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The Impact of Access to Intermediate Inputs on Export Margins: Firm-Level Evidence from the Regression Decomposition Approach

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Abstract: This paper analyzes how export margins responded to an intermediate input supply shock caused by the 2020 lockdown in China. We use regression decomposition with triple and quadruple difference-in-differences models to identify causal impacts and mitigate potential heterogeneity in transaction-level customs data from the Bangladesh apparel manufacturing industry. The triple difference estimate shows that the average export value per firm–product–destination combination declined by approximately 65%, leading to a decrease in overall exports of woven apparel from Bangladesh. The input supply shock also adversely affected the subgroups of firms across various firm-level characteristics along the intensive margin. Moreover, the export market share decomposition reveals that the shock significantly affected intensive margins by decreasing incumbents' market allocation by 9%. An equivalent increase in extensive margins led to a readjustment in the market allocation, leading to fewer market leavers and slightly more new market entrants. Our results indicate that Bangladesh's exports mostly decreased due to the smaller quantities of products exported rather than there being fewer firms, destinations, or products involved in export trade. There were significant market share reallocations that occurred after the Chinese input supply shock. An appropriate policy stance is required for sustainable export sector growth strategies, which will enhance the country's defense against potential future shocks and foster the achievement of sustainable development goals (SDGs) in Bangladesh.

Keywords: firm sustainability; sustainable export growth; apparel industry in Bangladesh; sustainable economic development; sustainable development goals 2030; sustainable global supply chains; triple and quadruple difference-in-differences

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1. Introduction

Globalization and the emergence of global value chains (GVCs) have intensified firms' sourcing of intermediate inputs to increase production efficiency and export performance [1]. However, the 2020 lockdown in China, intended to contain COVID-19, caused an unprecedented and severe collapse in GVCs. The trade of raw materials and intermediate inputs, which is a crucial component of GVCs, suffered the most compared with other trades [2,3]. Given China's role as the central hub of many GVCs, the disruption in access to Chinese intermediate inputs severely exacerbated the situation, leading to an abrupt decline in manufacturing production and export performance from developed to least-developed countries [4]. The Bangladeshi apparel manufacturing industry, which heavily relies on

Chinese intermediate inputs, has suffered severe production disruptions due to difficulties when accessing intermediate inputs from China and has experienced a sharp decrease in exports [5]. Therefore, understanding the impact of input supply shocks on export margins is of the utmost importance for sustainable export development, especially for countries that heavily rely on Chinese intermediate inputs.

The main objective of this paper is to investigate the impact of the Chinese intermediate input supply shock on GVCs, an exogenous factor triggered by the lockdown, on the extensive and intensive margins of exports. In this investigation, we use Bangladesh's apparel exports as a reference. The extensive margin refers to the changes in the number of exporting firms, the number of export destination countries each exporter sells to, and the number of products each exporter ships to each country. In contrast, the intensive margin refers to the average change in export value per firm–product–destination country. First, the average changes in firm–product–destination level exports are decomposed into extensive and intensive margin components following the decomposition method used by Behrens et al. [6]. This method was proposed by Bernard et al. [7]. Then, we estimate the effects of the input supply shock on each margin component using the difference-in-difference-in-differences (DDD) estimation approach. The conventional difference-in-differences (DID) approach may be biased due to potential endogeneity issues and unobserved heterogeneity that may originate from a firm's production network or heterogeneous input sourcing decisions. In addition, firms may experience different set economic conditions that could differentially affect the margin of exports. Moreover, when the DID method is used for unnatural experiments or purposeful policy action as a treatment event, such as the lockdown in China, endogeneity critiques may arise, as discussed in the work by Besley and Case [8]. The DDD approach provides an advantage in circumventing endogeneity biases and unobserved heterogeneity. Therefore, a DDD framework is constructed by comparing two product-specific DID models, woven-DID and knit-DID, to estimate the unbiased causal impact of Chinese input shocks on Bangladesh's export margins. With our woven-DID model, we compare the changes in the number of woven-product-exporting firms, the number of export destination countries, the unique number of export products (extensive margins), and the average value of exports per firm–product–destination (intensive margin) between the treatment and the control groups before and after the lockdown. A similar approach is followed for the knit-DID model by comparing the corresponding changes in the outcome variables mentioned above for knit apparel products between the treatment and control group firms during the same period. Notably, in this paper, treatment is defined at the firm and product levels; firms that are heavily reliant on Chinese intermediate inputs are referred to as the treatment group and those dependent on the rest of the world (ROW) are defined as the control group firms. Woven apparel is treated as a targeted product, and knit apparel is the comparison group for woven products. We utilize unique transaction-level customs data from Bangladesh apparel manufacturing firms to facilitate this analysis.

To further elucidate whether all firms were affected by shocks of the same magnitude and dimension, we replicate the decomposition analysis by dividing the sample into smaller subgroups across different firm-level characteristics. Therefore, we illustrate the heterogeneous impact of input shocks on the export margins for various firm types. To check for heterogeneity, we employ the quadruple difference-in-differences (DDDD) framework, as suggested by Muralidharan and Prakash [9] and Sytsma [10]. The DDDD estimates also address the remaining omitted variable biases originating from firm, product, and market characteristics.

Then, we investigate the changes in market shares in the aftermath of the lockdown. Following Khandelwal et al. [11], we decompose export growth into one intensive margin, i.e., an incumbent, and two extensive margins, i.e., an entrant and a leaver. An incumbent refers to a firm that continues exporting the same products to the same destination before and after the lockdown. An entrant refers to a firm that appears in the sample after the lockdown and is not present before the lockdown. A leaver is the opposite of an entrant. Using the DDD estimation, we compare the average changes in the market share of the incumbent firms and the changes in entry and exit across woven and knit apparel firms at the product–destination pair between the treatment and control groups before and after the lockdown. Finally, to confirm the validity of our results, we provide multiple robustness checks, including placebo treatment tests and an even-study analysis.

This paper contributes to the literature in three significant ways. First, we find that the contraction of Chinese intermediate inputs in GVCs due to the lockdown seriously negatively affected the intensive margin of apparel exports from Bangladesh. The findings show that the intensive margin, i.e., the average value of exports per firm–product–destination combination, declined by approximately 65% in the treatment group relative to that of the control group in the posttreatment period. This significant drop in the intensive margin contributed to an overall decrease in woven apparel exports despite an increase in the extensive margin. The changes in the intensive margin of Bangladesh's exports were primarily influenced by changes in the quantities shipped, product quality, and quality-adjusted prices. On average, after the input supply shock, the firm–product–destination quantities decreased by 66%, quality decreased by 12%, and quality-adjusted prices increased by 16%. Second, by using the DDDD method to perform decomposition analysis across various firm-level characteristics, we show that the impact of an input supply shock on the export margin primarily holds at heterogeneous firm dimensions, with various subgroups of firms experiencing the input supply shock slightly differently in terms of the margin components. However, the overall heterogeneity analysis depicts that all the subgroups experienced a large magnitude of export degrowth along the intensive margin, which was mainly driven by the decrease in shipment quantities. Third, another novel contribution is made by empirically estimating how the influence of the Chinese intermediate input shock affects the firm–product–destination level market share and the entry and exit of the export market. The market share decomposition analysis reveals that the incumbent firm lost approximately 9% of its market share, which was readjusted by a gain in the net growth of market entry of 9%. This study further indicates that product entrants and destination leavers increased significantly. However, the primary mode of market entry, such as brand-new firms starting to export woven apparel, and the primary mode of leavers, such as the complete exit from exporting woven apparel, did not significantly differ. Additionally, we supplement our principal analysis and show that our main results are robust by performing multiple robustness analyses in various directions, conducting placebo tests, adopting an event study, and using an alternative control group.

Bangladesh's apparel industry provides an interesting setting for investigating the effects of China's intermediate input shock on export margins, as it heavily depends on Chinese intermediate inputs to produce export goods. Despite being one of the world's leading apparel producers and exporters, Bangladesh's backward linkage industry has yet to be developed to fulfill the growing demand in the apparel industry. Due to government cash incentives and subsidized rate credit facilities, the backward linkage of the knit apparel industry has expanded in recent years [12]. However, due to the capital intensity of woven fabric production [13], this sector has remained underdeveloped despite its recent inclusion in cash incentive plans, which has led to the reliance of woven apparel production almost entirely on imported inputs from abroad [14], especially from China. Studies show that more than 50% of woven fabrics come from China [5], which is also evident in our data. Figure 1a shows the total imports of intermediate inputs by Bangladeshi firms over the sample period, while Figure 1b shows the total exports over the sample period. A sharp decrease in intermediate input imports led to an abrupt decline in exports. As Bangladesh is moving ahead with export-led economic growth and development, access to manufacturing inputs may destabilize the export sector growth, which will impede the achievement of SDGs through trade and industrial development. Given this background, examining the impact of the Chinese intermediate input supply shock in GVCs induced by the lockdown on Bangladesh's export margins motivates us to use the empirical set for this study.

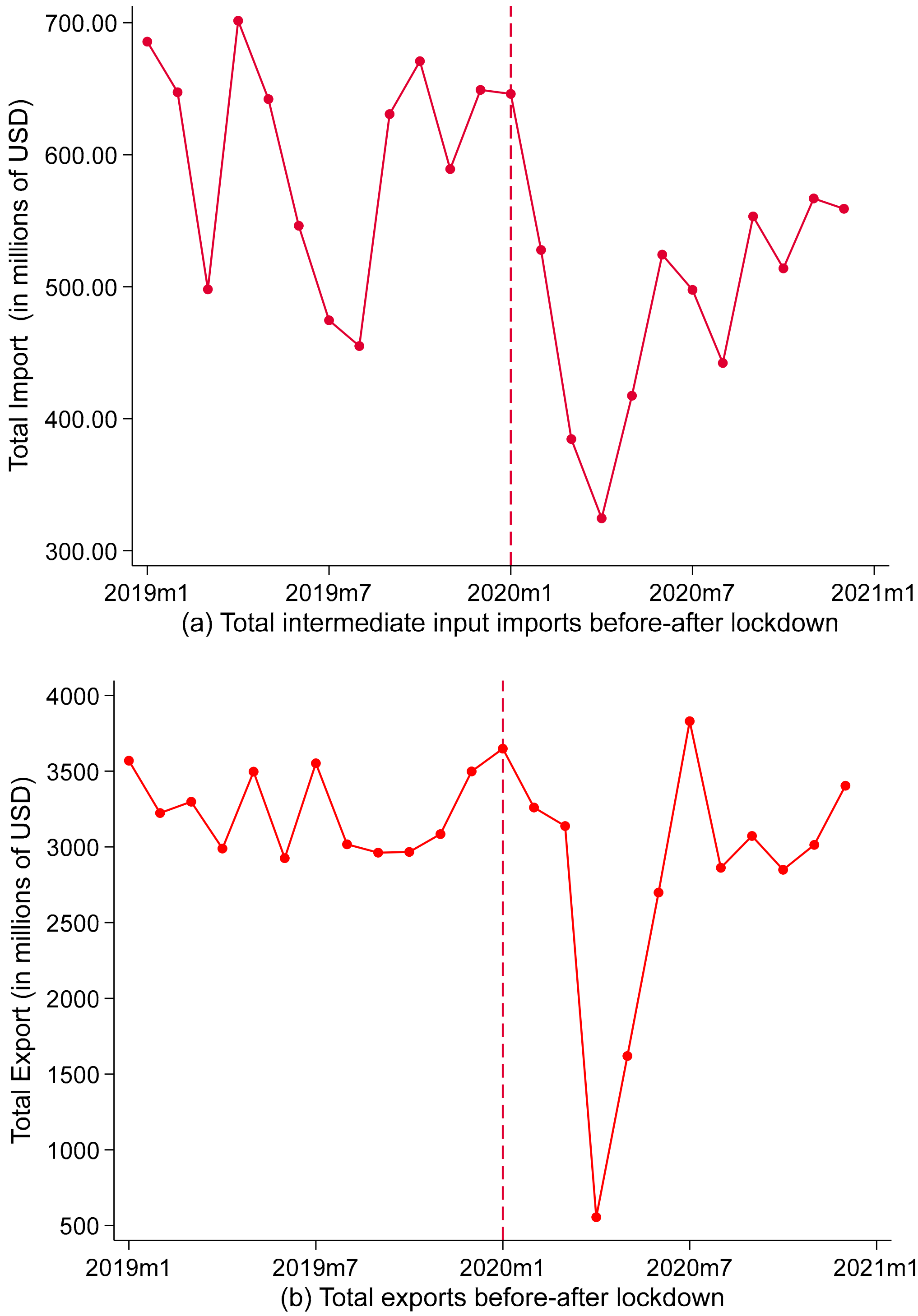


Figure 1. Total export and import flows before and after the 2020 lockdown in China. Notes: Panel (**a**) displays the total imports of intermediate inputs, and Panel (**b**) shows the total exports over the sample period.

The remainder of this paper is organized as follows. Section 2 provides the literature review. Section 3 describes the data and descriptive statistics. In Section 4, we present the empirical strategy. Section 5 provides the estimation results and discussion. In Section 6, we present the conclusion.

2. Literature Review

Previous research that assessed the impact of the 2020 lockdown in China mainly addressed firm-level export performance. However, research on the effects of lockdowns on export margins is still limited. For instance, Pei et al. [15] examined the consequences of the lockdown in China on city-level exports and reported that the lockdown affected both intensive and extensive margins of exports from cities that were on lockdown. Lafrogne-Joussier et al. [16], who estimated the effects of China's lockdown on French firms, revealed that firm-level exports were affected along the extensive margins and that the intensive margins remained nonsignificant in response to the lockdown. In a contemporary study focusing on the impact of the COVID-19 pandemic on trade adjustment in France, Papageorgiou et al. [17] also reported that extensive margins, rather than intensive margins, played a vital role in adjusting French firm-level trade. Previously, Bernard et al. [7] used the Asian financial crisis of 1997 to investigate the margins of U.S. trade with partner countries and found that most of the trade adjustments occurred at the intensive margin level, which intensified the quick recovery of U.S. trade. Utilizing the Global Financial Crisis (GFC) of 2008–2009 as a shock and using French firm-level data, Bricongne et al. [18] showed that large firms were affected by intensive margins and exported a smaller number of products to export destinations, while smaller firms were impacted both by extensive and intensive margins. Moreover, Behrens et al. [6] utilized the Global Financial Crisis of the 2008–2009 trade collapse to investigate how Belgian exports and imports fell and reported that intensive margins of trade were mainly affected by the shock of the financial crisis. In this paper, we attempt to bridge the gap in the literature and estimate the impact of the lockdown on exports by decomposition into extensive and intensive margins and analyzing the effects on export market share reallocation in terms of stayers (incumbents), leavers, and entrants. This study focuses on the apparel manufacturing industries in small export-oriented economies such as Bangladesh, which heavily depend on China for manufacturing inputs.

This paper also relates to another strand of the literature that has studied the impact of input trade liberalization and positive trade policy changes on trade margins. For instance, Khandelwal et al. [11] examined the impact of removing the Multifiber Arrangement (MFA) quota on Chinese textile and clothing exports and reported an increase in export value and a decrease in export price after quota removal. Martincus and Carballo [19] studied the effects of export promotion on the firm-level extensive and intensive margins of trade and reported that export promotion influences the increase in exports along the extensive margins of trade. Dutt et al. [20] showed that WTO/GATT membership significantly positively affects extensive margins of trade. However, intensive margins are negatively affected. Focusing on the impact of bilateral investment (BTI) treaties, Xiong (2022) [21] reported that BTIs also increase the extensive margins of exports and decrease the intensive margins of developed countries. Concentrating on the impact of the revision of Rules of Origin (RoO) in 2011 by the European Union (EU), Sytsma [10] reported that apparel exports from Bangladesh to the EU increased significantly along the intensive margin of exports, and extensive margins remained insignificant. It was also found that the revision of the RoO significantly altered the market share allocation of apparel exporting firms. Andersson [22] reported that the RoO increased southern Mediterranean countries' exports to the EU-15 by approximately 20%. This study mainly focused on the positive impact of input trade liberalization on the extensive and intensive margins of trade. In contrast, in this study, we employ the Chinese intermediate input supply shock in GVCs as an exogenous factor to investigate how export margins respond to such an input supply shock.

3. Data

In this study, transaction-level customs data from January 2019 to December 2020 were obtained from the Bangladesh National Board of Revenue (NBR). These data were made available by Bangladesh Bank (the Central Bank of Bangladesh). The data were recorded daily for each export and import transaction of Bangladeshi firms in the industry and maintained separately as export and import files. Information on each firm's unique business identification number (BIN), trade value, shipment quantity, shipment date, destination or source country, 8-digit Harmonized System (HS) product classification, and port name of the trade is included in these data. The raw data included 3976,138 daily export observations of 8884 firms and 278,978 daily import observations of 2297 firms. The import data were limited to intermediate inputs only throughout the period of analysis. As China's input supply shock started in January 2020, we collapsed these daily data into monthly data and constructed panel data at the firm–product–destination level for each month. Since this study focuses on GVC firms that import intermediate inputs to produce final export goods, we constructed our sample of 507,286 monthly observations of 1858 firms by merging the import data with the export data to identify the firms' engagement in GVCs. Again, as this study focuses on apparel exports, we ignored all the other observations except for the two-digit HS headings for the HS61 and HS62 products that define apparel products. We further restricted our sample to positive export and intermediate import flows and eliminated all exports to and imports from other Bangladeshi counterparts. Our analysis sample included 226,415 observations of 1527 GVC firms.

In this study, firms that import intermediate inputs from China are defined as treatment firms and firms that collect inputs from the ROW are defined as control firms. Woven apparel products, which include all exports in two-digit HS heading 62 (HS62), comprise the treatment products, and knit apparel HS heading 61 (HS61) is the comparison group for woven apparel. The pretreatment period ranged from January 2019 to January 2020, and the posttreatment period ranged from February 2020 to December 2020. The firm–product–destination level export value is the unit of analysis for the baseline regression.

Table 1 provides the summary statistics. Panel 1 summarizes the use of woven apparel based on the treatment status, while Panel 2 shows the summary statistics for the knit products. We computed the summary statistics from January 2019 to December 2019, i.e., before the start of the lockdown. The means are reported in the table, and the standard deviations are in parentheses. Extensive margin components, such as the unique number of firms, the number of countries served by Bangladeshi firms, and the number of products shipped, are greater for knit and woven apparel in the treatment firms. However, the average export level per firm–product–destination combination is greater for the control firms than for the treated firms. Treated firms account for approximately 56% and woven products account for nearly 49% of the monthly export value in the estimation sample. There are 317 unique HS8-digit products in the woven and knit categories, 135 unique export destinations, and 120 export markets where Bangladeshi firms sell, considering the EU-15 and the US as single markets.

Table 1. Summary statistics.

	Overall	**Treatment**	**Control**
Panel 1: Woven			
Monthly exports (USD 1000)	1131.82	1127.10	1190.46
	(1604.88)	(1541.49)	(2250.13)
Number of firms	91.10	97.71	8.93
	(42.31)	(36.67)	(4.80)
Number of destinations	6.31	6.36	5.74
	(8.79)	(8.76)	(9.20)
Number of products	3.44	3.48	2.86
	(2.69)	(2.69)	(2.66)
Intensive margin (USD 1000)	1.07	0.47	8.57
	(5.60)	(1.70)	(18.03)
Average prices	5.81	5.85	5.34
	(16.24)	(16.85)	(3.54)

Table 1. *Cont.*

	Overall	Treatment	Control
Panel 2: Knit			
Monthly exports (USD 1000)	1212.92	1244.61	934.53
	(1917.91)	(1937.83)	(1709.71)
Number of firms	88.55	97.52	9.76
	(39.17)	(30.33)	(3.80)
Number of destinations	6.98	7.20	4.97
	(9.27)	(9.51)	(6.44)
Number of products	3.74	3.82	3.05
	(3.43)	(3.52)	(2.39)
Intensive margin (USD 1000)	0.84	0.42	4.60
	(5.83)	(1.47)	(12.88)
Average prices	4.23	4.28	3.88
	(4.76)	(4.91)	(3.04)

Notes: This table shows the summary statistics estimated from January 2019 to December 2019 before the lockdown started. Column 1 shows the overall summary statistics, and Columns 2 and 3 present the summary statistics for the treated and control firms. Treatment refers to the firms that source intermediate inputs from China, and control refers to firms that procure inputs from the rest of the world. Panel 1 shows the summary statistics for woven apparel, and Panel 2 provides the summary statistics for knit apparel. Woven represents the export of woven products (HS62), and knit refers to the export of knitted apparel (HS61). The means are presented in the table, with standard deviations in parentheses below. Summary statistics are based on Bangladesh customs data and elaborated by the authors.

4. Empirical Strategy

4.1. Endogeneity Issues and Motivation behind the Triple Difference Approach

The potential endogeneity biases originating from firms' endogenous production networks and unobserved product- and destination-specific heterogeneity are the main challenges in identifying the effects of supply shocks caused by the lockdown in China on export margins. Moreover, the time-varying confounding factors are also the sources of potential endogeneity in our identification, which are common in treated and control firms. For example, stimulus packages responding to pandemic and trade crises implemented through monetary and fiscal policy and corporate investment [23,24] may positively influence firms' export performance during shocks. Conversely, the increased uncertainty shocks [25], financial constraints, and sluggish labor market conditions may negatively influence firm performance, as discussed in Campello et al. [23,26]. These time-varying confounders affect both treated and control firms equally. For instance, suppose a firm's export performance is influenced by the endogenous nature of the firm's production network, heterogeneous input sourcing decisions, or other economic conditions. In this case, the standard DID approach using purposeful policy action, such as a lockdown in China as a treatment, will not recover unbiased estimates due to potential endogeneity. Moreover, when using unnatural experiments or purposeful policy action, the classic DID method often faces endogeneity critiques, as discussed in Besley and Case [8]. To circumvent such endogeneity and to control for unobserved heterogeneity issues, we adopt a DDD estimator to identify the unbiased causal impacts of input supply shocks on export margins. Our innovative DDD method compares the changes in the margins of woven apparel exports of the treated and control firms and compares the similar differences for knit apparel. The DDD is then constructed by comparing these two double differences, which estimate actual causal effects by canceling out such biases and removing unobserved shocks [27,28]. We construct the basic triple difference specification following Olden and Møen [29], which can be expressed as follows:

$$\begin{aligned} DDD = {} & [(lnX_{T=1,W=1,Post=1} - lnX_{T=1,W=1,Post=0}) - (lnX_{T=0,W=1,Post=1} - lnX_{T=0,W=1,Post=0})] \\ & -[(lnX_{T=1,W=0,Post=1} - lnX_{T=1,W=0,Post=0}) - (lnX_{T=0,W=0,Post=1} - lnX_{T=0,W=0,Post=0})] \end{aligned} \quad (1)$$

where X is the logarithm of the export margins and T and W refer to the treated firms and woven products, respectively. The term in the first square bracket refers to the woven DID, and the second term is the knit DID. The DDD is then constructed by comparing these two differences. The full specification can be expressed as follows:

$$lnX_{ipdt} = \beta_1(treated_i) + \beta_2(woven_p) + \beta_3(post_t) + \beta_4(treated_i * woven_p) + \beta_5(treated_i * post_t) + \beta_6(woven_p * post_t) + \delta(treated_i * woven_p * post_t) + \epsilon_{ipdt} \quad (2)$$

where the left-hand side variable $ln(X_{ipdt})$ represents all the margin components and the variable *treated* represents the firms that imported intermediate inputs from China before the lockdown, with a value of one and zero otherwise. Similarly, *woven* is a product dummy variable with a value of one if product *p* is a woven apparel product aggregated at HS62 and zero if product *p* is a knit apparel product aggregated at HS61. *Post* is a time dummy with a value of one for all firms and products from February 2020 to December 2020, i.e., when the 2020 Chinese lockdown occurred. The only coefficient of interest is δ, the coefficient for the triple interaction (*treated***woven***post*). Following Frazer and Van Biesebroeck [30], we controlled all the double-interaction-dummy and single-dummy variables in Equation (2) with a set of interaction-fixed effects. Therefore, to examine the impact of input supply shocks on export margins, we estimated the DDD model in Equation (3) below.

$$ln(X_{ipdt}) = \alpha_{ipd} + \gamma_{pdt} + \theta_{it} + \delta(treated_i * woven_p * post_t) + \epsilon_{ipdt} \quad (3)$$

The specification includes the firm–product–destination fixed effect (α_{ipd}) to account for the unobserved heterogeneity of product p exported to any destination d by firm i, the product–destination–month fixed effect (γ_{pdt}) for capturing the monthly demand shocks for product *p* in destination d during month *t*, and the firm–month fixed effect (θ_{it}) to capture the changes in the production of firm *i* during month *t*. Finally, ϵ_{ipdt} is the error term clustered at the export market level. The DDD approach allows us to control for firm–product-specific unobserved heterogeneity among destinations, product-specific monthly demand shocks across destinations, and firm-level monthly productivity shocks.

Two further issues make this identification challenging. As the lockdown policies in China affected global trade, one may wonder whether our control group was also prone to policy change. However, we have addressed these critiques carefully in our research design. First, this study focuses on a comparatively shorter window and implicitly concentrates on the firms that had direct exposure to Chinese input supply shocks. Second, this study exploits the temporal and cross-country variation in lockdown measures following Lafrogne-Joussier et al. [16]. For instance, when the Chinese government mandated lockdown measures at the end of January 2020 to contain the spread of COVID-19, the ROW was not affected. Therefore, we choose firms that rely on the ROW for inputs as the control firms.

4.2. Decomposition of Firm–Product–Destination Level Export Growth

To examine the effects of the Chinese input supply shock caused by the lockdown on export margins, we decompose the total exports (X_{ipdt}), aggregated with firm–product–destination combinations, into the unique number of firms (F_{ipdt}), the unique number of destinations (C_{ipdt}) served by Bangladeshi firms, the unique number of woven and knit apparel products (P_{ipdt}) exported by Bangladeshi firms, and the average value of exports per firm–product–destination combination ($\overline{X}_{ipdt}$), following the methods of Behrens et al. [6], Bernard et al. [7], and Sytsma [10]. Therefore, the total firm–product–destination level exports are calculated as the product of the number of firms, the number of exporting destination countries, the number of exported products, and the average value of exports per firm–product–destination triplet. The entity $X_{ipdt} \equiv F_{ipdt}C_{ipdt}P_{ipdt}\overline{X}_{ipdt}$ can express the above decomposition. Taking the log, we rewrite the entity as follows, providing the basis for the regression decomposition of exports from Bangladesh to the world.

$$ln(X_{ipdt}) = ln(F_{ipdt}) + ln\left(C_{ipdt}\right) + ln\left(P_{ipdt}\right) + ln\left(\overline{X}_{ipdt}\right) \quad (4)$$

where the intensive margin can be defined by $\overline{X}_{ipdt} = X_{ipdt}/(F_{ipdt} * C_{ipdt} * P_{ipdt})$.

Then, again following Behrens et al. [6] and Sytsma [10], the intensive margin can further be decomposed into the average change in quantity $(\overline{q}_{ipdt})$, the average change in unit price $(\overline{p}_{ipdt})$ adjusted by quality, and the average change in quality $(\overline{\lambda}_{ipdt})$. Specifically, $\overline{X}_{ipdt} \equiv \overline{q}_{ipdt}\overline{p}_{ipdt}\overline{\lambda}_{ipdt}$ gives the intensive margin. Taking the log, we express the intensive margin in a regression format.

$$ln(\overline{X}_{ipdt}) = ln(\overline{q}_{ipdt}) + ln\left(\overline{p}_{ipdt}\right) + ln\left(\overline{\lambda}_{ipdt}\right) \quad (5)$$

The data show the nominal quantities for each firm–product–destination level export. The quantity of units varies across products, such as pieces or numbers for some and kilograms or tons for others. Therefore, we use the unit values as a proxy for prices. We divide the nominal value of each firm–product–destination level export by quantity to derive prices. The expression $ln\left(\overline{p}_{ipdt}\right) = ln\left(\overline{X}_{ipdt}\right)/ln(\overline{q}_{ipdt})$ provides the average unit prices. To derive quality, we rely on the method by Khandelwal et al. [11]. This method was also used by Fan et al. [31] and Bas and Strauss-Kahn [32]. The product quality $(\overline{\lambda}_{ipdt})$ can be given by the preference of consumers for goods in the constant elasticity of substitution (CES) utility function, $U = (\int_{p\in\Omega} (\lambda(p)q(p))^{\frac{\sigma-1}{\sigma}} dk)^{\frac{\sigma}{\sigma-1}}$, where $\lambda(p)$ is the quality of typical product variety p, $q(p)$ is the quantity consumed, $\sigma > 1$ is the elasticity of substitution, and Ω is the set of available product varieties in the market. Given these preferences and depending on the product price and quality, the function $q_{ipdt} = \lambda_{ipdt}^{\sigma-1}\overline{p}_{ipdt}^{-\sigma}P_{dt}^{\sigma-1}E_{dt}$ gives the demand for a particular firm's product in the export destination country, where $\overline{p}_{ipdt}$ is the raw price (unit value) of typical product variety p, P_{dt} is the aggregate quality-adjusted price index in destination country d during month t, and E_{dt} is the expenditure on export destination d during month t. Taking the log of the corresponding demand function and rearranging it in the regression format, we can express it as $ln\left(q_{ipdt}\right) + \sigma * ln\left(\overline{p}_{ipdt}\right) = \alpha_{dt} + \alpha_p + \epsilon_{ipdt}$, where $ln(q_{ipdt})$ and $ln(\overline{p}_{ipdt})$ represent the quantity and price, respectively, of product p exported to destination country d by firm i during month t. α_{dt} is the destination–country–month fixed effect used to control the destination country's price index and income distribution, α_p is the product fixed effect used to control variation across products, and ϵ_{ipdt} is the residual term. The quality for each firm–product–destination is derived from the residual of the demand function's ordinary least squares (OLS) regression. The estimated quality depends on the residual term ϵ_{ipdt} and the elasticity of substitution σ, which can be given by $\hat{\lambda}_{ipdt} = \hat{\epsilon}_{ipdt}/(\sigma - 1)$. We rely on Broda et al. [33], who estimated Chinese elasticities of substitution at the HS3 product level and applied an elasticity of $\sigma = 4$ to infer quality. This approach was also used by Khandelwal et al. [11] and Sytsma [10]. The quality measure reflects the demand for a firm's product and does not account for the individual firm quality choice, which is the understanding behind this approach [11,31]. Finally, the quality-adjusted price is derived by subtracting quality from the raw prices, such as $ln\left(qp_{ipdt}\right) = ln\left(\overline{p}_{ipdt}\right) - ln\left(\hat{\lambda}_{ipdt}\right)$. We then use all these margin components, defined in Equations (4) and (5), as dependent variables to estimate the effects of supply shocks on export margins using the triple DDD model depicted in Equation (3).

4.3. Heterogenous Impacts

We then turn to decomposition analysis among various subgroups of firms by dividing the sample more narrowly along different dimensions. The purpose is to examine whether the effects of input supply shocks vary depending on firm-level characteristics, such as the distributions of export markets and products. We have conducted four types of subgroup analysis based on the firm characteristics: (a) core and frequent export markets, (b) top and secondary exporting products, (c) small and medium-sized firms, and (d) shipment mode, i.e., sea freight versus other transportation modes. The intuition behind such types of clustering firms is manyfold. For instance, Bangladesh apparel exporters sell their products in almost 200 destination countries. Nevertheless, most of the exporters' markets are concentrated in major EU-15 countries and the United States (US), which absorb 60% and 18%, respectively, of Bangladesh's apparel products as a single market and country, respectively [34]. Therefore, we consider the EU-15 (EU-15 countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the U.K.) and US markets the core and all other markets, respectively, as the benchmark. Next, the product concentration of Bangladeshi apparel exports is much greater than that of other products [35]. For example, Bangladesh produces almost 98 categories of apparel products aggregated with two-digit HS codes, but the maximum revenues come from only a few products [35]. Cajal-Grossi et al. [14] identified seventeen major woven products that cover most woven apparel exports. As a result, we treat the major seventeen woven products as the top woven products (these include the following HS6 products: 620341, 620342, 620343, 620349, 620461, 620462, 620463, 620469, 620510, 620520, 620530, 620590, 620610, 620620, 620630, 620640, 620690) and all the others as the benchmark woven products. Similarly, based on the monthly median shipment frequency, we define small firms whose monthly shipment frequency is less than the median and all other firms as reference firms. Again, considering the shipment mode, we segregate firms into two subgroups: sea freight and the other transport modes. We follow similar approaches as those by Behrens et al. [6] to decompose the subgroups of firms and adopt the DDDD framework as in the work by Muralidharan and Prakash [9] and Sytsma [10] to estimate heterogeneous effects. We express the DDDD framework as follows:

$$ln(X_{ipdt}) = \alpha_{ipd} + \gamma_{pdt} + \theta_{it} + \delta_1 * \left(treated_i * woven_p * post_t\right) + \delta_2 * \left(treated_i * woven_p * post_t * type_i\right) + \epsilon_{ipdt} \quad (6)$$

where type is a dummy equal to one if a firm belongs to the subgroup of firms defined by the quadruple interaction term and zero otherwise. There are four main types of firms: firms with a concentration in core markets, firms skewed toward top products, firms with a shipment frequency less than the median shipment frequency, and firms relying more on sea routes. The coefficient δ_2 captures an additional average impact of the supply shock on the group defined by the quadruple interaction term compared to that of the benchmark group. In contrast, $\delta_1 + \delta_2$ captures the total effect of the intermediate input supply shock. Similar to Equations (1) and (2), both δ_1 and δ_2 are decomposed into margin components and estimated using Equation (4) to investigate the impact of an input supply shock on the export margins for the subgroup of firms. The quadruple differences provide us with finer insights and address the remaining omitted variable biases originating from firm, sector, and market characteristics.

4.4. Decomposition of Export Market Share

Next, we examine how the market share of each firm changed due to the adverse effects of the Chinese input shock caused by the lockdown. For this purpose, we decompose the export market share into incumbents, entrants, and leavers based on the methods by Khandelwal et al. [11] and Sytsma [10]. The incumbents constitute the intensive margin, and the entrants and the leavers constitute the extensive margins of export growth. A firm may be counted in more than one margin of adjustment depending on the product. Therefore, Equation (7) below gives the market share decomposition.

$$X_{ipdt} = \sum_{i \in IN} X_{ipdt} + \sum_{i \in EN} X_{ipdt} + \sum_{i \in LV} X_{ipdt} \quad (7)$$

where X_{ipdt} refers to the share of the export market. IN, EN, and LV denote incumbent, entrant, and leaver firms, respectively. We further decompose the entrants into destination adders (DAs), product adders (PAs), and brand-new entries (BNs). The leavers can be decomposed into destination leavers (DLs), product leavers (PLs), and complete leavers (CLs). Therefore, Equation (7) can be rewritten as follows:

$$X_{ipdt} = \sum_{i \in IN} X_{ipdt} + \left(\sum_{i \in EN,DA} X_{ipdt} + \sum_{i \in EN,\ PA} X_{ipdt} + \sum_{i \in EN,BN} X_{ipdt}\right) + \left(\sum_{i \in LV,DL} X_{ipdt} + \sum_{i \in LV,PL} X_{ipdt} + \sum_{i \in LV,CL} X_{ipdt}\right) \quad (8)$$

The market share of each margin (m) as computed above within the product–destination (pd) pair across all firms (i) in each month (t) can be given by

$$\Phi_{mpdt} = \left(\sum_{i \epsilon m} X_{ipdt}\right) / \left(\sum_{m} \sum_{i} X_{ipdt}\right) \quad (9)$$

We then estimate all these market shares using the DDD specification in Equation (10) below.

$$\Phi_{mpdt} = \alpha_0 + \beta_1(treated_m) + \beta_2(woven_p) + \beta_3(post_t) + \beta_4(treated_m * woven_p) + \beta_5(treated_m * post_t) + \beta_6(woven_p * post_t) + \delta(treated_m * woven_p * post_t) + \epsilon_{mpdt} \quad (10)$$

where Φ_{mpdt} represents the share of each margin at the product–destination pair, as described in Equations (7)–(9).

4.5. Robustness Check

We perform several robustness analyses in different directions to supplement our primary analysis. First, to confirm the validity of our research design and empirical strategy, we conduct placebo tests by changing the timing of the Chinese lockdown policy and performing a series of DDD estimations using fake post variables in Equation (3). In this case, we suppose that the treatment event takes place one, two, three, and up to twelve months before the actual lockdown month (January 2020), and we exclude all observations from January 2020 onwards. Second, we perform placebo treatment tests by changing the treatment variable and replicating our main results in Table 2. In the false treatment case, we treat firms that import inputs from Hong Kong as treated, and the ROW is the comparison group. We repeat these exercises for India, Singapore, and Taiwan, as these are the major suppliers of inputs in Bangladesh after China. Third, we adopt an event–study framework to decompose the effects of input supply shocks over time, giving us the dynamic treatment effects on each margin component. Hence, we replace the post dummy in the triple interaction term in Equation (3) with the *month* dummies to construct the event–study framework. The China lockdown began in the last week of January 2020. Therefore, we measure the impact of supply shocks over the twelve months before and eleven months from February 2020 through December 2020. January 2020 is the base month. The event-study framework is given as follows:

$$ln(X_{ipdt}) = \alpha_{ipd} + \gamma_{pdt} + \theta_{it} + \sum_{t=-12}^{11} \delta_t * (treated_i * woven_p * month_t) + \epsilon_{ipdt} \quad (11)$$

where $ln(X_{ipdt})$ represents the extensive and intensive margin components, as discussed earlier in Equations (4) and (5). We estimated the dynamic response of all the margin components using the event–study framework in Equation (11).

Furthermore, we replicate the estimation of Equation (3) using an alternative control group to verify the sensitivity of the main results reported in Table 2. The corresponding control group firms do not import intermediate inputs from abroad, are small on average, and are not directly involved in the GVC. However, the rationale is to compare the treated firms to those not directly exposed to the Chinese intermediate input supply shock in the post shock period.

Table 2. Decomposition of firm–product–destination level exports.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Decomposition of Total Export				Decomposition of Intensive Margin		
		Extensive Margins			Intensive Margin			
Dependent variable	Total $ln(X_{ipdt})$	Firms $ln(F_{ipdt})$	Country $ln(C_{ipdt})$	Product $ln(P_{ipdt})$	Avg. expt. $ln(\overline{X}_{ipdt})$	Quantities $ln(q_{ipdt})$	Qual-adj Price $ln(qp_{ipdt})$	Quality $ln(\lambda_{ipdt})$
Woven∗Treated∗Post	−0.454 *** (0.141)	0.404 *** (0.031)	0.018 (0.067)	0.180 *** (0.035)	−1.057 *** (0.169)	−1.083 *** (0.167)	0.151 *** (0.047)	−0.126 ** (0.050)
Margin's contribution		0.89%	0.04%	0.40%	−2.33%			
Intensive margin's contribution						−1.02%	0.14%	−0.12%
Observations	160,991	160,991	160,991	160,991	160,991	160,991	160,991	160,991
Firm–product–destination FE	y	y	y	y	y	y	y	y
Prod–destination–month FE	y	y	y	y	y	y	y	y
Firm–month FE	y	y	y	y	y	y	y	y
Adjusted R-squared	0.714	0.992	0.995	0.991	0.839	0.828	0.748	0.607

Notes: This table shows the results estimated from Equation (3). The outcome variable in Column (1) is the firm–product–destination level of exports. The dependent variables in Columns (2) to (8) are the extensive and intensive margin components defined in Equation (4) and Equation (5). The margin's contribution is calculated as the coefficient of the given margin divided by the coefficient of the total. The intensive margin's contribution is derived as the coefficient for a given margin divided by the coefficient of the intensive margin. The marginal effect is converted into a percentage as follows: $100 * \left(\exp(\hat{\delta}) - 1\right)$. Robust standard errors in parentheses are clustered at the market level. *** $p < 0.01$, and ** $p < 0.05$.

5. Results and Discussion

Table 2 reports the results of the regression decomposition estimated from Equation (3) using the DDD method. The coefficient in Column (1) represents the total decrease in exports associated with the firm–product–destination combinations during the post shock period. The results in Columns (2) to (5) denote the decomposition analysis of the coefficient in Column (1) into three extensive margins, namely the average changes in the number of firms, the average number of export destination countries, the average number of products exported, and an intensive margin, such as the average value of exports per firm–product–destination combination. The margin components are defined in Equation (4) and Equation (5). The sum of the coefficient of each margin in Columns (2) through (5) equals the overall decline in firm–product–destination level exports, as shown in Column (1).

The decomposition results show that the average number of firms and the average number of products exported increased significantly by 50% (the marginal effect is converted to a percentage as follows: $100 * \left(\exp(\hat{\delta}) - 1\right)$ and 20%, respectively. When the percentage of countries where Bangladeshi firms served increased by 1.82%, this difference became statistically nonsignificant. Therefore, the overall change in the extensive margins is (1.00404 × 1.00018 × 1.0018 − 1) × 100 = 0.60%. Hence, the extensive margins contribute to 0.603/0.454 = 1.33% of the total changes in firm–product–destination–level exports. The coefficient in Column (5) shows that the intensive margin, i.e., average firm–product–destination level exports, decreased by 65% after the Chinese input supply shock, which led to overall exports decreasing by a large margin despite the increase in extensive margins. As shown in Table 2, the decrease in overall exports is mainly due to the intensive margin, and the contribution of the intensive margin to the total decrease in exports accounts for approximately −2.33%. Combining the extensive and intensive margins, we find that the change in exports is (1.00404 × 1.00018 × 1.0018 × 0.98943 − 1) × 100 = −0.46%.

In Columns (6) to (8) of Table 2, we report the results of further breakdown of the coefficient of the intensive margin in Column (5) into the changes in average quantities, quality-adjusted prices, and qualities. Column (6) shows that, in terms of quantity, Bangladesh's exports decreased by approximately 66% overall. In contrast, the average quality-adjusted prices rose by 16%, as seen in Column (7). Finally, as can be seen in Column (8), the average quality of Bangladesh woven apparel products decreased by 12% after the shock. The changes in quantities, prices, and qualities contribute −1.02%, 0.14%, and

−0.12%, respectively, to the overall changes in the intensive margin. Using all the margin components together, we find that the change in overall exports is (1.00404 × 1.00018 × 1.0018 × 0.98917 × 1.00151 × 0.99874 − 1) × 100 = −0.46%. From the decomposition, it can be concluded that the Chinese input shortage severely affected the intensive margin of Bangladesh exports.

To confirm the validity of the identifying assumptions, the exports of woven apparel by treated firms must follow similar trends to those without the Chinese input supply shock. We check parallel trends in the margin component of woven and knit apparel between treated and control firms separately over the sample period. The results are shown graphically in Figure 2. Figure 2a–c shows common trends for the extensive margin components between the treated and control groups. Figure 2d represents common trends among the treatment and comparison groups for the intensive margin.

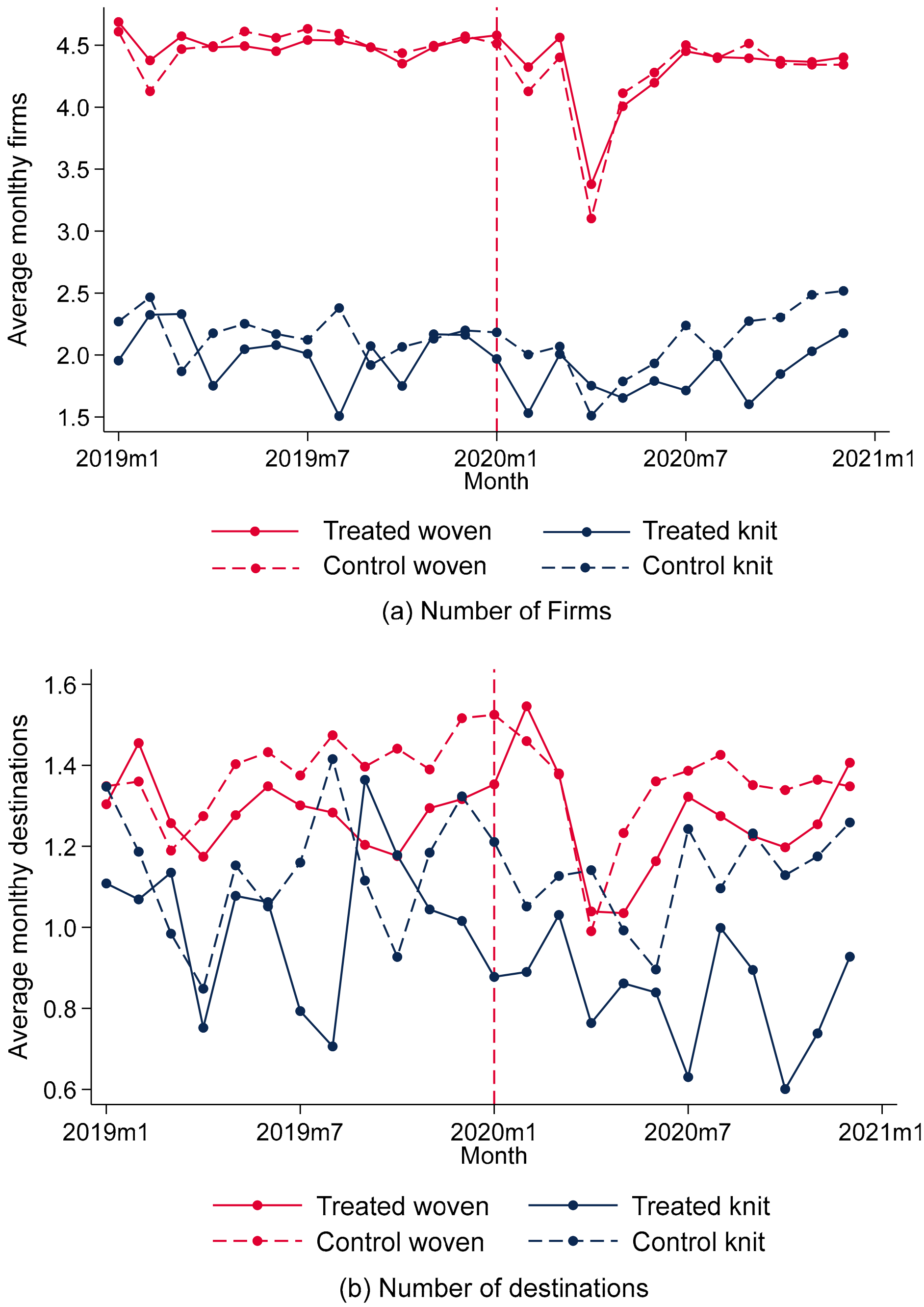
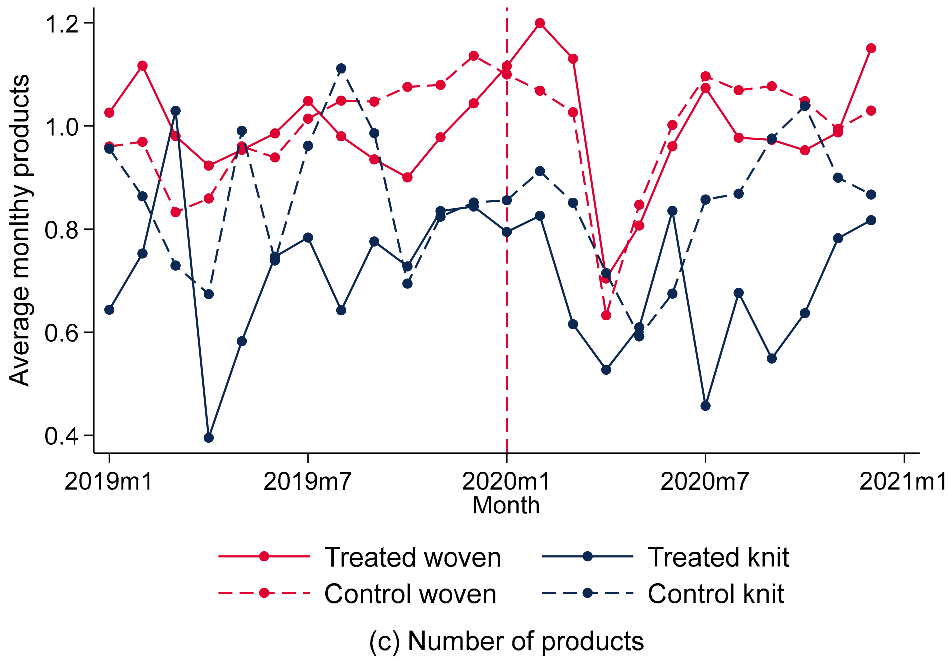


Figure 2. *Cont.*



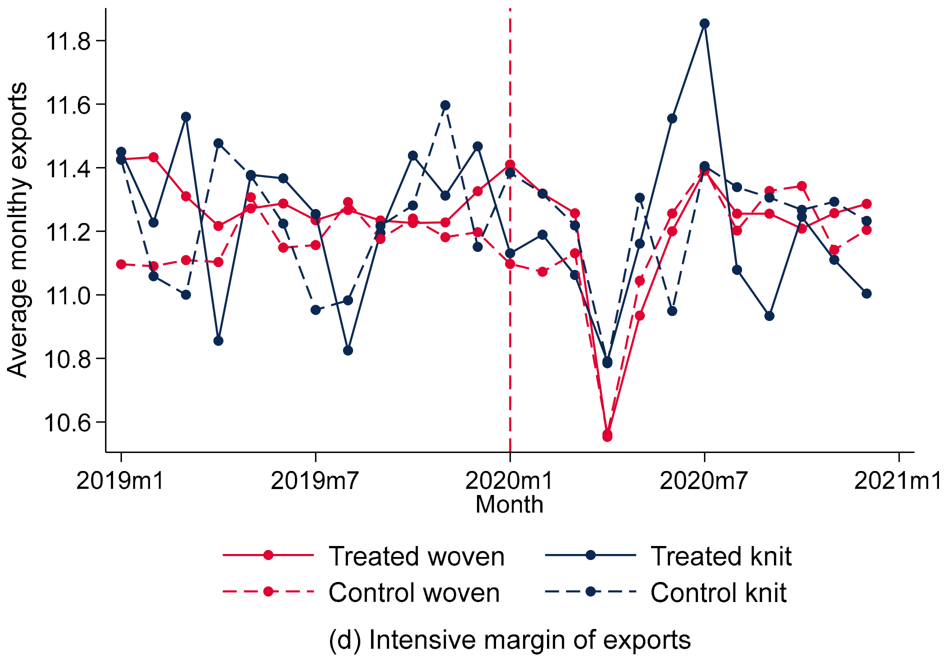


Figure 2. Trends of extensive and intensive margins. Notes: This figure displays the extensive and intensive margin trends before and after the Chinese input supply shock. Panels (**a**–**c**) display the trends of the number of firms, destinations and products, and Panel (**d**) shows the intensive margin, i.e., the changes in the average value of exports per firm–product–destination combination.

Table 3 presents the decomposition results for different subgroups estimated from Equation (6) applying the DDDD approach. We decompose the estimates δ in Table 2 into δ_1 and δ_2 by different firm-level characteristics. The dependent variables are the margin components, as defined in Equations (4) and (5), and analysis is conducted at the disaggregated level by considering different subgroups of firms. The columns represent the subgroups, and the rows reflect the decomposition of the total firm–product–destination level exports to various margin components. Table 3 displays partial results. Table A1 in the Appendix A shows the full results.

Table 3. Changes in the margin of exports by subgroup before and after the lockdown.

	Core Market		Top Products		Small Firms		Shipment Mode	
Margins	**DDD (δ_1)**	**DDDD (δ_2)**	**DDD (δ_1)**	**DDDD (δ_2)**	**DDD (δ_1)**	**DDDD (δ_2)**	**DDD (δ_1)**	**DDDD (δ_2)**
Total	−0.307 * (0.179)	−0.202 *** (0.063)	−0.548 *** (0.163)	0.155 (0.110)	−0.003 (0.143)	−1.253 *** (0.031)	−0.265 * (0.139)	−0.223 *** (0.023)
Firms	0.442 *** (0.043)	−0.052 (0.038)	0.354 *** (0.039)	0.082 *** (0.029)	0.404 *** (0.031)	0.001 (0.001)	0.405 *** (0.031)	−0.001 (0.001)
Countries	0.011 (0.070)	0.010 (0.007)	0.034 (0.068)	−0.026 ** (0.012)	0.020 (0.068)	−0.004 *** (0.001)	0.018 (0.069)	0.001 (0.003)
Products	0.181 *** (0.037)	−0.002 (0.004)	0.168 *** (0.034)	0.019 ** (0.009)	0.181 *** (0.035)	−0.002 (0.001)	0.180 *** (0.035)	0.001 (0.001)
Intensive	−0.942 *** (0.197)	−0.158 ** (0.075)	−1.105 *** (0.176)	0.079 (0.101)	−0.607 *** (0.160)	−1.248 *** (0.030)	−0.867 *** (0.179)	−0.224 *** (0.025)
Quantities	−0.964 *** (0.191)	−0.163 ** (0.073)	−1.188 *** (0.267)	0.174 (0.177)	−0.630 ** (0.257)	−1.257 *** (0.022)	−0.919 *** (0.258)	−0.192 *** (0.033)
Quality-adjusted prices	0.102 * (0.060)	0.067 *** (0.021)	0.183 *** (0.054)	−0.052 (0.037)	0.001 (0.048)	0.418 *** (0.010)	0.088 * (0.046)	0.074 *** (0.008)
Quality	−0.080 (0.065)	−0.063 ** (0.026)	−0.100 (0.062)	−0.043 (0.047)	0.021 (0.049)	−0.409 *** (0.009)	−0.036 (0.050)	−0.106 *** (0.007)

Notes: This table displays the results estimated from Equation (6) for various subgroups of firms across firm-level characteristics, where the outcome variables are the extensive and intensive margin components defined in Equations (4) and (5). This table shows a subset of results. The full results are given in Table A1. Robust standard errors in parentheses are clustered at the market level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Columns (1) and (2) in Table 3 show firms whose export markets clustered highly with respect to a specific export market, such as the EU-15 countries and the US. The decomposition of the values in Column (1) shows that, despite a significant increase in the numbers of firms and products, overall exports declined by approximately 30% at the firm–product–destination level. This is mainly due to the decrease in the intensive margin of 85%, resulting from the decrease in the average shipped quantities of 62%. The quality-adjusted prices increased by 8%. The second column provides the decomposition for the core market. The findings reveal that the number of firms concentrating on the EU-15 and the US experienced an additional 18% decrease in overall exports. The δ_2 coefficient further shows that this subgroup of firms was less affected by the input supply shock than was the benchmark group, and the intensive margins decreased by 13%, mainly due to exported quantity and product quality decreases. The quality-adjusted prices slightly increased, and the quality decreased marginally. However, extensive margin components remained statistically insignificant. The second and third columns of Table 3 present the results for firms whose exports are highly skewed to top products relative to other woven products separately. The coefficients in Column (3) for the benchmark group show that the numbers of firms and products increased significantly by 42% and 18%, respectively, but the number of countries remained insignificant. The intensive margin was strongly affected, with a value of 67%, which was driven by the decrease of 70% in quantities exported. The average quality-adjusted prices of the benchmark group also increased by 20%, which is statistically significant at the 1% level, while product quality remained unaffected. The findings in Column (4) indicate that the supply shock did not affect the leading products; instead, the numbers of firms and products increased by approximately 8.5% and 2%, respectively.

Columns (5) and (6) in Table 3 provide the decomposition results for small versus larger firms in a quadruple difference framework. The findings in Column (5) indicate that benchmark group firms were not affected by ample margins but faced a significant drop in intensive margins, which is associated with a considerable drop in the quantities shipped. In contrast, the results in Column (6) show that small firms were strongly affected by supply shocks in terms of both the extensive and intensive margins. Our results are consistent with those of Behrens et al. [6]. However, the distinction between small and large firms differs from that in the literature, such as [36] and [37]. We create such attributes based on trade frequency, and the actual size of the firm is unknown due to the lack of data. On the other hand, Columns (7) and (8) of Table 3 show the results for firms based on shipment mode. The findings indicate that ocean-going vessels were affected along the intensive margins but remained unaffected through the extensive margins. At the same time, the firms that use other transport modes were severely affected along the intensive margin despite an increase in extensive margin components.

Overall, the key findings of the heterogeneity analysis reveal that (a) exports in core markets decreased more than did exports in the other markets, (b) exports of top woven products were not significantly affected compared to those of small woven products, (c) smaller firms in terms of the median shipment frequency were affected more severely along the intensive margin, and (d) firms with more significant portions of trade through the ocean experienced a large drop in the average value of firm–product–destination level exports relative to the other mode of trade. These results further show that the coefficients of almost all margin components remain quantitatively and qualitatively stable across all specifications compared to the overall decomposition of the export margins. Like the total decomposition, the intensive margin mainly led to a decrease in exports, while the contribution of the extensive margin components remained less dominant. The changes in the intensive margin were primarily influenced by the changes in the quantities shipped, which are similar to the overall decomposition.

Finally, in Table 4, we provide the results of market share reallocation estimated from Equation (10) using the DDD method. Equations (7)–(9) describe the derivations in the margin components for market share reallocation. Table 4 presents the coefficients and the standard errors in parentheses. The whole table can be found in Table A2 in the Appendix A.

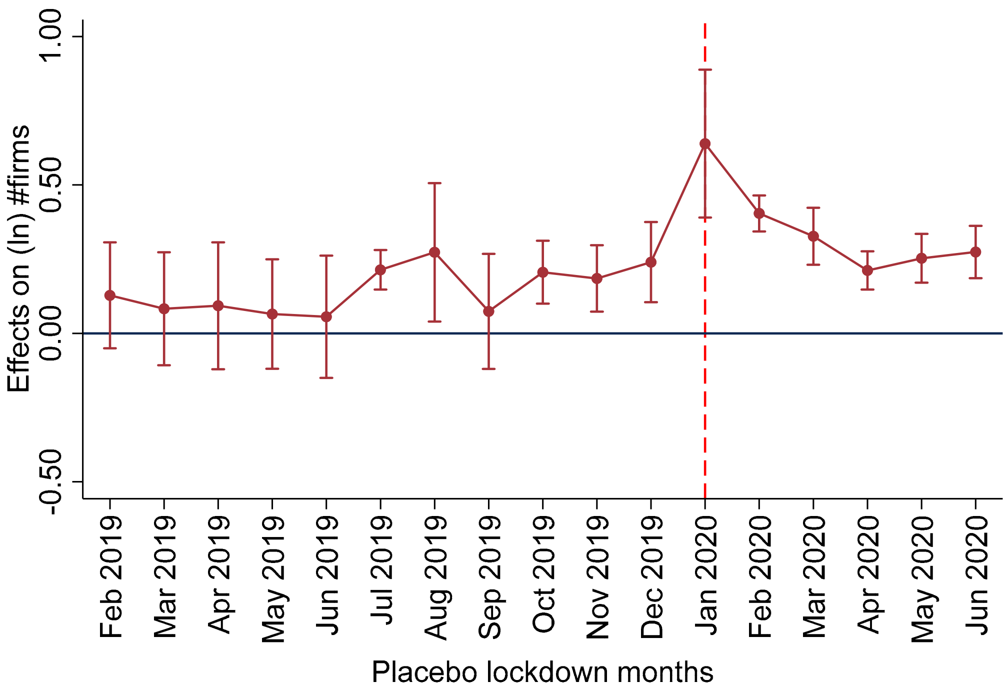
Table 4. Market share changes.

Firm Type	Market Share Readjustment
Incumbent	−0.091 **
	(0.040)
Net Entry	0.091 **
	(0.040)
Entry	0.055 *
	(0.032)
Product Adders	0.024 ***
	(0.006)
Destination Adders	0.037
	(0.028)
Brand-New Entries	−0.006
	(0.018)
Leaver	0.036
	(0.029)
Product Leavers	−0.032 ***
	(0.008)
Destination Leavers	0.055 **
	(0.022)
Complete Leavers	0.013
	(0.024)

Notes: This table presents the average changes in market share before and after the Chinese input supply shock across firm–product–destination triplets, estimated from Equation (10) using the triple difference-in-differences method. The margin components are defined in Equations (7)–(9). The table presents the coefficient and the standard errors in parentheses. The full results are shown in Table A2. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

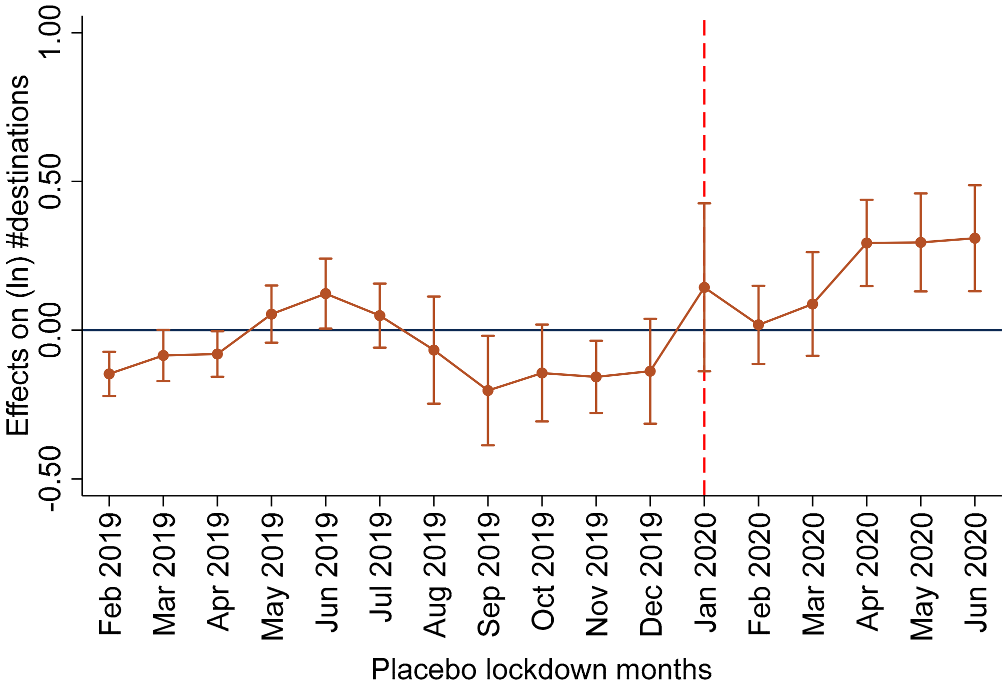
The decomposition of market share reallocation reveals that the incumbent firms' market share decreased by approximately 9% in response to product–destination combinations after China's input supply shock. The decline in the incumbents' market share was readjusted by a 9% increase in the growth of net market entry, which is a necessary condition. Market entrants and leavers contributed 5.5% and 3.6%, respectively, to such gains in net market entry. Among the entrant firms, the percentage of product adders increased significantly by 2.4%, while the percentage of destination adders and brand-new entries did not change significantly. On the other hand, within the leaving firms, the percentage of product leavers changed by −3.2%, and the percentage of destination leavers increased by almost 5.5%, while the complete leavers did not change significantly. The market share decomposition indicates that incumbent firms failed to maintain their market shares due to the input supply shock in the value chain, which was offset by the readjusting changes of the entrants and leavers.

In this section, we report the sensitivity analysis of the results in Table 2. First, the results of placebo tests using fake lockdown months are graphically presented in Figure 3. Figure 3a–c shows extensive margins, and Figure 3d presents the intensive margin of exports. We see that most of the coefficients of extensive margins and all coefficients of intensive margins are statistically insignificant, and some are close to zero, which adds to the validity of our identification strategy. Second, in Figure 4, we present the results of placebo tests using fake treatments (see Figure 4a–c for extensive margins, and Figure 4d for intensive margin). We see that coefficients on extensive and intensive margins show the opposite trend while using fake treatment compared to the actual treatment, indicating the validity of our empirical specification.

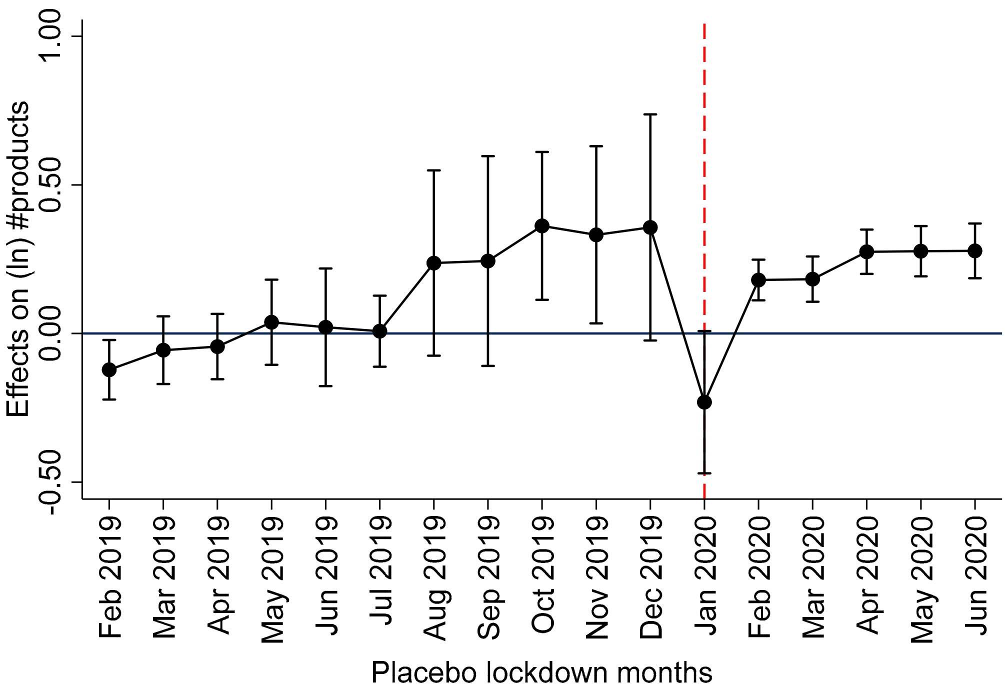


(a) Number of firms

Figure 3. *Cont.*

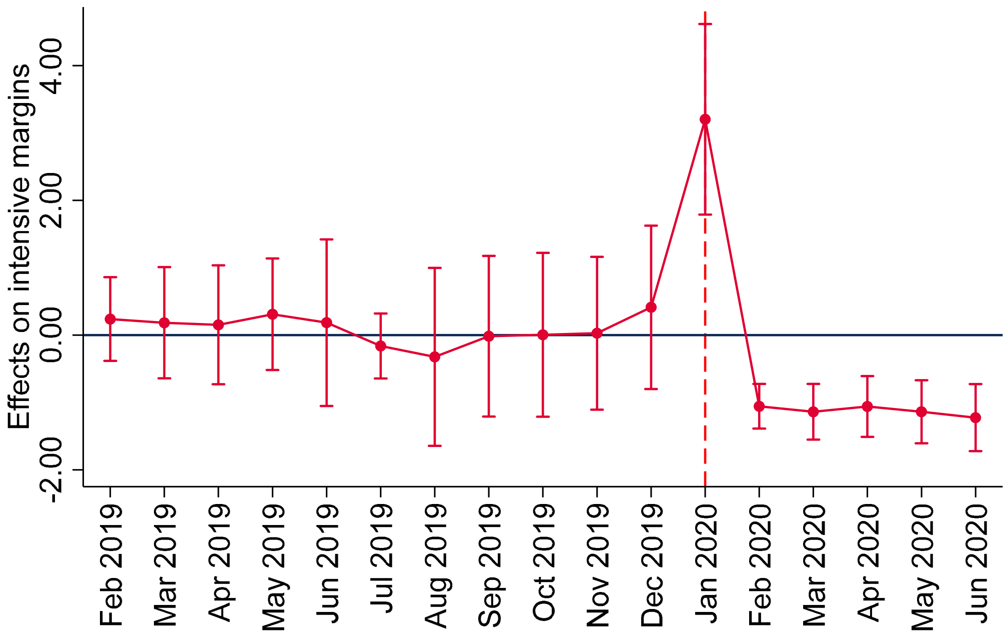


(b) Number of destinations



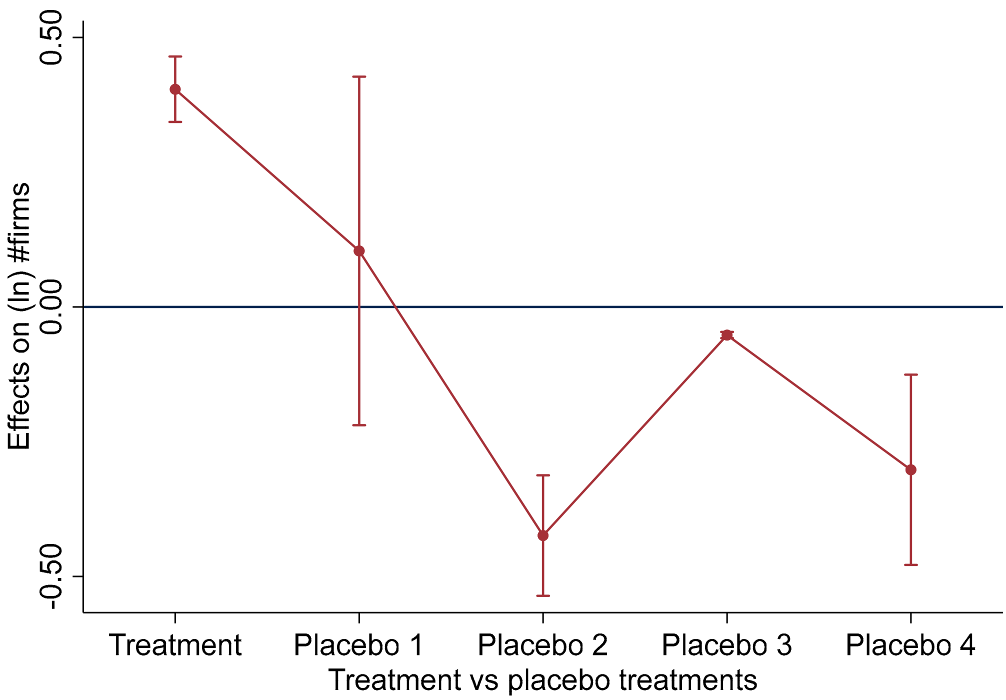
(c) Number of products

Figure 3. *Cont.*



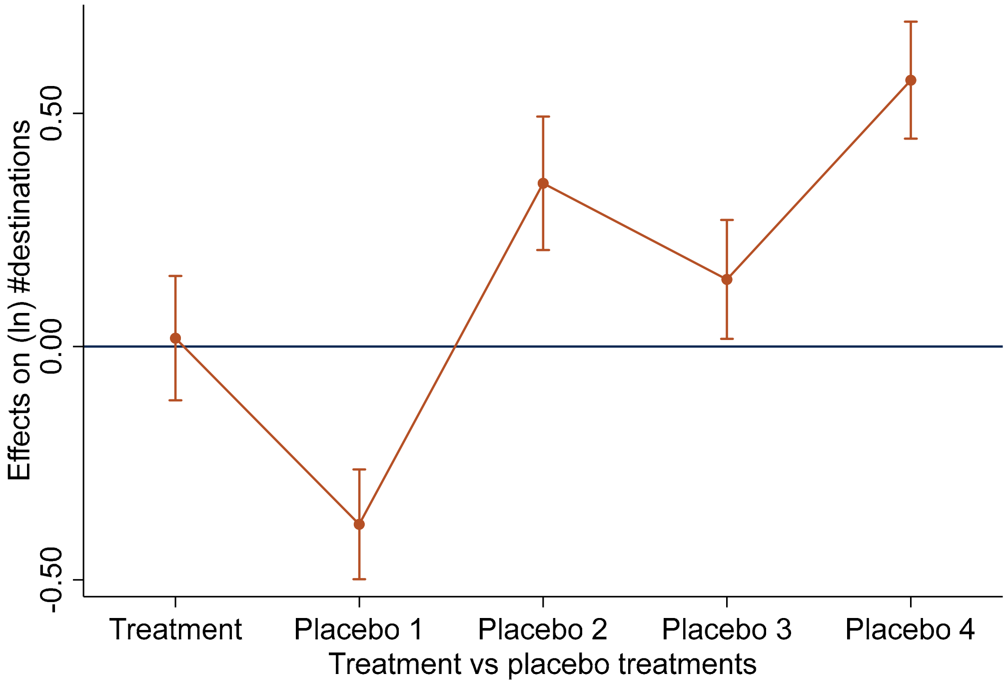
(d) Intensive margin

Figure 3. Robustness checks—placebo lockdown months. Notes: This figure depicts placebo test results using fake months of the treatment event estimated from Equation (3) using the DDD approach. Panels (**a**–**c**) denote the responses of the number of firms, destinations, and products to the placebo treatment months compared to the actual treatment months. Panel (**d**) presents the changes in the average value of exports per firm–product–destination combination. Except for January 2020, all other months are considered to be the fake months of the lockdown that occurred.

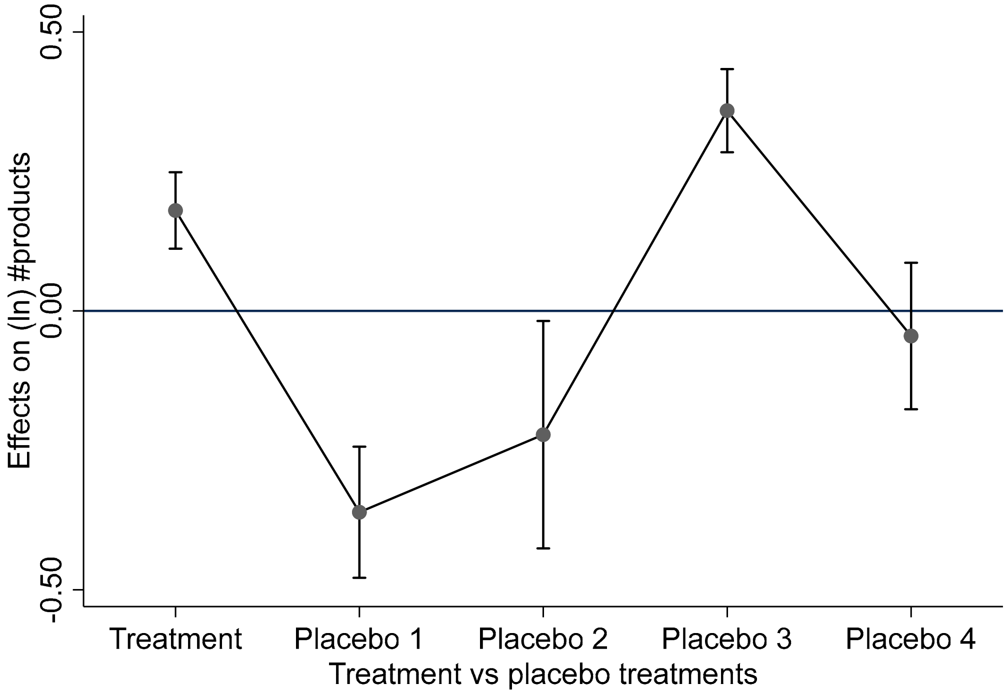


(a) Number of firms

Figure 4. *Cont.*



(b) Number of destinations



(c) Number of products

Figure 4. *Cont*.

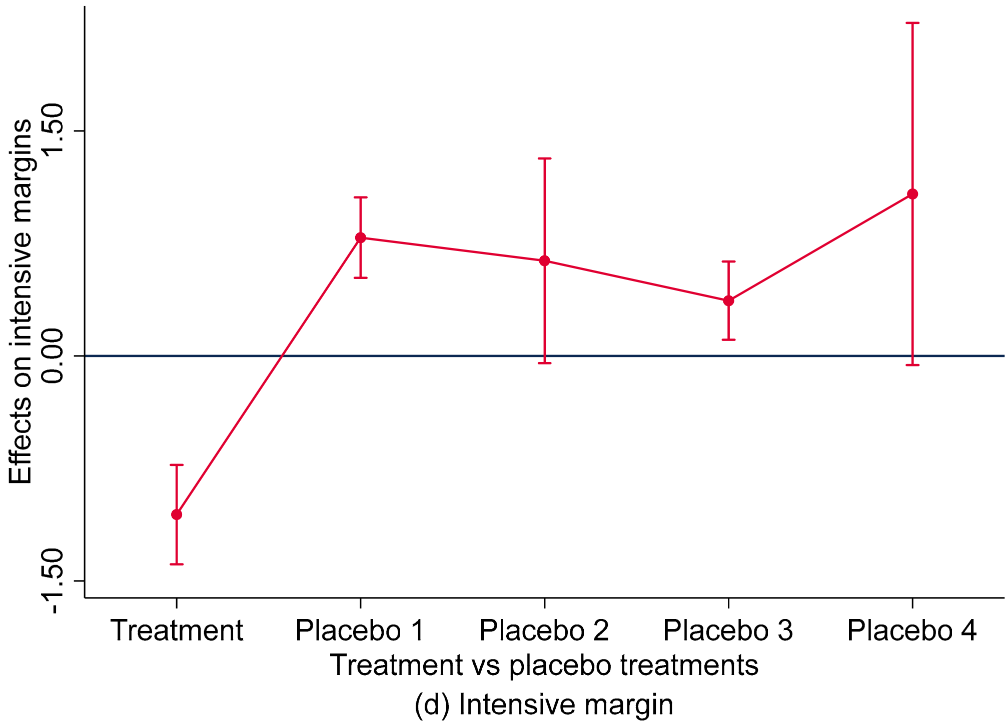
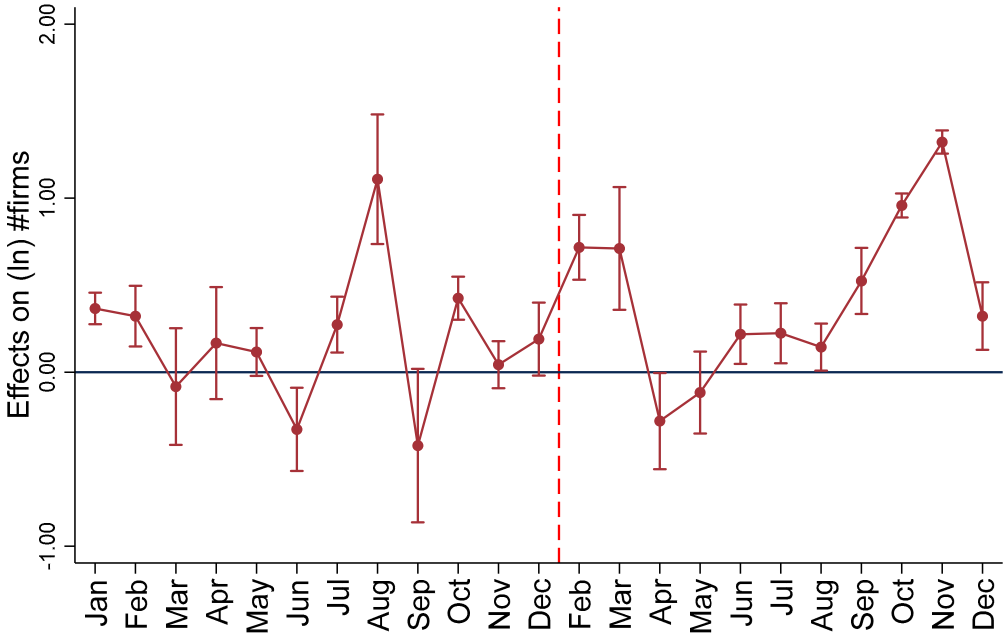
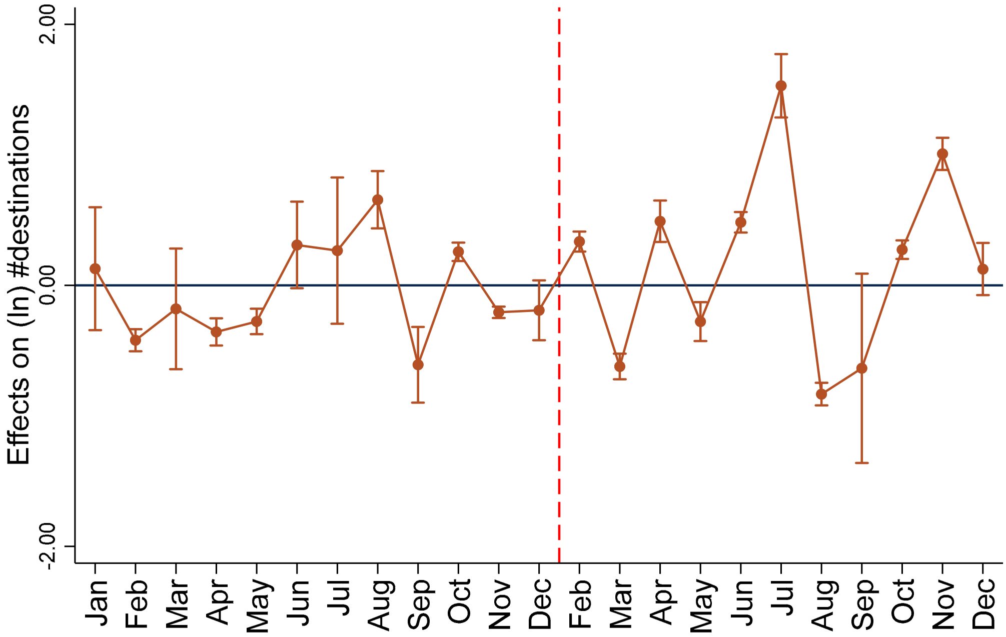


Figure 4. Robustness check—placebo treatment. Notes: This figure depicts placebo test results using fake treatment estimated from Equation (3) using the DDD approach. Each point estimate represents separate DDD regression using placebo treatments. Panels (**a**–**c**) display the responses of the number of firms, destinations, and products to the placebo treatments compared to the real treatment. Panel (**d**) shows the changes in the average value of exports per firm–product–destination combination. Placebo treatment groups 1–4 represent firms that import inputs from Hong Kong, India, Singapore, and Taiwan, respectively.

Third, the analysis of event–study results estimated from Equation (11) with a full set of fixed effects on the whole sample is presented graphically in Figure 5. Figure 5a–c shows the dynamic path of the extensive margins. In contrast, Figure 5d displays the changes in the average value of exports per firm–product–destination combination (the intensive margin) after the posttreatment. Finally, the robustness check results estimated from Equation (3) using an alternative control group are reported in Table A3 in the Appendix A. The results show that the sign and statistical significance of the differences remained almost unchanged, although the size of the coefficients was slightly smaller than that of the results reported in Table 2. The results indicate that the non-importers of intermediate inputs in the control group are similar to those of the baseline group.

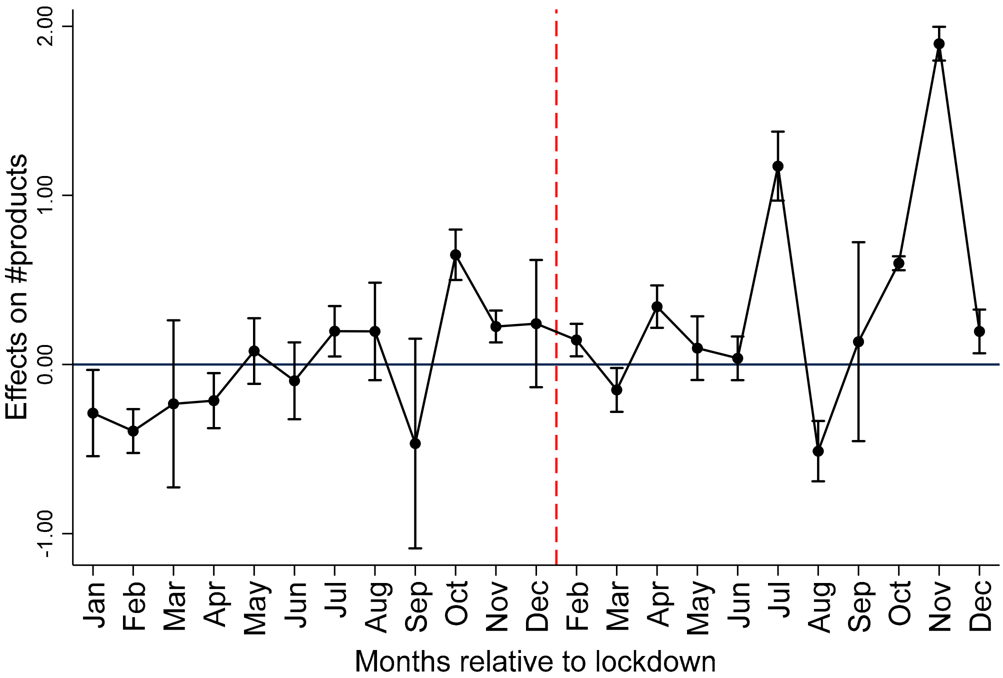


(a) Number of firms

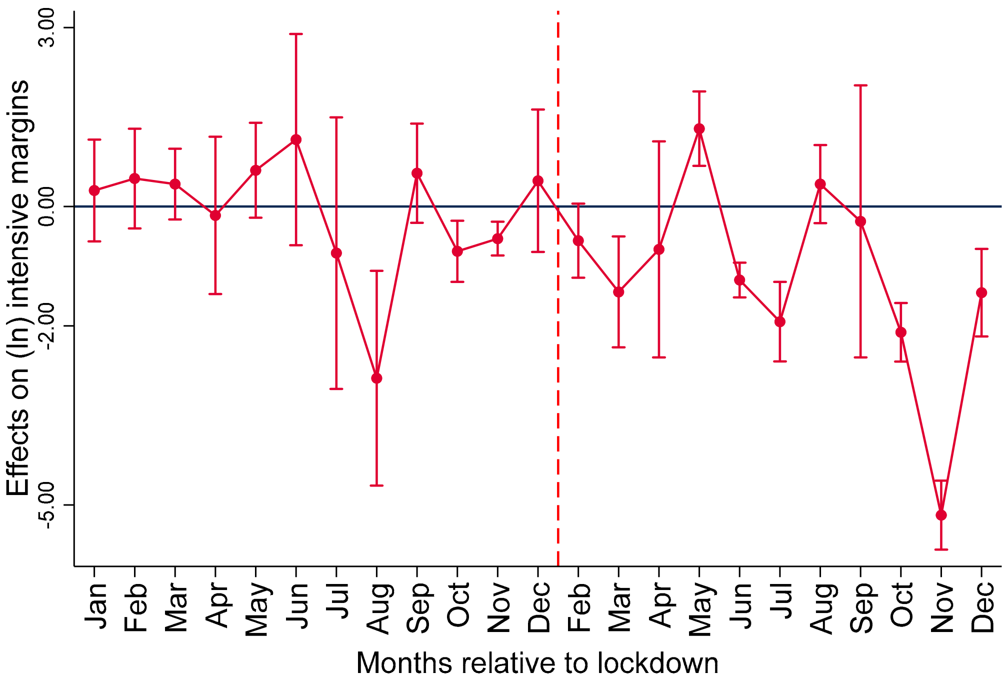


(b) Number of destinations

Figure 5. *Cont.*



(c) Number of products



(d) Intensive margin of exports

Figure 5. Dynamic effects of input supply shocks on export margins. Notes: This figure displays event study results estimated from Equation (11) using the DDD method. Panels (**a**–**c**) display the dynamic responses of the products, destinations, and firms. Panel (**d**) shows the changes in the average value of exports per firm–product–destination combination. The solid lines represent the estimates around the 95% confidence interval. January 2020 was used as a reference category.

6. Conclusions

In this paper, we conduct regression decomposition analysis using triple and quadruple difference-in-differences approaches to investigate the causal linkages of the Chinese intermediate input supply shock on export margins, focusing on Bangladesh's apparel industry. In this study, the decline in exports is explained by performing decomposition across firms, products, destinations, and market share reallocation. Our findings reveal several crucial aspects of Bangladesh's recent abrupt export decline during the firm-level propagation of input supply shocks induced by the lockdown in China in 2020. We can summarize three main points as follows:

First, the shock of the lockdown mainly affected Bangladesh's intensive export margins. The intensive margin, i.e., the average export value per firm–product–destination combination, decreased by approximately 65%, leading to an abrupt decrease in overall exports. On the other hand, the extensive margins, i.e., the average number of firms and the number of products exported, rose by approximately 50% and 20%, respectively. Further decomposition of the intensive margin indicates that the substantial changes were mainly due to changes in its elements, such as quantities, prices, and quality. The average quantities shipped in firm–product–destination triplets were reduced by approximately 66%. Moreover, after the shock, quality-adjusted prices increased by 16%, and the average product quality decreased by 12%. Second, the decomposition using the DDDD method shows that the intensive margin of exports was strongly affected for firms whose exports were highly concentrated in the core market, smaller firms in terms of shipment frequency, and firms trading through sea routes. The decrease in shipment quantities mainly influenced the decrease in exports. In contrast, the intensive margin was not affected for firms whose exports were top products. Moreover, while not identical, the changes in extensive margins for the different subgroups increased across various firm characteristics and remained analogous to the overall decomposition. The Chinese input supply shock primarily adversely affected apparel exports from Bangladesh along the intensive margin. Finally, the decomposition of market share reallocation reveals significant market share readjustment after China's input supply shock. The shock decreased the incumbent firms' market share by approximately 9% for product–destination pairs. This decline was offset by an equivalent 9% gain by net market entry for an average change of zero, of which entrants and leavers contributed 5.5% and 3.6%, respectively. The critical point of these findings is that the shrinking market was mild during the post shock period.

There are several points to consider regarding policy implications. First, single-country input dependency directly increases the vulnerability of Bangladesh's apparel industry to Chinese input supply shocks through the intensive margin. This evidence may help in diversifying the intermediate input supply chain. Second, promoting the backward linkage of industries may help maintain sustainable export growth in the case of future supply shocks. Third, our empirical results in relation to Bangladesh's apparel industry may lead to a lesson for other least-developed nations with high exposure to foreign shocks by relying on imported intermediate inputs. Finally, our findings may help pertinent countries to formulate proper trade policies to accelerate the achievement of SDGs.

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Abbreviations

DDD	Difference-in-difference-in-differences
DDDD	Difference-in-difference-in-difference-differences
GVC	Global value chain
ROW	Rest of the world
HS	Harmonized system

Appendix A

Additional results.

Table A1. Full results for the heterogeneous effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	**Total Export**	**Firm**	**Country**	**Product**	**Intensive**	**Quantities**	**Quality-Adjusted Prices**	**Quality**
(a) Firms concentrated on core market								
Treated∗Woven∗Post	−0.307 *	0.442 ***	0.011	0.181 ***	−0.942 ***	−0.964 ***	0.102 *	−0.080
	(0.179)	(0.043)	(0.070)	(0.037)	(0.197)	(0.191)	(0.060)	(0.065)
Treated∗Woven∗Post∗Core-market	−0.202 ***	−0.052	0.010	−0.002	−0.158 **	−0.163 **	0.067 ***	−0.063 **
	(0.063)	(0.038)	(0.007)	(0.004)	(0.075)	(0.073)	(0.021)	(0.026)
(b) Firms skewed on top products								
Treated∗Woven∗Post	−0.548 ***	0.354 ***	0.034	0.168 ***	−1.105 ***	−1.188 ***	0.183 ***	−0.100
	(0.163)	(0.039)	(0.068)	(0.034)	(0.176)	(0.267)	(0.054)	(0.062)
Treated∗Woven∗Post∗Top_products	0.155	0.082 ***	−0.026 **	0.019 **	0.079	0.174	−0.052	−0.043
	(0.110)	(0.029)	(0.012)	(0.009)	(0.101)	(0.177)	(0.037)	(0.047)
(c) Small firms								
Treated∗Woven∗Post	−0.003	0.404 ***	0.020	0.181 ***	−0.607 ***	−0.630 **	0.001	0.021
	(0.143)	(0.031)	(0.068)	(0.035)	(0.160)	(0.257)	(0.048)	(0.049)
Treated∗Woven∗Post∗Small_firm	−1.253 ***	0.001	−0.004 ***	−0.002	−1.248 ***	−1.257 ***	0.418 ***	−0.409 ***
	(0.031)	(0.001)	(0.001)	(0.001)	(0.030)	(0.022)	(0.010)	(0.009)
(d) Sea routes as shipment mode								
Treated∗Woven∗Post	−0.265 *	0.405 ***	0.018	0.180 ***	−0.867 ***	−0.919 ***	0.088 *	−0.036
	(0.139)	(0.031)	(0.069)	(0.035)	(0.179)	(0.258)	(0.046)	(0.050)
Treated∗Woven∗Post∗Sea_route	−0.223 ***	−0.001	0.001	0.001	−0.224 ***	−0.192 ***	0.074 ***	−0.106 ***
	(0.023)	(0.001)	(0.003)	(0.001)	(0.025)	(0.033)	(0.008)	(0.007)
Observations	160,991	160,991	160,991	160,991	160,991	160,991	160,991	160,991
Firm–product–destination FE	y	y	y	y	y	y	y	y
Prod–destination–month FE	y	y	y	y	y	y	y	y
Firm–month FE	y	y	y	y	y	y	y	y
Adjusted R-squared	0.714	0.992	0.995	0.991	0.839	0.834	0.748	0.607

Notes: This table provides the detailed results estimated from Equation (6) for four different subgroups of firms. Columns (2) to (5) present the decomposition of the total export, as shown in Column (1). Columns (6) to (8) display the further decomposition of the intensive margin shown in Column (5). Robust standard errors in parentheses are clustered at the market level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A2. Market share reallocation—full results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable	**Incumbent Share**	**Net**	**Leaver Share**	**Product Leaver Share**	**Dest. Leaver Share**	**Total Leaver Share**	**Entry Share**	**Product Adder Share**	**Dest. Adder Share**	**Brand New Entry**
Treated	0.079 *** (0.023)	−0.079 *** (0.023)	0.079 *** (0.023)	−0.007 ** (0.003)	−0.046 ** (0.021)	0.132 *** (0.014)	−0.152 *** (0.021)	0.001 (0.004)	0.043 ** (0.017)	−0.196 *** (0.015)
Woven	−0.036 (0.029)	0.036 (0.029)	−0.036 (0.029)	−0.019 *** (0.006)	−0.027 (0.022)	0.010 (0.017)	0.011 (0.026)	0.031 *** (0.008)	−0.021 (0.016)	0.001 (0.023)
Treated∗Woven	0.055 * (0.032)	−0.055 * (0.032)	0.055 * (0.032)	0.024 *** (0.006)	0.037 (0.028)	−0.006 (0.018)	0.036 (0.029)	−0.032 *** (0.008)	0.055 ** (0.022)	0.013 (0.024)
Post	0.038 * (0.023)	−0.038 * (0.023)								
Treated∗Post	0.073 *** (0.027)	−0.073 *** (0.027)								
Woven∗Post	0.026 (0.036)	−0.026 (0.036)								
Treated∗Woven∗Post	−0.091 ** (0.040)	0.091 ** (0.040)								
Observations	5596	5596	3115	3115	3115	3115	2481	2481	2481	2481
R-squared	0.038	0.038	0.023	0.008	0.003	0.071	0.036	0.018	0.016	0.144

Notes: This table presents the full results estimated from Equation (10). Columns (1) and (2) display incumbents' shares and net market entry growth, respectively. Columns (4) to (6) represent the decomposition of the share of market leavers, as presented in Column (3). In contrast, Columns (8) to (10) present the breakdown of the entrants' shares shown in Column (7). Robust standard errors in parentheses are clustered at the market level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A3. Robustness check: an alternative control group.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	**Total**	**Firms**	**County**	**Product**	**Intensive**	**Quantity**	**Quality Adjusted Prices**	**Quality**
Treated∗Woven∗Post	−0.120 **	0.203 ***	0.040 **	0.124 ***	−0.487 ***	−0.513 ***	0.040 **	−0.013
	(0.055)	(0.004)	(0.017)	(0.016)	(0.060)	(0.062)	(0.018)	(0.024)
Observations	386,307	386,307	386,307	386,307	386,307	386,307	386,307	386,307
Firm–product–destination FE	y	y	y	y	y	y	y	y
Prod–destination–month FE	y	y	y	y	y	y	y	y
Firm–month FE	y	y	y	y	y	y	y	y
Adjusted R-squared	0.718	0.989	0.994	0.990	0.828	0.818	0.751	0.632

Notes: This table presents the results from estimating Equation (3) using an alternative control group. The alternative control group comprises firms that do not directly rely on foreign intermediate inputs. Columns (2) to (5) are the decompositions of the overall exports in Column (1). Columns (6) to (8) are the decompositions of the intensive margin in Column (5). Robust standard errors in parentheses are clustered at the market level. *** $p < 0.01$ and ** $p < 0.05$.

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