporters continued to prioritize the US market through March by diverting flows from third destinations with similar import profiles. When reciprocal tariffs escalated in April and May, shipments to the US fell sharply, but much of this decline was offset by increased exports to other destinations, consistent with cross-destination intertemporal reallocation.

Additionally, we find that the recent frontloading episode was more pronounced than in 2018. Our decomposition of export adjustments in 2024–25 along both the extensive and intensive margins reveals a multi-phase timeline of adjustment, whereas the more limited frontloading in 2018 largely reflected isolated increases in shipments to the US. This difference may reflect greater preparation and investment by Chinese producers and exporters, informed by lessons from the 2018 episode. From a policy perspective, these findings underscore the importance of recognizing how past shocks shape behavior and expectations when evaluating the effects of future trade policies.

We conclude by highlighting several avenues for future research that follow from the preliminary findings of this paper. A first question concerns horizontal supply chain integration: to what extent were investments in production capacity in Vietnam driven by the incentive to hedge against future tariff risks, as opposed to factors rooted in fundamentals and comparative advantage? Were FDI inflows disproportionately concentrated in industries most exposed to the 2018 tariffs? Further analysis of firm-level data and changes in input–output linkages could provide valuable evidence on how producers reorganized production across borders.

A second question concerns the role of vertical integration in enabling firms to retain intermediates for domestic use, and how this interacted with incentives for horizontal integration through international supply chains as a means of mitigating tariff risks. A further consideration is whether others were adversely affected by this integration—for instance, did it disadvantage producers dependent on China for intermediate inputs, and might this episode incentivize them to diversify suppliers as a hedge against future risks?

It would also be valuable to investigate whether there is evidence of cross-destination inventory adjustments, consistent with our hypothesis of intertemporal reallocation across destinations. Finally, future modeling work could aim to capture these dynamic supply chain and exporter responses, allowing frontloading behavior to emerge endogenously and providing a framework for conducting policy analysis.

Finally, a promising extension of this basket-based framework could be to jointly model export and import flows across multiple economies to identify common factors driving global trade dynamics. For instance, combining China's export data with US import data could help trace indirect export flows from China through ASEAN to the US, and assess the extent to which fluctuations in bilateral trade reflect shared underlying shocks. A model of this type could distinguish global, regional, and destination-specific components of trade variation, offering a more comprehensive understanding of how trade shocks propagate across economies.

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A Baseline Estimation: HS2 Basket Weights

Table 3: HS2 Product Categories and Basket Weights

HS2 Code	Category	Basket 1	Basket 2	Basket 3
01	Live animals	0.0000	0.0000	0.6920
02	Meat and edible meat offal	0.0000	0.0000	0.6220
03	Fish, crustaceans, molluscs	0.0974	0.1210	0.0918
04	Dairy produce, eggs, honey	0.0389	0.0218	0.3720
05	Products of animal origin n.e.s.	0.1010	0.1390	0.0206
06	Live trees, plants, cut flowers	0.1130	0.1660	0.0333
07	Edible vegetables, roots, tubers	0.0467	0.1640	0.1660
08	Edible fruits, nuts, citrus peel	0.0219	0.2240	0.0725
09	Coffee, tea, spices	0.0925	0.0924	0.0601
10	Cereals	0.0093	0.2270	0.0332
11	Milling products, malt, starches	0.0355	0.1480	0.0742
12	Oil seeds, oleaginous fruits	0.0523	0.1590	0.0501
13	Lac, gums, resins	0.1530	0.0535	0.0803
14	Vegetable plaiting materials	0.0702	0.1150	0.0531
16	Prepared meat, fish products	0.0949	0.1180	0.0799
17	Sugars and sugar confectionery	0.0879	0.1230	0.0278
18	Cocoa and cocoa preparations	0.0602	0.0778	0.1820
19	Cereal preparations, baked goods	0.0840	0.0781	0.1900
20	Vegetable, fruit, nut preparations	0.1090	0.1210	0.0366
21	Miscellaneous edible preparations	0.1090	0.0670	0.1490
22	Beverages, spirits, vinegar	0.0294	0.0309	0.3640
23	Food industry residues, animal feed	0.0791	0.1790	0.0090
24	Tobacco and substitutes	0.2290	0.0047	0.0158
25	Salt, sulphur, stone, cement	0.0688	0.1380	0.0803
26	Ores, slag, ash	0.0380	0.2530	0.0156
27	Mineral fuels, oils	0.0316	0.0645	0.2200
28	Inorganic chemicals	0.0573	0.2190	0.0082
29	Organic chemicals	0.0837	0.1120	0.0062
30	Pharmaceutical products	0.1700	0.0117	0.0498
31	Fertilizers	0.0059	0.1700	0.0000
32	Tanning/dyeing extracts, pigments	0.0356	0.1520	0.0131
33	Essential oils, cosmetics, perfumery	0.1510	0.0403	0.1070
34	Soap, lubricants, waxes	0.0913	0.1040	0.0307
35	Albuminoidal substances, enzymes	0.0612	0.1610	0.0211
36	Explosives, pyrotechnics	0.2900	0.0000	0.0000
37	Photographic goods	0.0342	0.1630	0.0349
38	Miscellaneous chemical products	0.0721	0.1360	0.0129
39	Plastics and articles thereof	0.1460	0.0851	0.0176
40	Rubber and articles thereof	0.0986	0.0796	0.0098
41	Raw hides and skins	0.0000	0.4020	0.0712
42	Articles of leather, travel goods	0.1520	0.0495	0.0266
43	Furskins, artificial fur	0.0264	0.1870	0.0485
44	Wood and wood articles	0.1610	0.0578	0.0253

Table 3 (continued)

HS2 Code	Category	Basket 1	Basket 2	Basket 3
45	Cork and articles of cork	0.0984	0.2640	0.0000
46	Straw, basketware, wickerwork	0.1910	0.0425	0.0040
47	Pulp of wood, fibrous materials	0.0231	0.1770	0.0536
48	Paper and paperboard	0.1170	0.0859	0.0367
49	Printed books, newspapers	0.2520	0.0000	0.0717
50	Silk	0.0274	0.1450	0.0346
51	Wool and animal hair	0.0232	0.1850	0.0328
52	Cotton	0.0000	0.2950	0.0214
53	Vegetable textile fibres n.e.s.	0.000048	0.2460	0.0013
54	Man-made filaments	0.0067	0.2110	0.00047
55	Man-made staple fibres	0.0038	0.2180	0.0029
56	Wadding, felt, nonwovens	0.0927	0.1420	0.0220
57	Carpets and floor coverings	0.1910	0.0385	0.0125
58	Special woven fabrics	0.0513	0.1560	0.0769
59	Impregnated or coated fabrics	0.0412	0.1870	0.0271
60	Knitted or crocheted fabrics	0.0000	0.2970	0.0157
61	Apparel, knitted or crocheted	0.1990	0.0355	0.0152
62	Apparel, not knitted	0.1670	0.0487	0.0201
63	Made-up textile articles	0.2530	0.0063	0.0063
64	Footwear, gaiters	0.1680	0.0554	0.0158
65	Headgear	0.1980	0.0318	0.0056
66	Umbrellas, walking sticks	0.1610	0.0705	0.0038
67	Prepared feathers, artificial flowers	0.3420	0.0000	0.0000
68	Stone, plaster, cement articles	0.0899	0.1390	0.0548
69	Ceramic products	0.1130	0.0973	0.0308
70	Glass and glassware	0.1330	0.0853	0.0468
72	Iron and steel	0.0087	0.2070	0.0095
73	Articles of iron or steel	0.1300	0.0762	0.0261
74	Copper and copper articles	0.0455	0.1860	0.0129
75	Nickel and nickel articles	0.0305	0.1870	0.0119
76	Aluminium and aluminium articles	0.1110	0.1010	0.0264
78	Lead and lead articles	0.00048	0.2760	0.0040
79	Zinc and zinc articles	0.1090	0.1580	0.0269
80	Tin and tin articles	0.0218	0.2050	0.0208
81	Other base metals	0.1230	0.0840	0.0258
82	Tools, implements, cutlery	0.1680	0.0473	0.0106
83	Misc. articles of base metal	0.1530	0.0709	0.0180
84	Machinery, reactors	0.1390	0.0606	0.0736
85	Electrical machinery, electronics	0.1030	0.0809	0.1640
86	Railway equipment	0.0989	0.0023	0.2630
87	Vehicles	0.1070	0.0620	0.0122
88	Aircraft, spacecraft	0.1160	0.0254	0.0859
89	Ships, boats	0.0239	0.0294	0.3480
90	Precision, optical, medical instruments	0.1420	0.0657	0.0692
91	Clocks and watches	0.0774	0.0327	0.2660
92	Musical instruments	0.2110	0.0188	0.0144

Table 3 (continued)

HS2 Code	Category	Basket 1	Basket 2	Basket 3
94	Furniture, bedding, lamps	0.2060	0.0240	0.0138
95	Toys, games, sports goods	0.2520	0.0036	0.0121
96	Miscellaneous manufactured articles	0.1720	0.0539	0.0223

B Comparisons Between Baskets and Across Time

Table 4 reports the five largest differences in weight between basket 2 and 1. Reflecting the differences in end use, basket 2 places greater weight on raw textiles and related inputs, while carrying lower weight in a range of final goods categories.

Table 4: Largest Differences in HS2 Weight Between Baskets 2 and 1

HS2	Description	Difference
41	Raw hides, skins and leather	0.401
60	Knitted or crocheted fabrics	0.297
52	Cotton	0.295
78	Lead and articles thereof	0.277
53	Other vegetable textile fibers; paper yarn and woven fabrics of paper yarn	0.246
67	Prepared feathers, down, artificial flowers, articles of human hair	−0.342
36	Explosives, pyrotechnic products, matches, pyrophoric alloys	−0.289
49	Printed books, newspapers, pictures and other printed products	−0.252
95	Toys, games, and sports requisites; parts and accessories thereof	−0.249
63	Other made-up textile articles; worn clothing, rags	−0.246

Figure 16 reviews how the composition of basket 2 has evolved over time. The largest increases are concentrated in raw materials and textiles, while the largest declines are in agricultural and food-related categories. Over the same period, the largest allocation share has shifted from Japan (0.15) to Vietnam (0.19). Accordingly, the basket has moved toward greater weight in industrial inputs and away from food and other consumables.

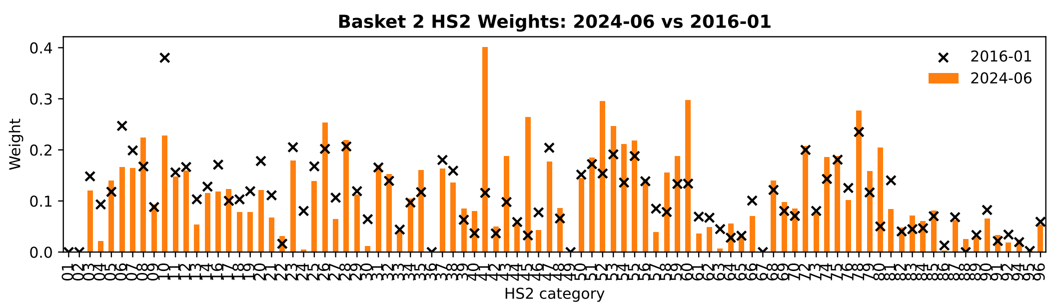

Figure 16: Change in Normalized Basket 2 Weights from 01-2016 to 06-2024