Global Supply Chain and Trade Shocks: Evidence from Chinese Trades during COVID-19 *

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Abstract

This paper analyzes how governmental interventions in response to COVID-19 affected global supply chains, shedding light on negative supply and demand shocks. Specifically, we examined China's Zero-COVID policies and their impact on trade dynamics during the COVID-19 period, utilizing disaggregated data and decomposing it into extensive and intensive margins. Our results reveal that the lockdown policy led to a significant reduction in both Chinese imports and exports, with the reduction primarily attributed to the intensive margin rather than the extensive margin. Notably, Chinese exports displayed greater resilience compared to imports, with intermediate goods emerging as the primary driver of import declines. Additionally, we introduced a machine learning approach, which identified "workplace closure," "public transport closure," and "stay-at-home orders" as the most impactful COVID lockdown policies, leading to a substantial decline in Chinese trade. Furthermore, our analysis indicates countries' role in the China-centered supply chain, with countries heavily involved in trading intermediate goods experiencing higher demand shocks for Chinese imports than the supply shocks for Chinese exports.

Keywords: Zero-COVID Policy, China, International Trade, Global Supply Chain

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1. Introduction

Since 2020, in response to the COVID-19 pandemic's substantial toll on public health, countries worldwide have enacted lockdown measures. A pronounced downturn in global trade ensued during these years of pandemic spread, with lockdown policies widely adopted, affecting the flow of goods between nations. China, a dominant player in global trading, adopted a "Zero-COVID" policy, involving extensive testing, state-managed quarantines, and rigorous, sweeping lockdowns spaning the majority population in China. At the same time, the COVID-19 crisis has revealed vulnerabilities in global supply chains, particularly for companies in Asia and North America that heavily rely on supply chains connected to China (Javorcik, 2020). While China's historical contribution to the total foreign value-added in trade has been substantial, there is a pressing need to examine the repercussions of supply chain disruptions on firms' trading activities, especially in light of China's pivotal position in the global supply chain. This calls for a thorough analysis with a particular focus on China's "Zero-Covid" lockdown policies and their consequences, especially considering the supply and demand shocks caused. Additionally, given China's position in the global supply chain, it's important to understand how the shocks channel through which lockdowns impact trade diversification and decompose them into the intensive and extensive margins.

The growing literature on quantitative implication of COVID-19 shows that COVID-19 caused shocks on international trade. Studies by Liu et al. (2022); Fang et al. (2022); Hayakawa and Mukunoki (2021a,b); Bas et al. (2023) and Friedt and Zhang (2020) show that China's COVID-19 policies negatively affected its imports and exports with focus on product and country heterogeneity. For example, using the evidence of the first wave of the COVID-19 pandemic, Fuchs et al. (2020) find that countries with stronger past economic ties with China import more critical medical goods from China at both the national level and the level of Chinese provinces. Meier et al. (2020) focus on the intermeidate goods, finding that US sectors with a high exposure to intermediate goods imports from China contracted significantly and robustly more than other sectors. Similar works done by Cardoso and Malloy (2021, 2023) to study the COVID impact using countries such as Canada and United States. There is another strand of literature focusing on the study of pandemic and the sub-national lockdown interventions. For instence, Wu et al. (2023) study the early evidence using the first wave lockdown policy to investigate the economic impact. **?** on the other hand, find more comprehensive Chinese city level data and finding that the lockdown impacted the intensive and extensive margin, with higher exit and lower new entry into foreign markets.

Facing with the Covid-19 supply chain disruption, China is important in global value chain to be substituted for in the current world economy Qin et al. (2020). This calls for the investigation of supply chain resilience such as COVID-19 disruptions on international production networks. Ando et al. (2021) examined changes in trade in the trade-fall periods amid COVID-19 in 2020 using Japan's machinery trade. Additionally, there is substantial evidence showing that product with a higher reliance on China as input suppliers saw stronger declines in exports as a result of the COVID-19 shock (Bas et al., 2023). Cardoso and Malloy (2023) study individual policy interventions at the state and provincial level. Especially, Berthou and Stumpner (2022), Bonadio et al. (2021) and Bricongne et al. (2021) provided evidence that at least in the short-term, the disruptions rise vulnerabilities in of global supply chain.

Unfortunately, the lack of variation in observed lockdown severity hampered ability to accurately estimate the economic impacts of lockdown restrictions across sub-nations. It's important to study the reaction of the sub-national governments because it's regions and municipalities that are at the frontline of the crisis management and recovery cause by COVID-19 crisis Allain-Dupré et al. (2020). This is also true for China that Chinese regions exhibited notable divergence in their policy approaches. While certain Chinese provinces promptly eased lockdown restrictions, others maintained stringent measures for prolonged durations throughout the pandemic. Additionally, some provinces employed a diverse set of different governmental response policies, while others implemented a more restricted set of policy over the course of pandemic. When estimating governmental response policies, including different sets of policies in a single estimation may lead to multicollinearity issue. This can make it challenging to interpret coefficients and diminishes the model's power to accurately identify estimates of policy variables.

In this paper, we quantify the impact of COVID-19 lockdown policies in China on international trade, with a focus on their effects on exports and imports. We first discuss a conceptual framework to understand the influence of lockdown measures on various trading costs, encompassing border-related costs, transport costs, and costs associated with behind-the-border issues. We then propose two testable hypotheses: firstly, that COVID-19 lockdown measures lead to a decrease in exports; and secondly, that these measures result in a reduction in imports for the country. To empirically test these hypotheses, the paper delves into detailed analyses of how lockdown measures affect different aspects of trade, including trade flows, trade margins, and trade diversification.

Our empirical model address potential concerns about spillover effects and endogeneity by considering factors such as internal product movement and financial assistance from local governments. Based on a comprehensive Chinese trade flow dataset and lockdown policy data at the provincial level, the results reveal a statistically significant negative correlation between the strictness of China's lockdown measures and its exports and imports, with reductions of 5.99% in exports and 17.3% in imports due to a complete lockdown. This suggests that stringent lockdowns had a greater impact on Chinese importers and foreign exporters. We also examines the trade response in terms of product diversification and intensive/extensive margin adjustments.

Additionally, the study shows that lockdowns had a negative impact on both intensive and extensive margin trade flows, indicating a potential reduction in product diversification. Furthermore, the paper analyzes the dynamic trade response to lockdowns over a three-year period, finding that the effects of Chinese lockdowns on were volatile for both exports and imports. Additionally, we employ a machine learning approach to demonstrate that (???) emerged as the most impactful COVID-related measures on trade. Furthermore, our analysis highlights notable variations in trade outcomes based on product and geographical characteristics. We observe a shift in China's role within the China-centered supply chain, as the disruptions induced by COVID-19 led to a decrease in the participation of China's trade partners in processing trade with the country. To ensure the robustness of our findings, we conduct a set of supplementary analysis focusing on city-level evidence of lockdown policies, which align closely with our baseline findings.

The remainder of the paper is structured as follows: Section 2 presents the conceptional framework, and section 3 details our quantity analysis methods. Second 4 discusses empirical methods. Section 5 presents regresion results and introduces several different set of evidences. Section 5 conclude the paper.

2. Conceptional Framework

In this section, we discuss the theoretical framework on how the COVID-19 lockdown policy affect imports and exports on the county. The lockdowns introduce various channels to increase the following three source of trading costs: the border-related costs, transport costs, and costs related to behind-the-boarder issues (Liu et al., 2022; Fang et al., 2022). By influencing these categories of trading costs, the particular lockdown policies can independently or collectively impact the supply and demand shocks experienced by policy-implementing countries. We posit the following two testable hypotheses: First, we hypothesize that the imposition of COVID-19 lockdown measures leads to a decrease in the exports. Second, lockdown measures cause reduction of imports of the country.

2.1 Lockdown on Exports and Imports

The COVID lockdown affect exporters by increasing the transport costs and costs related to behind-the-boarder issues. First, these policies lead to higher trading costs, ultimately decreasing exports. Internal movement restrictions impede domestic logistics, raising transport expenses for raw materials and finished products transported to and from domestic ports. China, a major global exporter, relies on processing trade for over 18% of its exports, underscoring the importance of smooth raw material and final goods circulation between factories and ports (Ministry of Commerce China, 2023). Reduced air and marine transportation during crises result in elevated flight and freight rates, potentially hampering exports, depending on importers' demand.

Second, increasing costs related to behind-the-border issues also reduce exports. Lockdown measures, such as travel restrictions and workplace closures, disrupt manufacturing capacities. Negative supply shocks can lead to demand shortages, causing output and employment contractions larger than the supply shock itself, leading firms to scale down production and export supply (Guerrieri et al., 2022). Additionally, lockdown-related effects increase costs for firms due to policy uncertainty, impacting their trade (Novy and Taylor, 2020). For example, China's Zero-COVID policy introduced uncertainty in importing and exporting times, potentially reducing orders for Chinese firms. Research, as shown by (Helble et al., 2007), underscores that trade transparency significantly influences bilateral trade. Consequently, foreign buyers may seek alternative trading relationships to avoid uncertainty in importing products, affecting exporters in the policy-implementing country.

As a response to COVID-19, lockdown measures in importing countries introduce additional trading costs, impacting the demand side of the economy. First, border measures increase border-related costs. For instance, Chinese customs implemented testing and disinfection measures for imported goods, leading to stricter customs clearance procedures and delays at the border. The more stringent disinfection procedures also necessitate trading partners to incur additional costs in transportation to prevent the spread of the virus (Portugal-Perez and Wilson, 2008). These delays incur expenses like storage and wage charges, elevating opportunity costs for trading firms on both sides and ultimately passing on to the buyers, resulting in demand shocks.

Second, COVID-induced supply chain disruptions raise transport costs for importers. Taking the bilateral trading routes between China and the United States across the Pacific as an example, westbound freight rates have experienced an uptick over the COVID period (Carter et al., 2022, 2023). Additional freight expenses, along with charges incurred due to extended vessel waiting times, amplify overall transport costs, influencing importers' demand. Thirdly, diminished earnings due to COVID lockdowns lead to reduced consumption demands, increasing behind-the-border costs. Even with sustained incomes, concerns about infections reduce visits to retail outlets and supermarkets, resulting in a contraction in demand. Additionally, lockdown measures such as gathering restrictions, stay-at-home orders, and internal movement restrictions limit people's opportunities to purchase products from public places, further contributing to the decrease in demand. It's important to note that the impact on demand may vary across product categories, with some, like online shopping goods, essential daily products, and infection-prevention items, experiencing smaller or even positive effects (Hayakawa and Mukunoki, 2021b).

2.2 Transmission of Lockdown and Trade Diversification

We identify various channels through which lockdowns impact trade diversification and decompose them into the intensive and extensive margins. The core hypothesis posits that lockdown policies increase trade costs, thereby reducing the profitability for more firms to enter export markets and subsequently leading to a decline in exports at both the intensive and extensive margins.

As illustrated in Figure 1, lockdown policies are associated with increased trade costs, encompassing transportation expenses and costs related to behind-the-border issues. Heterogeneous-firm trade literature, as exemplified by Chaney (2008), Helpman et al. (2008), and Melitz (2003), has shed light on the pivotal role of trade costs in shaping trade dynamics across both intensive and extensive margins. These costs can be further categorized into fixed and variable components. The model proposed by Melitz (2003) posits that within a landscape of heterogeneous firms, only a subset will engage in exporting or importing, contingent upon specific levels of fixed and variable trade costs, owing to inherent disparities in productivity. Building on this foundation, Chaney (2008) extends the framework introduced by Melitz (2003) to a global context, involving diverse countries with varying barriers. This expanded perspective allows for a nuanced analysis of how alterations in fixed and variable trade costs impact both the intensive and extensive dimensions of trade. According to Chaney (2008)'s theory, a reduction in variable trade costs not only increases the share of exports or imports for each trader (intensive margin) but also stimulates the entry of new firms enticed by improved profit prospects in trade markets (extensive margin). Simultaneously, a decrease in fixed trade costs lowers the productivity threshold, enabling less productive firms to engage in trading activities. This influx of active traders can drive trade growth at the extensive margin, while the intensive margin remains unaffected, given that fixed costs are regarded as sunk expenses for existing firms.

In light of these findings, we can posit that lockdown policies play a pivotal role in shaping trade diversification, influencing both export and import margins. These policies have a substantial impact on trade costs, encompassing transportation expenses and non-tariff barriers, thereby altering the landscape for traders. Without a thorough comprehension and successful mitigation of these costs, policies may fail to act as powerful tools in encouraging diversification in trading activities, potentially hindering the development of a more resilient and robust economic environment.

3. Data and Stylist Facts

3.1 Data Sources

The analysis relies on two primary data sources. The first dataset is sourced from the "The Oxford COVID-19 Government Response Tracker (OxCGRT) Data", compiled by Hale et al. (2021). We collect data period from January 2020 to December 2022, and this dataset offers multiple types of daily measurements of COVID-related policy, including the stringency index and various indicators of targeted policies. To ensure consistency with the monthly trade flow data, we compute the average of the stringency index. Notably, this dataset encompasses lockdown information for over 180 countries, with detailed records of Chinese lockdown measures at the province level. In our core analysis and baseline estimations, we employ the composite stringency indexes for Chinese provinces and trading partner countries.

The second dataset is the detailed bilateral trade data between China and all other countries, sourced from Chinese General Administration of Customs. This data records the monthly bilateral trade flow information of trade volume and value at the province-country-HS 6 product level. We restrict our sample data covering periods from January 2019 to December 2022. The COVID-19 pandemic outburst in early 2020, our inclusion of 2019 trade data works as control group trade flow that are not affected by the COVID-19 Pandemic. We report 560 HS-6 commodity groups trading between 31 Chinese provinces and 243 foreign countries, consisting 4,274,264 unique province-country-product pairs for the export data, and 951,359 unique pairs for import data.

3.2 *Trade Diversification and Margins*

Trade diversification involves expanding the range of products, rather than focusing solely on a single specialization. Among multiple trade diversification indicies, we apply the Theil index to gauge the level of diversification in both exports and imports of Chinese firms at the province level. This index assesses the disparity in trade values across various trade connections by quantifying the concentration of Chinese firms' import across different countries and sectors (the same apply to exports). Following the approach of Cadot et al. (2011) and Engemann and Jafari (2022), we compute the Theil entropy index ($T_{i,m,t}$), serving as a comprehensive measure of diversification for product k in importing province i in time t, is calculated as follows:

$$T_{ikt} = \frac{1}{N_{ikt}} \sum_{j=1}^{N_{ijkt}} \frac{V_{ijkt}}{\mu_{ikt}} \ln \left(\frac{V_{ijkt}}{\mu_{ijt}} \right), \tag{1}$$

where $\mu_{ikt} = \frac{1}{N_{ikt}} \sum_{j=1}^{N_{ikt}} V_{ijkt}$, and V_{ijkt} represents the value of trade for product k from source country j to importing province i in time t. N_{ikt} represent the total number of trade links (extensive margin) available for an importing province i.

Figure 3 provides an overview of traded product diversification with China's trade partners for both imports and exports, using the Theil index as a reference. When considering China's trading destinations and comparing them to the baseline year of 2019, the three-year average changes in product diversification show a wide range. The size of each circle represents the comparative trading volume; major trading partners like the United States, Hong Kong, and India exhibit a relative reduction in product diversification. Conversely, Chinese imports demonstrate a predominantly positive diversification change when compared to 2019.

As presented in our theoretical framework, the link between trade diversification and policy implication can be better understood by dinstiguishing the different margins of trade diversification. The intensive margins involves examining changes in diversification within a set of commonly traded goods over a period, which the extensive margin takes into account the impact of newly traded (or disappearing) goods with trade partners on diversification. Therefore, we adopt the definition of extensive and intensive margin from Bista (2015), where the decomposition of Y_{ijt} (import or export trade value) can be expressed as:

$$V_{ijt} = N_{ijt} \times \frac{V_{ijt}}{N_{ijt}}, \tag{2}$$

where V_{ijt} is decomposed into the extensive margin N_{ijt} and intensive margin $\dfrac{V_{ijt}}{N_{ijt}}$, respectively. N_{ijt} measured the number of product level province-country pair trade links, and the $\dfrac{V_{ijt}}{N_{ijt}}$ is the average of the trade values per trade link N per month. Consequently, we can deduce changes in the intensive trade margin (N) from shifts in total trade values (V) and changes in the extensive trade margin ($\dfrac{V_{ijt}}{N_{ijt}}$). The increase in diversification at the extensive margin entails an augmentation in the number of actively engaged export lines, while diversification at the intensive margin denotes a convergence in export shares.

In Figure 2, Panels A and B illustrate the changes in both the extensive and intensive margins of

China's exports and imports, respectively. Prior to and after the outbreak of COVID-19, both the extensive and intensive margins of Chinese exports exhibit similar trends, albeit with the intensive margin displaying greater fluctuation. On the other hand, Chinese imports demonstrate a more pronounced divergence post the COVID disruption in January 2020. Specifically, the intensive margin experiences a significant drop compared to the counterparts of the extensive margin.

3.3 Lockdown Stringency in China

The COVID-19 pandemic prompted a diverse array of government responses in China aimed at reducing the spread of the virus within communities and preventing the healthcare system from being overwhelmed. These measures include the closure of workplaces, schools, and public facilities, along with restrictions on domestic and international travel, among other policies. The stringency of these lockdown policies has been systematically consolidated into a composite COVID-19 stringency index within the OxCGRT dataset, which encompasses countries worldwide. In our discussion, we specifically concentrate on analyzing the COVID-19 stringency index in the context of China (Hale et al., 2021).

As depicted in the heatmap of Figure 4, from January 2020 to December 2022, several provinces in China implemented restrictions affecting various aspects of economic and social activity, as indicated by the OxCGRT lockdown stringency index. Following China's initial large-scale lockdowns in February 2020, restrictions were gradually eased, while the stringency of lockdown policies varied by province. In 2021, the policies were less strict, and the stringency measures began to intensify in 2022, coinciding with the emergence of the Omicron variant.[1] Notably, by December 2022, there was a significant reduction in stringency measures, aligning with China's policy lift from the "Zero-Covid" policy.

4. Empirical Methods

Our baseline specification establishes the trade effects of strictness of COVID-19 lockdown policy on Chinese trades, with the focus of exploiting variation in COVID-19 stringency at the provincial

[1] The variance of COVID-19 can be roughly classified into three major waves, the first wave, Delta, and the Omicron.

level, taking the following form:

$$Y_{ijkt} = exp\left(\beta_0 + \beta_1 \text{GRSI}_{it} + \alpha_{ijk} + \alpha_{jkt}\right) + \eta_{ijkt}, \tag{3}$$

where, the dependent variable Y_{ijkt} denotes export outcomes for product k exporting from province i to foreign country j at calendar month t. In our analysis, we focus on three major aspect of export outcomes, including trade flows, trade diversification, and trade margins, highlighting the policy implication of supply shock caused by COVID-19. Similarlly, when Y_{ijkt} represents import outcomes, the notation means province i imports product k from foreign country j. $GRSI_{it}$ represents the Lockdown Stringency Index, which systematically assesses the comprehensiveness of lockdown measures, taking into account a wide range of social, economic, health, and containment policies as outlined in the source data (Hale et al., 2021). To enhance interpretability, we rescaled the lockdown stringency index, originally ranging from 0 to 100, to a standardized range of 0 to 1. Therefore, β_1 being the coefficient of interest, can be interpreted as the impact of changes in lockdown stringency from no lockdown policy (stringency index equals 0) to full lockdown policy (stringency index equals 1) on trade outcomes. The stringency index used as the policy variable is improvement than using COVID death or case for lockdown policy measurement in literature, which introduce measurement errors, as they are influenced by regional variations in COVID testing capabilities, mainly determined by local government financial situations, demographic characteristics, and economic developments.

The baseline specification given by Equation 3 incorporates fixed effects for the Chinese province-foreign country-product combination, denoted as α_{ijk}. These are designed to absorb all time-invariant characteristics of province-country-product pairs, including distance, historical trade relationships, pre-existing infrastructure and transportation networks, as well as geographical, cultural considerations, and other unobserved time-invariant factors. Further, the model includes country-product-time fixed effects α_{jkt} capture both the demand and supply shock with either China being exporter or importer. When Y_{ijkt} stands for Chinese export outcomes, α_{jkt} captures the full spectrum of product demand shocks originating from foreign countries. These shocks can arise from factors such as foreign lockdown stringency, fiscal policy, and import tariff and non-tariff measures. Given that the dataset encompasses solely China, α_{jkt} also adjusts for the time-varying supply shocks across all China-foreign country-product pairs, which include variations due to China's export policy changes and bilateral transport costs. Conversely, when Y_{ijkt} represents Chinese import outcomes, α_{jkt} fully accounts for factors linked to foreign demand shocks and certain country-pair specific supply shocks. The inclusion of α_{jkt} fixed effects make sure that one country's foreign supply or demand shock affect different Chinese provinces trade equally, which help to interpret the identification in a Difference-in-Difference (DiD) fashion. For instance, to identify the effects of China's lockdown stringency on it's exports, the specification compares the export changes from Shanghai (stricter lockdown policy) to the United States against those from Zhejiang province (less strict lockdown measures) to the United States.

We apply Poisson Pseudo Maximum Likelihood (PPML) estimation to estimate Equation (3) due to its ability to preserve the multiplicative structure inherent in gravity-type models (Silva and Tenreyro, 2006). Additionally, it exhibits resilience against unknown patterns of heteroskedasticity and allows the dependent variable to remain in its original levels. In contrast to utilizing aggregated trade data, we exploit trade data at a more detailed HS 6-digit level leads to a relatively increased occurrence of zero-values. Since omitting zero trade flows could potentially lead to a misrepresentation of the COVID-19 stringency impact on trade in specific months, this methodology permits us to incorporate instances of zero trade flows in our estimation process.

Several concerns have been raised regarding the model strategy. There's a suspicion of potential internal product movement leading to a spillover effect. Specifically, firms in provinces with stricter lockdown measures might relocate to those with more lenient restrictions. Given that a significant proportion of lockdowns include movement restrictions, such relocations are unlikely. According to the OxCGRT data, China's COVID restriction on domestic internal movement policy was implemented 93.97% of the time over the course of three-year COVID lockdowns. One endogeneity concerns in our analysis could be the financial assistance from local governments, which may act synergistically with lockdown policies, thereby weakening the observed impact on trade. We will discuss these issues in the result discussion.

5. Results

5.1 Trade Responses to Lockdowns

In examining the causal relationship between lockdown stringency and trade patterns, our baseline results, presented in columns (1) and (3) of Table 1. The results reveal a statistically significant inverse correlation between the stringency of China's lockdown measures and its respective exports and imports, with coefficients estimated at -0.0618 and -0.1899, respectively. It indicate that a complete lockdown, characterized by a stringency shift from 0 to 1, leads to a reduction in China's exports by 5.99% (derived by $exp(-0.0618) - 1$), indicating that with the fixed demand shocks by forign countries, the COVID leaded supply shock reduced production and trade capability of Chinese firms for 5.99%. On the other hand, with fixed supply shocks of foreign countries, the COVID caused demand shock dropped overall imports in China for 17.3% (derived by $exp(-0.1899) - 1$), which surpasses the effect on exports. A potential confounding factor in our analysis could be the financial assistance from local governments, which may act synergistically with lockdown policies, thereby populate the observed impact on trade. When incorporating measures of this economic support in our baseline model, as illustrated in columns (2) and (4), the coefficients are similar to that of the coefficients in columns (1) and (3). The results ensure the robustness of our baseline results.

We proceed to examine the impact of COVID-19 lockdown stringency on China's trade diversification, as depicted in Table 2. Employing the Theil index as the outcome variable, we calculate the diversification index at two levels of aggregation. Specifically, the Theil index for columns (1) and (3) is aggregated at the Chinese province-product-time level, while that for columns (2) and (4) is aggregated at the province-country-time level. By combining different sets of fixed-effects, this varied approach to aggregation enables us to investigate how the disruptions in the supply chain induced by COVID-19 channels into changes in trade diversification. The coefficients in columns (2) and (4) are negligible, whereas those in columns (1) and (2) are of significantly larger magnitude. This indicates that the COVID-19 lockdown stringency yields two major implications. Firstly, when comparing coefficients between column (1) and (3), the Chinese lockdown policies have a notable reducing effect at 10.4% and 19.3% on both export and import diversification, respectively, although the coefficient in column (1) does not attain statistical significance. This suggests that, given a fixed supply shock, provinces in China respond to lockdowns by increasing their demands for less diversified products from foreign countries. As China serves as the global manufacturing hub, it would be intriguing to understand whether this contraction in port products stems from reductions in raw materials. Secondly, the higher in coefficient magnitude in column (1) and (3) than that in column (2) and (4) means indicates that, in response to stricter lockdown stringency measures at the provincial level, Chinese firms reduced their trade diversification primarily by reallocating trade across products rather than re-diversifying across different countries.

As described in the theoretical framework about the relationship between trade diversification and trade margins, the aggregate impact of lockdowns on bilateral trade flows combines two margins of adjustment: the reaction of the bilateral export or import value by product (intensive margin), and the reaction through the number of sector or products traded within country pairs (extensive margin). These two effects combined explain the impact of lockdowns on the value of bilateral aggregate exports or imports. Results of Table 3 show a significant negateive effects of the lockdowns on both exports and imports, which is inline with results in Table 1. We estimate the effect of lockdowns on the number of trade links across province-country-product pairs, with the products are at HS-2 and HS-6 level. Additionally, we discuss the effect of lockdowns on HS-6 products within the broader HS-2 sectors. This approach allows for the examination of the impacts of COVID-19 on diverse sectors, as well as specific products within these sectors.

As specified in columns (2) and (8), lockdowns affected both Chinese exports and imports at the HS-6 product level through the extensive margin. This result can be attributed to the decline in the number of HS-2 sectors traded (columns (1) and (7)), as well as a reduction in the number of HS-6 products traded within specific province-country-sector pairings (columns (3) and (9)). The same applies to the intensive margin. However, when it comes to the COVID lockdown policy on Chinese imports, the intensive margin dominates the trade diversification more than the extensive margin, as shown by the higher magnitude of coefficients for columns (10)-(12) compared to those for columns (7)-(9) in panel B. On the other hand, the similarity in the magnitude of coefficients when comparing the extensive and intensive margins in the corresponding specifications in

Panel A shows that the intensive margin (higher volumes) and extensive margin (new trade lines) contribute equally to the export flows.

5.2 Dynamic Trade Response to Lockdown

Over the course of the COVID-19 pandemic from January 2020 to December 2022, Chinese provinces implemented lockdown measures in response to changing case numbers, fatalities, and the emergence of different virus variants. These policies were customized to suit the specific characteristics and severity of the COVID-19 variants in each province. This customization led to a range of changes in trading costs, stemming from disruptions in areas like supply chains, distribution channels, and transportation logistics. As a result, shocks on both the supply and demand affected trade in China.

In this analysis, we investigate how the impact of lockdown measures on trade patterns evolved over the course of the three-year COVID-19 pandemic. We revisit our baseline model, incorporating interaction terms between the lockdown strigency and a set of time dummy $Quarter_q$, with interval by three-month periods from January 2020 to December 2022. As Equation 4 shown, each coefficient β_q in this specification signifies the effects of lockdown stringency on bilateral exports or imports within specific product categories at different time periods. For a more comprehensive analysis, we utilize data from January to December 2019 as a comparison group.

$$Y_{ijkt} = exp\left(\beta_0 + \sum_{q=1}^{12} \beta_q \text{GRSI}_{it} \times Quarter_q + \alpha_{ijk} + \alpha_{jkt}\right) + \eta_{ijkt}, \tag{4}$$

The results in Figure 6 illustrate the impact of lockdown stringency on Chinese trade over time, using the first quarter of 2020 as the base period. As depicted in panel (A), the effects of the Chinese lockdown on its exports are strongest in early 2020 and late 2022, showing statistically significant negative impacts. Between the fourth quarter of 2020 and the second quarter of 2022, these effects diminish and are largely statistically insignificant. A potential reason for these changes is that both firms and households were able to maintain their economic activities by adapting to frequent lockdowns (Berthou and Stumpner, 2022). For instance, the rise of online shopping and teleworking has increased trade demand for specific products (Hayakawa and Mukunoki, 2021b).

Regarding the influence of lockdown policies on Chinese imports, the effects are less volatile, and the impact of the lockdown is greater on imports than on exports. The findings suggest that firms and households are less adept at adapting to the recurrent norms of COVID-related lockdowns.

5.3 Analysis of China-Centered Global Supply Chain

Our baseline results have confirmed that stringent COVID-19 lockdown measures significantly impacted China's trade dynamics, potentially challenging its role as a global production hub. Processing trade has played a pivotal role in China's merchandise trade, and the COVID-19 pandemic has caused significant fluctuations in China's portion of processing trade, as depicted in Figure 5. The pandemic may have reshaped China's position as the epicenter of the global supply chain globally. Therefore, we have two main goals for this analysis. First, we aim to answer how raw materials contribute to the notable drop in Chinese imports, a question raised in section 5.1. Second, we seek to understand how the Chinese lockdown policy affects foreign countries with high involvement in their supply chain network with China.

To address the first question, Figure 7 presents coefficients of lockdown policies on trade flows within different product groups, as classified by the United Nations Broad Economic Categories (BEC) scheme. The BEC scheme categorizes each HS 6-digit product into one of three classifications: "intermediate inputs," "capital goods," and "final consumption." Given the heightened importance of global value chains, this analytical differentiation between intermediate and final goods trade becomes particularly significant, especially in light of China's dual role as both the epicenter of COVID-19 and a major manufacturing hub. To further refine our analysis, we adopted the BEC Rev.5 to classify intermediates for countries' participation in Global Value Chains (GVCs).[2] The findings in Figure 7 indicate that intermediate goods account for a significant proportion of the trade losses in both Chinese imports and exports, at 20.6% and 9.7% respectively. This allows us to conclude that raw materials played a substantial role in the notable drop in Chinese imports. Additionally, it is noteworthy that the lockdown policies led to a considerable

[2] Due to the broad definition of intermediates in BEC Rev.4, we opted for BEC Rev.5, which introduced a specific category for processed intermediate goods. This adjustment enabled us to more accurately identify processing trade related to China.

decrease in imports of Chinese consumption goods, while the resilience of Chinese consumption goods exports remained evident.

Table 4 presents a heterogeneity analysis of the impact of lockdown stringency on trade outcomes, with a special focus on China's role in the global supply chain involving other countries. To do so, we define a variable ValueAdded to identify countries that have high involvement with intermediate goods with China. The variable is defined at two levels: one at the foreign country level and one at the foreign country-product level. When ValueAdded$_j$ is defined at the country level, it represents a "country with a high involvement (share) of trade with China," which equals one when the country is ranked as one of the top 20 countries that China has intermediate goods trade with, and zero otherwise based on global trade data as of the year 2019. Further elaboration on the calculation process can be found in the appendix. ValueAdded$_{jk}$ is set to one when the share falls within the first 20 percentile of countries with respect to their share of trade across all trade partners, and it's identified at the product-country level. This distinction helps demonstrate how dependence on the supply chain with China affects the governmental response to COVID-19. By doing so, we are able to check whether the transmission of supply or demand shocks mainly occurs through the product or the country paths.

The coefficient of the interaction term in Column (2) indicates that countries importing from China and having higher involvement with China in their supply chain are largely unaffected by the Chinese supply shock. This result is reasonable given that China is typically an importer of raw materials rather than an exporter. On the other hand, when considering the product effect by examining the coefficient in column (1), it reveals that other countries involved in importing raw materials from China experience a slight reduction in their imports. This shows that the supply shock from China still has an impact on the foreign market, with China serving as the raw material supplier. Regarding Chinese imports, the significantly negative results of the interaction terms in columns (3) and (4) are not surprising. As China is the major production hub of the world, the demand shock from China significantly harms countries that heavily rely on China as the source of raw materials.

5.4 Binding COVID-19 Response Policies

In this section, we exploit specific Chinese governmental policies from the Oxford governmental response data by including all the specific trade policies in the model. As presented in the descriptive statistics in Table 5, we specify the seven specific policy as sets of dummy variables. An starting point for this research target is implement similar model setup to our baseline Equation 5 as below:

$$X_{ijkt} = exp\left(P_{it}'\beta + \alpha_{ijk} + \gamma_{jkt}\right)\mu_{ijkmt}, \tag{5}$$

where, the i, j, k, and t respectively index province, country, product, and time. X_{ijkt} are bilateral trade flows, and the α_{ijk}, and γ_{jkt} are product-country-product, and country-product-time fixed effects. P_{it}' are our covariates of interest, constructed as dummy for the presence of a specific COVID-19 policies at province-year-month level, such as school closure, workplace closure, or other five COVID specific policies.

However, a major estimation challenge in our setting is that the large number of policies that could be highly correlated. For instance, it might be the case that one or more policies functions as the main binding policies, while the other policies are not. However, our existing regressions are limited in its ability to capture the impact of binding COVID-19 response policies as they suffer from endogeneity bias caused by multicolinarity issue. To deal with this issue, we modify the identifcation approach and use a machine learning approach that work as an approch of variable selections to identify the binding COVID-19 policies. We will implement a data-driven approach to mitigate potential endogeneity concerns associated with multicollinearity through repetitive simulations with all possible sets of policies. We augment the estimation equation with a regularization term in that enables us to identify binding policies. This penalty term modifies the Poisson PML minimization problem that defines the the causal problem as follows:

$$\left(\widehat{\alpha}, \widehat{\beta}, \widehat{\gamma}\right) := \arg\min_{\alpha,\beta,\gamma} \frac{1}{n}\left(\sum_{i,j,k,t}\left(\mu_{ijkt} - X_{ijkt}\ln\mu_{ijkt}\right)\right) + \frac{1}{n}\sum_{l=1}^{m}\widehat{\phi}_l\lambda|\beta_l|, \tag{6}$$

where the notations are the same as in Equation 5 and n denotes the number of observations. The right-hand side of this estimation equation consists of the standard Poisson PML minimization problem and the Lasso penalty term, which includes the tuning parameters $\hat{\phi}_l \geq 0$ and $\lambda \geq 0$. We include the diagonal matrix $\hat{\phi}_l$ for regressor-specific penalty weights in addition to the standard Lasso penalty λ (Belloni et al., 2016). Along with the standard tuning parameter λ, $\hat{\phi}_l$ refines the model iteratively across the set of regressors. As a result, larger Lasso penalties shrink the β-vector to zero, allowing us to identify the binding COVID-19 policies. We penalize the COVID-19 policies but leave the high-dimensional fixed effects unpenalized (Breinlich et al., 2022). This identification strategy implies that for given $\alpha, \beta, \gamma, \delta$ and ϵ, we obtain the estimates by solving the standard Poisson PML minimization problem (Correia et al., 2020). We use a "plug-in" LASSO approach, which we have detailed description in the Appendix.

The results for the LASSO approach are shown in Table 5. Column (1) of Panel A and B presents the results of our first-step LASSO regression, displaying only the coefficients that the LASSO identifies as non-zero. The LASSO selects a different number of individual lockdown measures related to the binding restrictions on Chinese exports, including "Workplace Closing," "Cancel Public Events," "Closing Public Transport," and "Stay at Home Requirement." Columns (2) to (6) in panel A represent the "post-LASSO" PPML regression, where we analyze the trade value in column (2) and the trade margins in columns (3) to (6). We observe that some of the selected individual policies have statistically significant coefficients. Specifically, "Workplace Closing" and "Stay at Home Requirement" are associated with a 8.5% and 1.5% decrease in Chinese exports, highlighting how these policies have slightly affected the trading capability of Chinese firms due to the COVID-induced supply shock. However, the changes in export values for these two individual lockdown measures are mainly derived by the reduction in the intensive margin of trade than a reduction in trade links. Interestingly, the "cancel public events" show a significant reduction in extensive margin, while the increase of intensive margin matches the the change of extensive margin. When it comes to the impact of individual lockdown measures associated with demand shocks, as presented in Panel B of Table 5, the"workplace closing" and "close public transport" are the driver of reduction of Chinese imports.

5.5 Dynamic City Evidence

In order to analyze the governmental response to COVID-19 in China, it's important to note that their lockdown policy is implemented at the local level. To address this, we conducted a comprehensive analysis using both provincial and prefecture-level trade data. The latter was collected from Chinese city-level trade data sources, providing monthly aggregate trade values from 195 cities across provinces. However, it's worth mentioning that this data lacks industry or product characteristics. To further enhance our analysis, we incorporated "Dynamic Zero-COVID risk area" data, obtained from the Chinese National Governmental Information Sharing Platform. This data outlines the risk-based approaches adopted by China in response to the pandemic. These measures vary based on the risk level of the regions and are designed to optimize resource allocation for COVID-19 containment. This integrated data allowed us to conduct a thorough event study framework, assessing the dynamic impact of COVID-19 lockdown on Chinese trade at the city level. Our approach categorized cities in middle and high-risk areas as treated, while cities in low-risk areas and non-designated areas served as controls. This method accounted for the transition from control group to treatment group, aligning with established methodologies for city-level analysis. The detailed construction of city level data and model setting are in Appendix. The model used in this study is summarized by the provided equation below:

$$I_{ist} = exp\left(\sum_{e=-6,e\neq-1}^{6} \beta_e 1\{e = t - G_i\} + \alpha_{s,yr} + \alpha_{i,m}\right)\eta_{it}, \tag{7}$$

where the city, and month are denoted by i, and t. The outcome of interest, I_{it}, is measured as the total import or export values from city i in time t. To control for unobserved factors that could affect the relationship of interest, we include fixed effects at the month (α_i) levels. These fixed effects allow us to account for supply shocks from the Chinese city over time. G_i indicate the time that treated city unit i is for the first time for the event window. Therefore, $t - G_i = e$ represents the "event time" that equals to the duration month of city i that has been treated. We include dummy variable $1\{t - G_{ijk} = e\}$ that equals to one when city i is treated for e periods away from G_i. The $e > 0$ corresponds to treatment effects e month after the event, and $e < 0$ are accord with the pre-trend of effects. We choose to use a 13-month event window that relates to 6 months lead and

6 months lags periods, and we omit the treatment lead indicators related with $e = -1$. Defined by the event window, η_{it} is the error term. Our parameter of interest is β_e, which measures how the relative trend of treated city.

Figure 8 displays event studies on China's trade response to risk-area policies in Chinese cities. The figures show dynamic treatment estimates along with their 95 percent confidence intervals. Additionally, estimates from static regression models are represented by dashed red lines. The figure's footnote includes Wald test statistics for pre-trends and p-values for the static effect. No significant pre-trends are observed for risk-area policies on both exports and imports. By conditioning on high-dimensional fixed effects, the treatment group demonstrates similar trends during the pre-treatment period compared to the control groups, validating the research design (Freyaldenhoven et al., 2019). As indicated by the overlaid static estimates and post average effects, all four categories of results show negative trade effects of lockdown policies, consistent with our province-level estimations. However, compared to the "middle-risk" lockdown policy, the "high-risk" area policy has a higher negative export effect of 11.57%, which is double the trade effect of the "middle-risk" policy. For both middle and high-risk policies, their impact on Chinese imports remains relatively similar, around 7.4%.

Both risk-area policies display volatile treatment effects over time. For imports, the trade effects of the middle-risk area policy are most significant at the contemporaneous level (event time 0), followed by several months of trade recovery. However, a noticeable drop in imports occurs five and six months after policy implementation. Interestingly, trade effects for the "high-risk" area remain relatively consistent, although months 2 and 6 experience less import disruption. Both risk-area policies exhibit similar temporal patterns in trade effects: Chinese exports witness a significant recovery for four consecutive months after policy implementation, followed by a trade drop in the fifth month and a subsequent recovery in the sixth month.

6. Conclusion

In this study, we conducted a comprehensive analysis of the impact of COVID-19 lockdown measures on China's trade patterns, drawing upon a rich dataset encompassing various dimensions of trade dynamics. Our findings shed light on the dynamic and multifaceted nature of the pandemic's effects by shedding light on how the supply chain disruption leaded supply and demand shock affect trades. Specifically, a complete lockdown, denoting a shift from no restrictions to comprehensive measures, resulted in a notable reduction of approximately 15.37% in China's exports and around 18.51% in imports. Furthermore, lockdowns led to a reduction in both export and import diversification, and Chinese provinces responded to lockdowns by increasing their demands for less diversified products from foreign countries. Among the transmission of supply chain disruptions, the shocks channels into the changes of Chinese imports majorly through intensive margin other than extensive margins, contributing to a comprehensive understanding of the trade dynamics during the pandemic.

We extended our analysis to investigate the dynamic response of lockdown measures, finding that the effects of lockdown stringency on Chinese exports were most significant in the early and late stages of the pandemic, with adaptations such as online shopping and teleworking partially mitigating the impact. Importantly, lockdown policies had a more substantial and enduring impact on imports, reflecting the challenges faced by firms and households in adapting to recurrent lockdowns. Our research contribute the broad literature by addressing the role of China in the global supply chain and examined how raw materials contributed to changes in Chinese imports. It highlighted that countries highly involved in China's supply chain network experienced limited disruptions in their imports, while China's demand shock significantly affected countries relying on it as a source of raw materials. Finally, we utilized a data-driven approach to identify the binding COVID-19 response policies and their impact on trade. This analysis provided insights into how specific policies, such as workplace closures and stay-at-home requirements, affected Chinese exports and imports, shedding light on the nuanced effects of different lockdown measures.

In summary, our study contributes to a comprehensive understanding of the complex relationship between supply chain disruptions and trade patterns. The findings have important implications for policymakers and businesses seeking to navigate the challenges posed by future supply chain shocks to global trade. Additionally, China's role in the global supply chain may be further evaluated using global level data that allow us to compute how China's role channels into their trade and supply chain. . Such insights will help advance the resilience of the global supply chain and make trade more robust to future disruptions.

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Figures and Tables

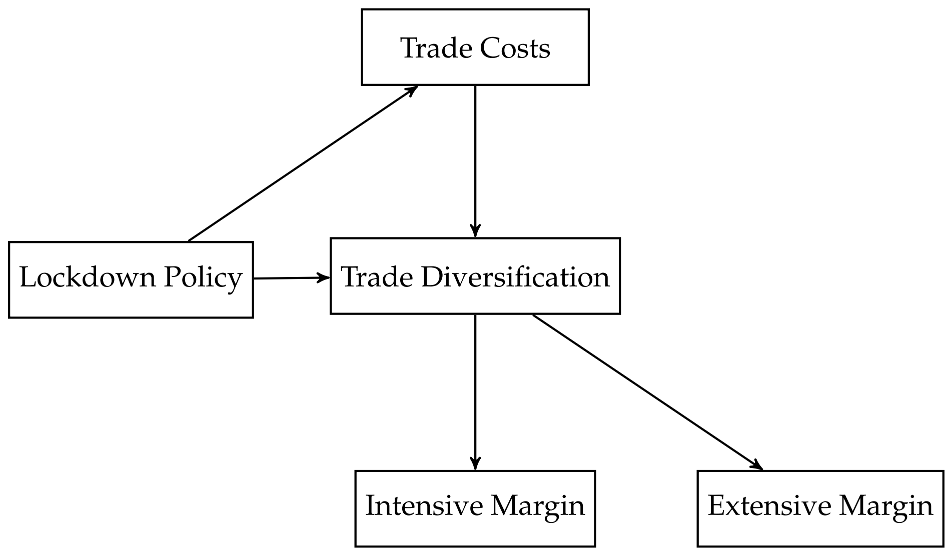
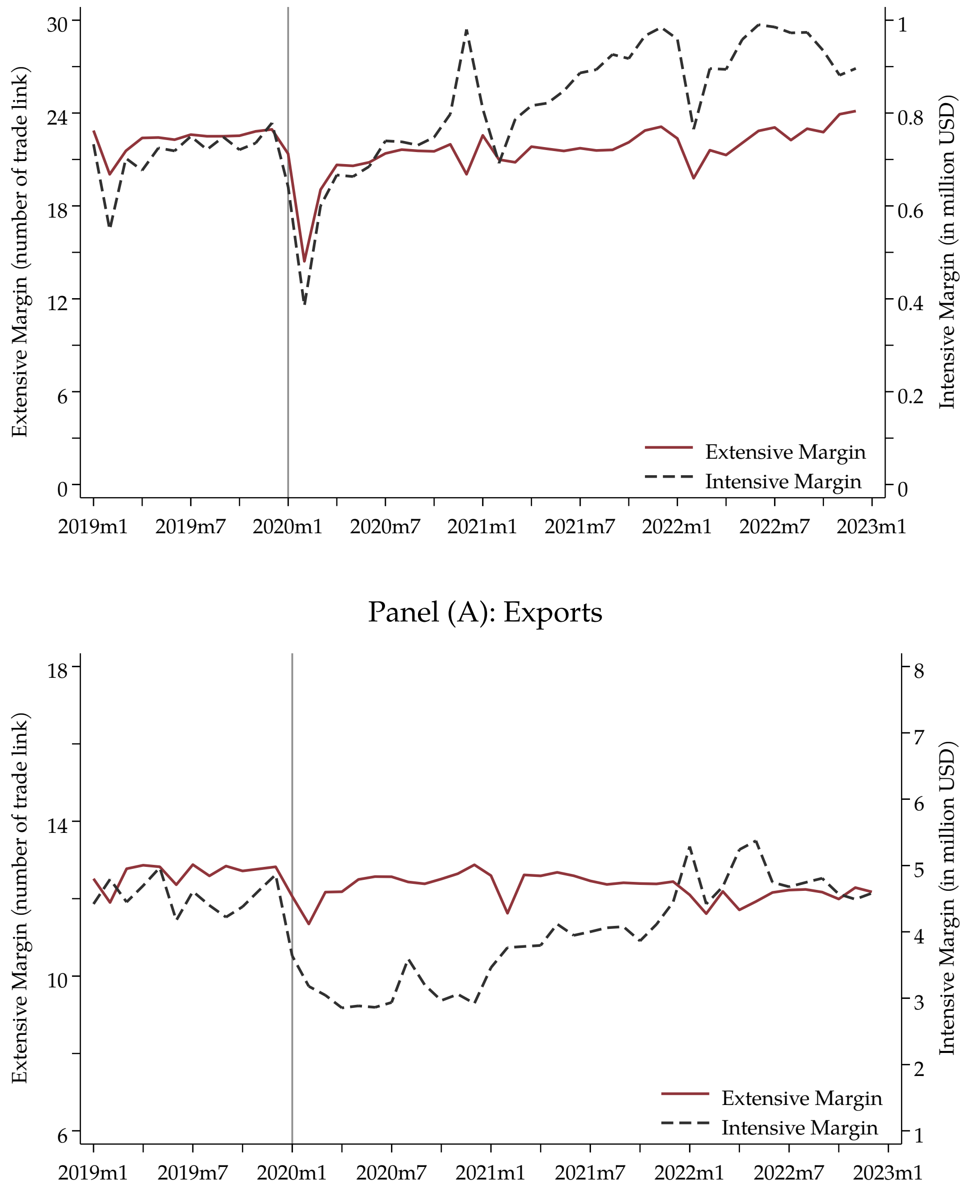


Figure 1: Transmission Channels Between Lockdown and Trade Diversification

Notes: This figure illustrates the conceptual work of transmission channel of lockdown policies and trade diversification.

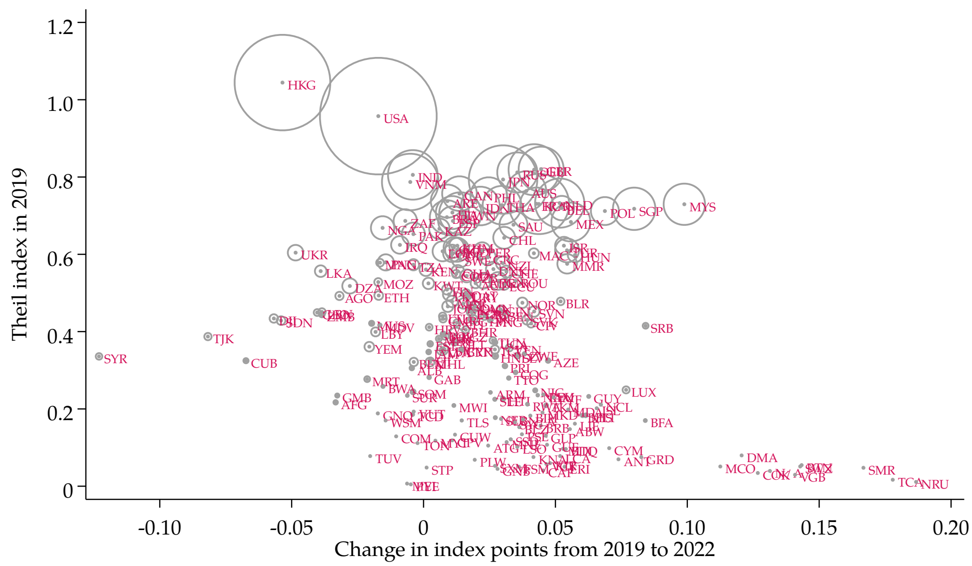


Panel (A): Exports

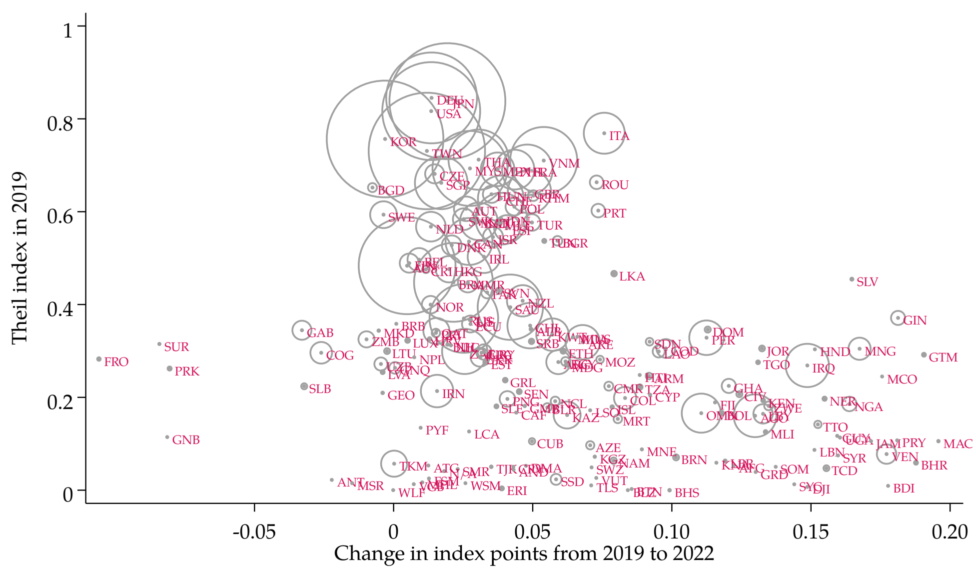
Panel (B) Imports

Figure 2: Extensive Margin and Intensive Margin in China

Notes: The figures illustrate the extensive margin and intensive margin for exports and imports of China. The extensive measure the numbers of trade links at the China-foreign country-product level. The intensive margin measures the average of the trade values per trade link, measuring at the million USD.



Panel (A): Exports



Panel (B) Imports

Figure 3: Theil index in 2019 and change in post COVID period compared with 2019

Notes: The figures show the diversification index (Theil index) comparison between 2019 and 2020-2022, with horizontal line representing averange changes and vertical line shows the unit Theil index level in 2019. The size of circle shows the average total value of exports and import for Panel A and B, respectively.

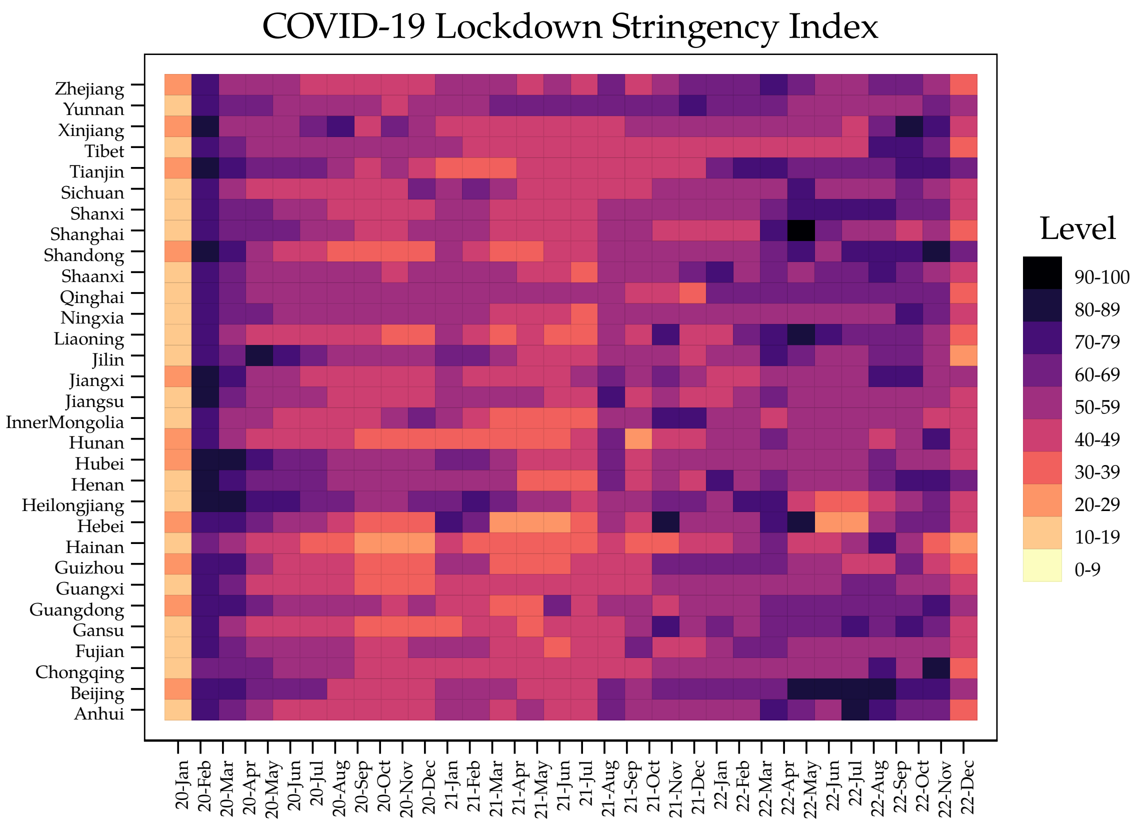
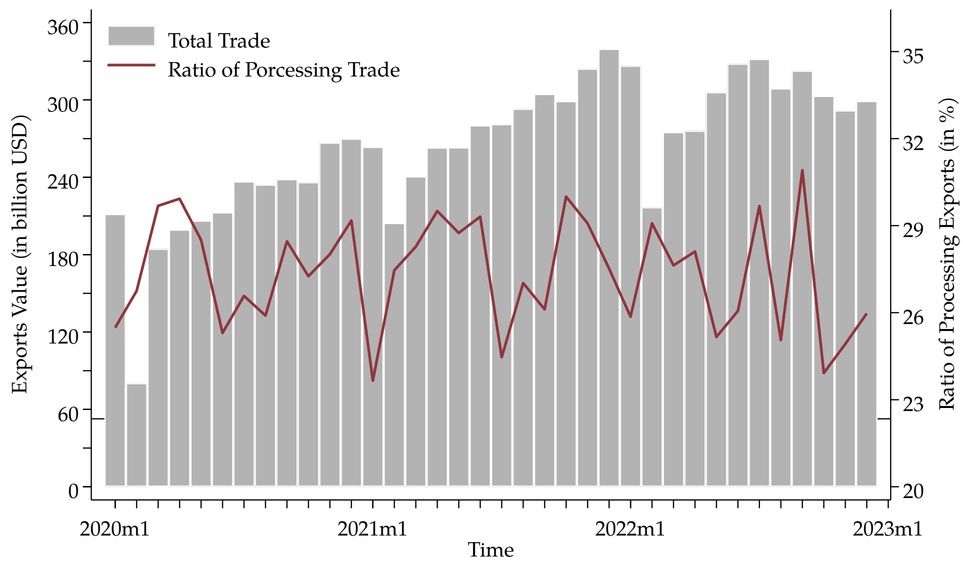
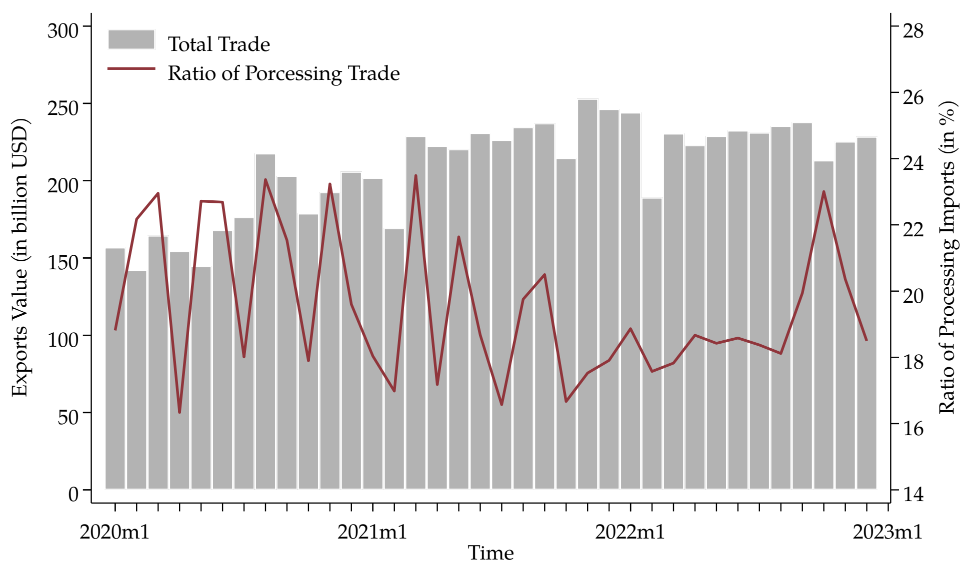


Figure 4: OxCGRT Lockdown Stringency Index in China

Notes: This figure illustrates provinces of China's COVID-19 lockdown strigency index from January 2020 to December 2022. The data is sourced from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021).



Panel (A): China's Exports



Panel (B) China's Imports

Figure 5: Total and Processing Trade in China

Notes: The bar figures illustrate China's total exports and imports overtime, and the units are at one billion USD. The red solid lines show the corresponding ratio of processing trade of China, measured in percentage.

Table 1: Lockdown Policy on Trade of China

	Exports		Imports	
	(1)	(2)	(3)	(4)
Stringency-Province	-0.0618*	-0.0630*	-0.1899***	-0.2033***
	(0.0337)	(0.0358)	(0.0465)	(0.0452)
Economic Support		-0.0072		-0.0794*
		(0.0368)		(0.0453)
Province-Country-HS2 FE	Yes	Yes	Yes	Yes
Country-Time FE	Yes	Yes	Yes	Yes
Observations	3,924,258	3,924,258	4,026,978	4,026,978
Pseudo R-squared	0.972	0.972	0.975	0.975

Notes: The table provides trade flow estimates between Chinese provinces and foreign countries over the period from January 2019 to December 2022. To calculate the trade impact using our estimated coefficients, we employ the formula $[Exp(\beta) - 1] \times 100\%$, where β represents the estimated coefficient. Roboust standard errors are clustered by province-country pairs. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table 2: Estimation of Lockdown Strigency on Diversification

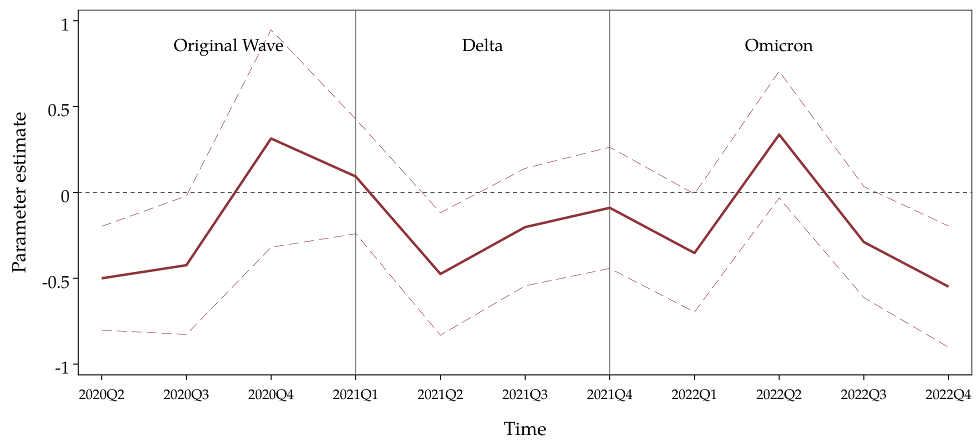
	Export		Import	
	(1)	(2)	(3)	(4)
Stringency-Province	-0.1096	-0.0017***	-0.2140***	-0.0016***
	(0.1044)	(0.0004)	(0.0448)	(0.0006)
Province-Country FE		Yes		Yes
Country-Time FE		Yes		Yes
Province-Product FE	Yes		Yes	
Product-Time FE	Yes		Yes	
Observations	3,187,295	245,785	2,100,497	150,347
Pseudo R-squared	.974	.987	.978	.973

Notes: The table provides estimates of lockdown strigency on Theil Index January 2019 to December 2022. The outcome variable for column (1) and (3) are the diversification at the Chinese province-product-time level, while that of the column (2) and (4) are at the province-country-time level. To calculate the trade impact using our estimated coefficients, we employ the formula $[Exp(\beta) - 1] \times 100\%$, where β represents the estimated coefficient. Roboust standard errors are clustered by province-country pairs. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

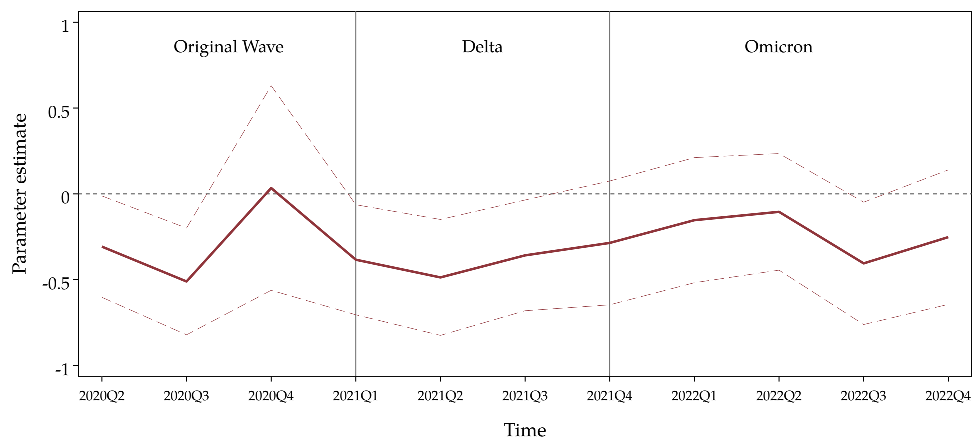
Table 3: Lockdown Policy on Extensive and Intensive Margin

	Panel A: China's Exports					
	Extensive Margin			Intensive Margin		
	HS-2	HS-6	HS-6 Nested	HS-2	HS-6	HS-6 Nested
	(1)	(2)	(3)	(4)	(5)	(6)
Stringency-Province	-0.107***	-0.183***	-0.156***	-0.184***	-0.163***	-0.099**
	(0.009)	(0.018)	(0.014)	(0.033)	(0.054)	(0.043)
Observations	245,785	245,785	245,785	245,785	245,785	245,785
Pseudo R-squared	.768	.954	.799	.953	.763	.896
	Panel B: China's Imports					
	Extensive Margin			Intensive Margin		
	HS-2	HS-6	HS-6 Nested	HS-2	HS-6	HS-6 Nested
	(7)	(8)	(9)	(10)	(11)	(12)
Stringency-Province	-0.068***	-0.110***	-0.070***	-0.325**	-0.573**	-0.282***
	(0.010)	(0.013)	(0.012)	(0.139)	(0.237)	(0.098)
Observations	151,801	151,801	151,801	151,801	151,801	151,801
Pseudo R-squared	.817	.977	.774	.921	.923	.923

Notes: The table provides trade flow estimates between Chinese provinces and foreign countries over the period from January 2020 to December 2022. To calculate the trade impact using our estimated coefficients, we employ the formula $[Exp(\beta) - 1] \times 100\%$, where β represents the estimated coefficient. Robust standard errors are clustered by province-country pairs. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).



Panel (A): China's Exports



Panel (B): China's Imports

Figure 6: China's Dynamic Trade Response to Lockdown Strigency

Notes: The solid lines in the figures illustrate China's trade response to lockdown stringency over time, and the dashed lines on either side of the parameter coefficients represent the 95% confidence intervals. The time periods in the horizontal line cover from second quarter of 2020 to fourth quarter of 2022, using the first quarter of 2020 as the reference group. The three intervals distinguished by solid black lines represent the three principal variants of the COVID-19 virus over time, including the original wave (2020Q1 - 2021Q1), Delta (2021Q1 - 2021Q4), and Omicron (2021Q4 - 2022Q4), respectively.

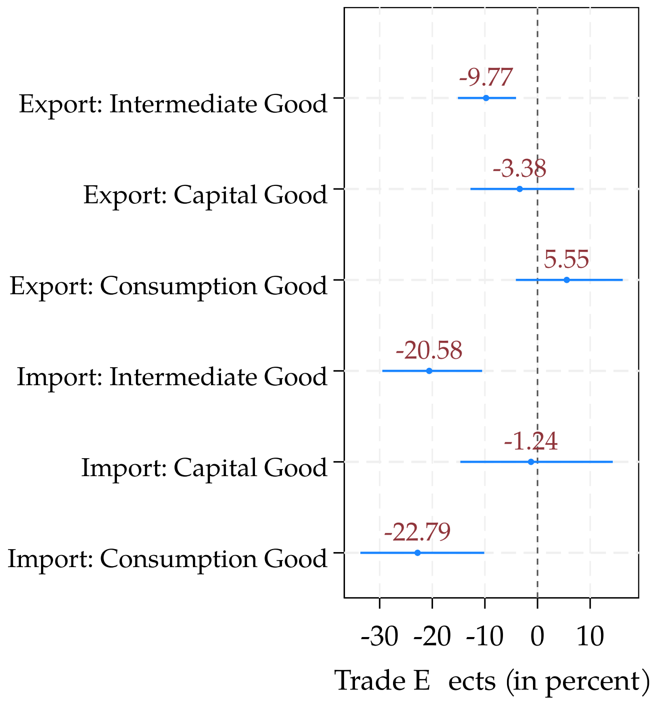


Figure 7: Lockdown Policy on Trade by Product Groups

Notes: This figure illustrates the trade effects by product types classified by BEC Rev.5.

Table 4: Lockdown Strigency on Value Added Trades

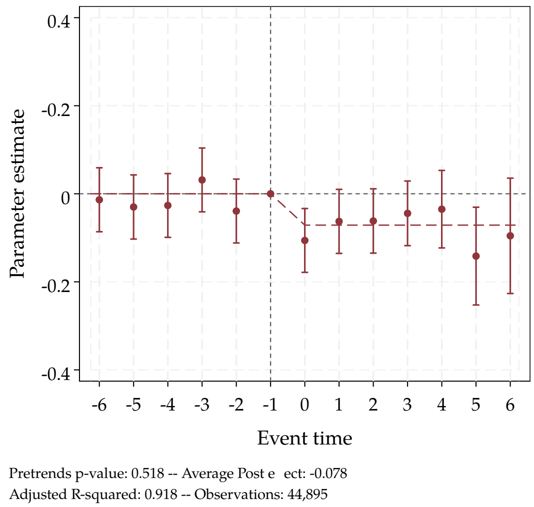
	Exports		Imports	
	(1)	(2)	(3)	(4)
Strigency	-0.0352	-0.0756	-0.0861**	-0.0280
	(0.0430)	(0.0479)	(0.0427)	(0.0592)
Strigency × $ValueAdded_{jk}$	-0.0677*		-0.1443**	
	(0.0393)		(0.0705)	
Strigency × $ValueAdded_j$		0.0255		-0.1513*
		(0.0710)		(0.0898)
Observations	36,615,298	27,269,382	9,740,545	8,664,283
Pseudo R-squared	.952	.955	.972	.971

Notes: Standard error clusters are applied at the import-export country pairs. Asterisks are used to denote p-values < 0.10 (*), < 0.05 (**), or < 0.01 (***). The second and third models introduce the interaction term between the stringency index and the variable dummy ValueAdded. Intermediate$_{jk}$ operates at the country-product level, signifying a value of one when product k of country j is categorized as intermediate goods as defined by BEC Rev.5, and zero otherwise. ValueAdded$_j$ is defined at the country level, representing a "country with a high involvement (share) of trade with China". This share is computed using global trade data as of the year 2019. Further elaboration on the calculation process can be found in the appendix. ValueAdded$_j$ is set to one when the share falls within the first 25 percentile of countries with respect to their share of trade across all trade partners.

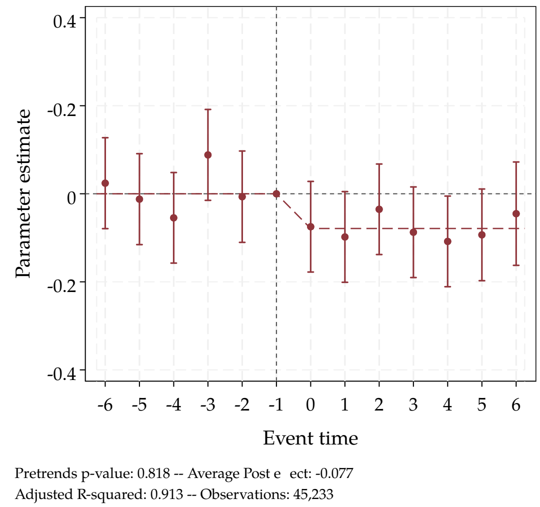
Table 5: Lasso Selection of COVID-19 Policies on Chinese Exports

	Plug-in LASSO	Post-LASSO	HS-2		hS-6 Nested	
	Value		Extensive	Intensive	Extensive	Intensive
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Exports						
Workplace Closing	-0.1168	-0.0890***	-0.0046	-0.0611*	-0.0151*	-0.0383
	(0.0342)	(0.0337)	(0.0068)	(0.0341)	(0.0082)	(0.0418)
Cancel public events	0.1398	0.0232**	-0.0596***	0.0506**	-0.0716***	0.0511*
	(0.0184)	(0.0118)	(0.0044)	(0.0197)	(0.0079)	(0.0297)
Close public transport	-0.0618	0.0083	0.0084***	-0.0015	0.0290***	-0.0081
	(0.0126)	(0.0075)	(0.0025)	(0.0098)	(0.0041)	(0.0121)
Stay at home Requir.	-0.0147**	-0.0147**	0.0083***	-0.0209***	-0.0050	-0.0106
	(0.0066)	(0.0066)	(0.0021)	(0.0070)	(0.0032)	(0.0092)
Observations	5,199,807	5,199,807	245,785	245,785	245,785	245,785
Pseudo R-squared	.971	.971	.768	.953	.799	.896
Panel B: Imports						
	Plug-in LASSO	Post-LASSO	HS-2		hS-6 Nested	
	Value		Extensive	Intensive	Extensive	Intensive
	(1)	(2)	(3)	(4)	(5)	(6)
Workplace Closing	-0.1431	-0.1236***	-0.1098***	-0.0318	-0.1079***	-0.0073
	(0.0352)	(0.0459)	(0.0109)	(0.0756)	(0.0223)	(0.0494)
Cancel public events	-0.1226	0.0408*	-0.0589***	0.1050**	-0.0255***	0.0206
	(0.0378)	(0.0216)	(0.0070)	(0.0443)	(0.0090)	(0.0349)
Close public transport	-0.0626	-0.0156**	0.0035*	-0.0239	0.0079***	0.0007
	(0.0138)	(0.0078)	(0.0021)	(0.0182)	(0.0028)	(0.0169)
Internal movement Restr.	-0.0159	0.0272	0.0290***	-0.1765***	0.0098	-0.0828**
	(0.0155)	(0.0209)	(0.0047)	(0.0439)	(0.0060)	(0.0335)
Observations	1,796,868	1,796,868	151,801	151,801	151,801	151,801
Pseudo R-squared	.971	.971	.817	.921	.774	.923

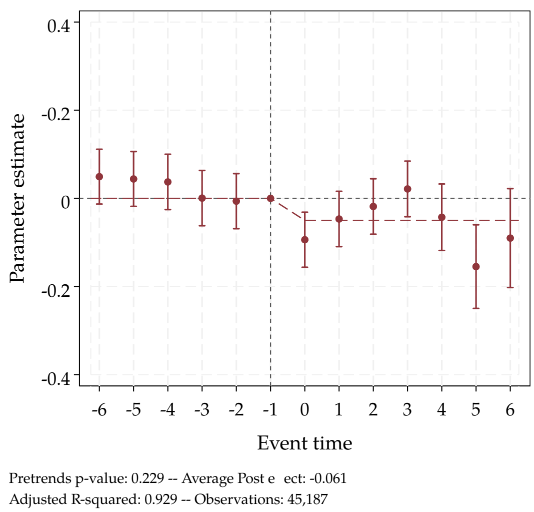
Notes: Column (1) presents the Lasso coefficients of the selected COVID policies. The remaining columns present the estimation results using the policies identified in the (1) Lasso step, namely the post-Lasso method estimated with PPML. Standard error cluster at import-export country pairs. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).



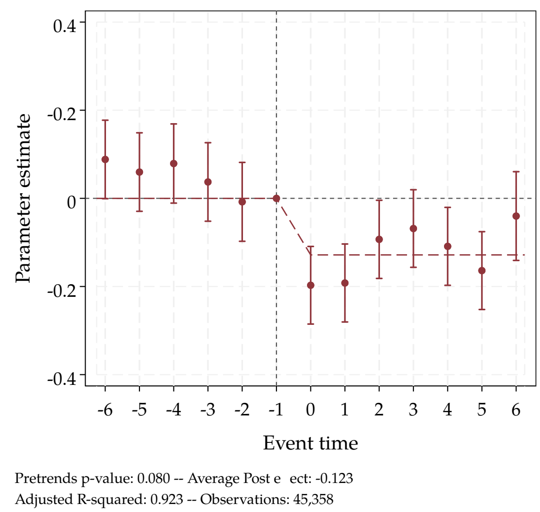
(a) Middle-risk, Imports.



(b) High-risk, Imports.



(c) Middle-risk, Exports.



(d) High-risk, Exports.

Figure 8: Event studies for U.S. containerized trade.

Note. All regressions include port-destination-product-year and port-destination-product-month fixed effects. Standard errors are adjusted for within-cluster correlation at the port-destination-product level. We plot the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. Results from a static model are overlaid as a dashed line. We report Wald tests for pre-trends, leveling off dynamic treatment effects, the pseudo/adjusted R-squared, and the panel size in the figure note. The event time is measured in months relative to April 2021.

Appendix

LASSO Approach

The vectors λ and $\hat{\phi}_l$ allow us to identify the specific COVID-19 policies with a binding effect on Chinese trade. An important consideration for the Lasso variable selection method is the procedure for choosing the tuning parameters. The standard method is cross-validation, which relies on a re-sampling procedure that repeatedly holds out a subset of the data and chooses the tuning parameters to maximize the model's predictive power (Breinlich et al., 2022). In this setting, $\hat{\phi}_l$ is set to 1. A drawback of this approach is that it could select many irrelevant variables because it ignores the regressor-specific penalty $\hat{\phi}_l$, implying that the cross-validation approach ignores heteroskedasticity and within-cluster correlation featured in the data (**?**).

We, therefore, rely on the 'plug-in' regularization approach that specifies the appropriate functional form for the penalty parameters based on statistical theory to identify the tuning parameters (Ahrens et al., 2020). Because the 'plug-in' approach is rooted in statistical theory and parsimonious in selecting the binding non-tariff provisions in preferential trade agreements, the method is superior to cross-validation in finite samples (Breinlich et al., 2022). Moreover, the post-Lasso estimates obtained using the selected variables through the plug-in approach have a 'near-oracle' property, ensuring that these estimates accurately capture the correct model (**?**).

The 'plug-in' Lasso approach has several advantages over alternative regularized regression techniques. Lasso finds the regression model with the best fit by selecting β_l. To do so, it updates the fit score from a small change in β_l only if the fit improvement is large relative to the penalty. One advantage of the 'plug-in' Lasso lies in the regressor-specific penalty $\hat{\phi}_l$, which enables us to adjust to the standard error of the score. By including this penalty term, we can prevent the inclusion of incorrect regressors due to estimation noise. Therefore, the values of λ and $\hat{\phi}_l$ must be set high enough so that the value of the score for β_l becomes large relative to the standard errors for selected regressors.[3] A potential disadvantage of the 'plug-in' Lasso approach is that

[3] Following standard practice in the gravity literature, we cluster that standard errors at the country-pair level (Cameron and Miller, 2015; **?**).

the algorithm may over-penalize highly correlated regressors (**?**). Because we aim to identify the non-tariff provisions in preferential trade agreements that affect agricultural trade, we complement the Lasso regressions by performing a second-stage Lasso analysis that identifies bundles of COVID policies highly correlated with those identified by the regularized regression analysis. These auxiliary regressions allow us to identify pivital COVID-19 policies that likely have a causal impact on Chinese trade. We later also implement the cross-validation Lasso approach to choose set of more "liberal" λ since the plug-in approach is relatively conservative (Breinlich et al., 2022)

City Data Evidence

One caveat of relying on our provincial trade data for analyzing the governmental response to COVID-19 is that China's COVID lockdown policy is implemented at the local level. Therefore, we address this limitation in our baseline analysis by providing a second set of evidence at the prefecture level, utilizing newly collected Chinese city-level trade data. This data, sourced from China's local customs administration office websites, encompasses monthly aggregate trade values from 195 cities across Chinese provinces.[4] To further enhance the city-level trade data, we incorporate novel "Dynamic Zero-COVID risk area" data (referred to as 'risk-area' data in the following text) to estimate the trade effect of the Chinese Zero COVID policy at the city level. This data, obtained from the Chinese National Governmental Information Sharing Platform, reflects the various versions of the Novel Coronavirus Pneumonia Prevention and Control Plan published and updated by the Chinese National Health Commission since February 2020 (National Health Commission of China, 2022). The data outlines the 'risk area' policy as the fundamental pandemic prevention and control approach in China, with three sets of strategies implemented based on the risk level of the regions in accordance with the confirmed spreading of the pandemic. These are the 'high-risk area', 'medium-risk area', and the 'low-risk area'. These risk-based approaches are designed to optimize resource allocation and maximize the effectiveness of containment measures

[4] One shortcoming of this prefecture-level data is that it is presented at the city-country-calendar month level and does not include industry or product characteristics.

for COVID-19 in each region.[5] This risk assignment data covers the same period as the OxCGRT data at the daily level, which we aggregate at the monthly level. Based on the risk-area and trade data collected, we use a event study framwork to study the dynamic treatment impact of COVID-19 lockdown on Chinese trade at the city level.

We employ a panel event study design to assess the treatment impact of the COVID-19 lockdown on Chinese trades. Since the middle and high-risk areas experienced different intensity of lockdown policies, whereas low-risk areas did not. For the sake of simplicity, we categorize cities in the ″middle″ and ″high″ risk areas as treated cities, while cities in the ″low″ risk area and non-designated areas serve as control cities. We follow a dynamic difference-in-differences setting that accounts for the "switch-in" but not "switch out" effect. This means that we only consider cities that transitioned from the control group to the treatment group, rather than the reverse. This approach aligns with the methodology proposed by De Chaisemartin and d'Haultfoeuille (2020), focusing on the city level. The model is summarized by the following equation[6]:

$$I_{ist} = exp\left(\sum_{e=-6, e\neq-1}^{6} \beta_e 1\{e = t - G_i\} + \alpha_{s,yr} + \alpha_{i,m} \right) \eta_{it}, \tag{8}$$

where the city, and month are denoted by i, and t. The outcome of interest, I_{it}, is measured as the total import or export values from city i in time t. To control for unobserved factors that could affect the relationship of interest, we include fixed effects at the month (α_i) levels. These fixed effects allow us to account for supply shocks from the Chinese city over time. G_i indicate the time that treated city unit i is for the first time for the event window. Therefore, $t - G_i = e$ represents the

[5] If a region reports more than 10 new confirmed cases within 14 days, the area will implement a full-scale lockdown, and it will be designated as a high-risk area. This high-risk designation places emphasis on preventing internal spread, avoiding external transmission, and implementing strict control measures. If there is at least one new confirmed case within 14 days in an area, the entire area is designated as a 'medium-risk area' and is obligated to implement a partial-scale lockdown. In comparison to the 'high-risk area', the 'medium-risk' area policy is relatively less strict, focusing on isolating close contacts of confirmed cases in the area. For the assignment of a low-risk area, the area implements no lockdown if there are no new confirmed cases for 14 consecutive days. Only when there are no new COVID cases for consecutive 7 days, can the 'high-risk' areas be converted to medium-risk areas, and the same applies for the conversion between medium-risk areas to low-risk areas.

[6] Although researchers have long thought that two-way fixed effects (TWFE) estimators are equivalent to difference-in-differences estimators, it's created biased estimates because simply using the TWFE would fail the parallel assumptions in a staggered adoption application (De Chaisemartin and d'Haultfoeuille, 2020).

"event time" that equals to the duration month of city i that has been treated. We include dummy variable $1\{t - G_{ijk} = e\}$ that equals to one when city i is treated for e periods away from G_i. The $e > 0$ corresponds to treatment effects e month after the event, and $e < 0$ are accord with the pre-trend of effects. We choose to use a 13-month event window that relates to 6 months lead and 6 months lags periods, and we omit the treatment lead indicators related with $e = -1$. Defined by the event window, η_{it} is the error term. Our parameter of interest is β_e, which measures how the relative trend of treated city.

Additionally, this model requires to construct a clean control group that allows us to compare the treated cites against untreated cities within the window. In each event window, we restrict sample to:

$$\begin{cases} \text{Lockdown cities} : D_{it} = 1, D_{i,t-1} = 0 \\ \text{Clean control cities} : D_{i,t+e} = 0, for - 6 \leq e \leq 6 \end{cases} \tag{9}$$

where, for all months t and for each event window, treated units are cities that has policy implemented at t, and control units are cities that have been not been treated across every time point at the same event window. D is dummy that equals to one when treated and zero otherwise. It's important to note that we exclude the sample from the treated as long as the city unit is involved with transition out of the treated group, while cities that experience a transition to autocracy at time t–1 or earlier are still used as controls. To avoid that we don't have enough control group if in some year, all cities in China has COVID-19 lockdown policy implemented. Our setting of control groups in this analysis is based on the assumption proposed by Marcus and Sant'Anna (2021), Dube et al. (2022), and De Chaisemartin and d'Haultfoeuille (2022), where the estimated coefficients of event dummies should not be different between control and treated groups in the pre-period. We stacked the data by creating each event window and select the cites with similar characteristics that were not be treated as the control group.

To ensure the robustness of our analysis, we undertake several lines of robustness checks. First, we reduce the window size further to incorporate more control units in the sample for a robustness check. As observed in **??**, a majority of units "switch into" treated units at the end of year

2022. However, including these units in the event window at event time zero may not provide a sufficient sample size for the end of periods at each window. Second, with an event window that includes more available control units, we also employ the propensity score matching (PSM) approach to obtain a better comparison group for robustness checks. The selection of control groups ensures that the treated trend exhibits a similar pattern to that of the control group items. Additionally, the PSM approach aids in alleviating self-selection and endogeneity issues in the implementation of lockdown measures, considering that the assignment of COVID-19 lockdown policy is non-random and contingent on city-specific factors such as pollution density, economic development, health infrastructure, and housing conditions.