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The U.S.–China trade war: Tariff data and general equilibrium analysis

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ABSTRACT

The current trade war between the United States and China is unprecedented in modern history. This study introduces a database of tariff increases resulting from the trade war and quantifies the impacts using the canonical GTAPinGAMS model calibrated to the recently released GTAP version 10 accounts. We find that the remaining tariff increases as of March 2020 after the phase one trade deal decrease welfare in China by 1.7% and welfare in the United States by 0.2%. Impacts on sectoral revenue are reported for both countries. China's exports to and imports from the United States are reduced by 52.3% and 49.3%. The trade flow between the United States and China will be diverted to their major trade partners resulting in higher welfare in those countries, including many Asian countries. The estimated impacts are robust to using alternative trade elasticities and are amplified in the absence of the phase one tariff reductions.

1. Introduction

Since 2018, the ongoing trade war between the United States and China has shaken the world economy. In early 2018, the United States invoked Section 232 of the Trade Expansion Act of 1962 (alleging a national security threat) to increase tariffs on steel and aluminum products, which started U.S. trade disputes with major steel and aluminum exporters including China. Some of these disputes, such as those between the United States and Canada and Mexico, have already been resolved through negotiations. In the meantime, U.S. trade disputes with China have quickly evolved into a full-blown trade war. After Section 301 (unfair trade) investigations, the United States increased tariffs on large swathes of Chinese goods. China was able to retaliate proportionally in early rounds but quickly ran out of U.S. exports to add tariffs to, given its large trade surplus with the United States (Li, Zhang, & Hart., 2018). As of the fall of 2019 more than 90% of products at the six-digit Harmonized System (HS6) Classification level have experienced tariff increases from one or both countries. The phase one trade deal signed by the two countries in January 2020 slows the pace of the trade war by reducing some of the previous tariff increases and suspending threatened tariff hikes. In fact, however, the phase-one tariff reductions are modest and the direction of the trade negotiation is uncertain (Bown, 2020). In this paper, we assess the impacts of the trade war using a Computational General Equilibrium (CGE) model with detailed tariff information and a focus on Asian countries.

CGE models are the standard tool for evaluating the impacts of changes in trade barriers. In the last three decades, these methods have been applied to analyze important events in international trade such as China's accession to the World Trade

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Organization (WTO) (e.g., Ianchovichina and Martin (2004)), the Uruguay (Francois, 2000; Harrison, Rutherford, & Tarr, 1997) and Doha (Bouët, Mevel, & Orden, 2007) rounds of WTO negotiation, the North America Free Trade Agreement (NAFTA, Caliendo and Parro (2015), Kehoe (2003)), and regional economic agreements (Jugurnath, Stewart, & Brooks, 2007; Kawasaki, 2015; Lee, Roland-Holst, van der, & Mensbrugghe, 2004). A barrier for conducting CGE analysis for the U.S.–China trade war is keeping up with the policy changes. There are numerous ongoing tariff disputes between the United States and its trade partners and repeated rounds of tariff increases between the United States and China. These policy changes need to be compiled and processed for analysis. This study fills this gap by presenting a comprehensive database on tariff increases, harmonized to the sectors in the recently released Global Trade Analysis Project (GTAP) 10 database.

There is an emerging literature that employs CGE analysis to study the impacts of the trade war. For the earlier stage of the trade war, Balistreri et al. (2018) combine a global CGE model and a regional CGE model of the United States and find that the tariff increases up to the $50 billion round in August 2018 cost Iowa, a major agricultural state in the United States, about 1% of Gross State Product. Using the GTAP model, Carvalho, Azevedo, and Massuquetti (2019) find that tariff increases in the $50 billion round decrease welfare by $39.7 billion to $43.1 billion for China and $19.3 to $23.6 billion for the United States. Guo, Lu, Sheng, and Yu (2018) use the Eaton and Kortum (2002) model to evaluate a 45% tariff increase, proposed by then presidential candidate Donald Trump, on all Chinese exports. In their scenarios where China retaliates with 45% tariff increases on U.S. exports, Guo et al. (2018) find real wage changes ranging from −0.37% to 0.08% in China and −0.75% to −0.32% in the United States. Since these studies either only use tariff increases in earlier rounds or use hypothetical tariff increases on all exports, their results cannot fully and accurately capture the impacts of the trade war.

Several new studies have examined the recent situation of the trade war. Charbonneau and Landry (2018) use the Caliendo and Parro (2015) model to study the trade war up to the $200 billion round of tariffs as of January 2019. Giesecke, Waschik, and Tran (2019) use a dynamic GTAP model (GTAP-MVH) to study tariff increases up to the $200 billion round. Their projections indicate the tariffs impacts, measured by GDP, employment, and real consumption, peak in 2020 and 2021 and attenuate significantly by 2025 as markets adjust. Bellora and Fontagné (2019) use a recursive dynamic model (MIRAGE-e) to study the tariffs in place after the phase one trade deal, same as the main scenario in this study. They find that, by 2030, GDP and real wages will decrease in both the United States and in China, with more severe impacts on China. To our knowledge, our study is the first to use the canonical GTAPinGAMS model (Lanz & Rutherford, 2016) calibrated to the GTAP version 10 accounts to study the impacts of recent tariff increases. Using this *off-the-shelf* model provides a transparent reference point for evaluating the trade war impacts under a generic neoclassical economic structure. By building scenarios using tariff increases with and without the recently signed phase one trade deal, our model provides an accurate and comprehensive estimate of the trade war impacts on the economies. Furthermore, this study focuses on Asian countries, which is unique among existing studies of the U.S.–China trade war.

We find that, first, under the remaining tariffs after the phase one trade deal, China's welfare (household well-being) falls by 1.7% while U.S. welfare falls by 0.2%.[1] Welfare increases in all other countries and regions in this study, with Southeast Asian countries such as Malaysia and Thailand among the major beneficiaries. Second, the tariffs have substantial effects on the output of targeted sectors as well as related sectors, particularly the “Oil seeds” sector (primarily soybeans) in the United States and the “Electronic equipment” sector in China. Third, China's exports to and imports from the United States will be reduced by 52.3% and 49.3% respectively under the tariffs even with the phase one trade deal. There is significant trade diversion as China increases its penetration into the markets in the EU, Canada, and Mexico, and as other countries such as South Korea displace China's exports to the United States. Shifting trade flows result in modest decreases in aggregate import and export for China and the United States. These results are robust to a wide ranges of trade elasticities (i.e. Armington elasticities).[2] To put our quantitative results in context, persistence of the trade war leads to welfare *losses* for the United States and China comparable to proportional welfare *gains* attributed to China's accession to the WTO, the Uruguay round, and even simulations of global free trade (as reviewed in Section 4).

The rest of this paper is structured as follows. Section 2 offers a description of the model and describe the tariff database. Section 3 presents results on overall welfare, industry output value, and trade flows. Section 4 concludes, discusses the limitation of the GTAPinGAMS model and compares findings with the impacts of other important events in international trade.

2. Method

2.1. The canonical GTAPinGAMS model and scenarios

The GTAPinGAMS model (Lanz & Rutherford, 2016) is a CGE model which we calibrate to the recently released GTAP 10 database described in Aguiar et al. (2019). The full mathematical structure of the model is provided by Lanz and Rutherford (2016). We provide, here, a summary description of the structure and the theoretic basis for our central welfare measure.

[1] Our goal is to report a theory consistent welfare analysis. We use Hicks' *equivalent variation* as our measure of welfare change. The measure is further explained in the following section.

[2] Current observed trade responses are not as large as the model indicates. This likely reflects sluggish responses and perhaps expectations of a pending resolution in the short-run. The trade elasticities in the GTAP model are generally interpreted as medium to long-run responses.

The GTAPinGAMS model includes a comprehensive division of the world into regions or countries. A region or country is defined by its non-traded primary factors of production owned by its representative agent. Preferences and production technologies for each region are of the constant-elasticity-of-substitution (CES) class, with production under perfect competition. There is a full input–output structure of production where an industry's technology includes value-added (primary-factor) and intermediate inputs as observed in the social accounts. All markets clear and the general equilibrium is characterized by a complete set of *relative* prices. The model is a static Arrow-Debreu general equilibrium in the tradition of Shoven and Whalley (1992).

We adopt the global multi-region trade version of the GTAPinGAMS model, which characterizes a full international trade equilibrium in relative prices among all countries.[3] China and the United States are important players in international trade. That is, they are large countries that influence global prices. Looking at the current trade war, thus, requires the adoption of a model with a multi-regional trade equilibrium. The model adopts a particular trade structure consistent with the Armington (1969) assumption—goods from different countries are treated as imperfect substitutes. We employ the standard CES nesting where imports from different sources are closer substitutes than are imports and domestic goods. The (Armington) composite of a given good is available for use in production (as an intermediate input) or final demand. The Armington elasticities of substitution are the most crucial parameters for assessing trade responses (McDaniel & Balistreri, 2003). Therefore, besides the central results, we conduct sensitivity analyses using one and two standard deviations around the original estimates adopted in the GTAP database, which come from Hertel, Hummels, Ivanic, and Keeney (2007). We also explore the impact of adopting an alternative source, Ossa (2015), for the estimated elasticities.[4]

Our measure of welfare change is Hicks' *equivalent variation* for the regional representative agents.[5] The representative agent's preferences are defined over household consumption.[6] Equivalent variation (EV) is the *real* money-metric utility value that the representative agent places on the policy scenario evaluated at benchmark prices. That is, it is the cash equivalent of the policy scenario, from the perspective of the agent, in the context of having a choice of adopting the policy or the cash. Calculating EV is relatively straightforward within the GTAPinGAMS structure. Consider that a representative agent's preferences and optimizing behavior are captured by the minimized expenditure function: $e_r(\boldsymbol{p}, u_r)$, where the arguments are the price vector ($\boldsymbol{p}$) and the level of utility or welfare (u_r), and r indexes the region or country. Under linearly-homogeneous CES preferences the expenditure function can be decomposed as follows:

$$e_r(\boldsymbol{p}, u_r) = u_r P_r(\boldsymbol{p}),$$

where $P_r(\boldsymbol{p})$ is a price index that represents the unit expenditure function (or true-cost-of-living index). Both u_r and P_r are solved in the equilibrium. In fact, u_r is the level of money-metric utility (welfare) if we choose units carefully such that $P_r(\boldsymbol{p}) = 1$ at the benchmark. The real welfare change (EV) for region r is simply the change in u_r as reported in the model solution.[7]

Distinct from our GTAPinGAMS model structure is the GTAP database used to establish the benchmark. The functions are calibrated to the newly released GTAP version 10 data (Aguiar et al., 2019). The GTAP data include a full set of input–output and bilateral trade accounts for 65 sectors and 141 regions/countries. The GTAP10 data are documented by Aguiar et al. (2019), and relevant baselines are reproduced in appendix tables. We maintain a high level of sectoral disaggregation with 57 distinct production sectors and associated commodities.[8] We aggregate the regions to reduce computational dimensions and focus our analysis on important trade responses, especially those from Asian countries. To this end, countries are individually included in the model if they are among the top twenty trading partners (import plus export) with either China or the United States in 2017 and are not a part of the European Union (EU), which is treated as a single aggregate region. Based on this criteria, 12 Asian countries and territories are included individually (see Fig. 1), including Southeast Asian countries such as Malaysia, Thailand, Singapore, Indonesia and Philippines and East Asian economies such as Japan, South Korea, Taiwan and Hong Kong. Aggregate regions include the rest of southeast Asia, the rest of south Asia, the rest of Asia, the EU, and rest of the world.

2.2. Tariff increases scenarios and data

In March 2018, the United States increased tariffs on aluminum and steel by 10% and 15% respectively. Canada, China, the EU, India, Mexico, and Turkey each retaliated with proportional tariff increases on U.S. goods. In May 2019, agreements were reached between the United States and Canada and Mexico to end U.S. tariffs on steel and aluminum and the retaliatory

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[3] The GTAPinGAMS model, as formulated by Lanz and Rutherford (2016), has two versions depending on model closure conditions: The global multi-regional (GMR) model and small open-economy model (SOE). The key difference between the two models is that only in the GMR model can import and export prices change. The rest-of-world region the in the SOE model has perfectly elastic import demand and export supply, which effectively holds trade prices constant, precluding any term-of-trade effects.

[4] Ossa (2015) estimates trade elasticities for commodities under Standard International Trade Classification (SITC). We construct a concordance between SITC to GTAP commodities by combining existing concordances between HS6 codes and SITC, and between HS6 codes and GTAP commodities. For most GTAP commodities, Ossa's elasticities calculated this way are smaller than the default elasticities in the GTAP model estimated by Hertel et al. (2007).

[5] Equivalent variation is a well-known and widely adopted measure of welfare change originating with Hicks (1939).

[6] As is standard in a static welfare analysis investment and government demand is held fixed in real terms. The assumption is that the benefits from these expenditures are separable from private consumption. The focus is thus on equivalent variation in private consumption.

[7] Under linearly-homogeneous preferences one can apply the duality identity $v_r(\boldsymbol{p}, e_r(\boldsymbol{p}, u_r)) \equiv u_r$ (where $v_r(\bullet)$ is the money-metric indirect utility function evaluated at benchmark prices) to prove that changes in u_r measure equivalent variation.

[8] The 57 sectors are consistent with the 57 GTAP 9 sectors. We aggregate to this level to maintain comparability with earlier versions of this research.

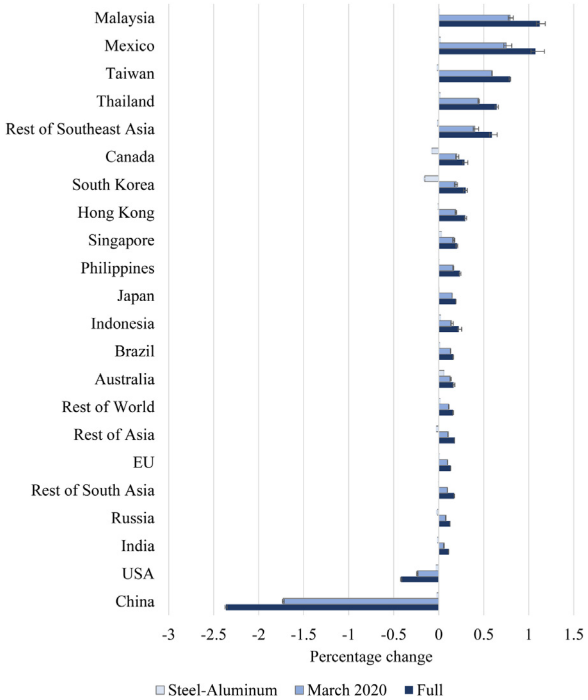

Fig. 1. Welfare impacts across regions (% change).

tariffs from Canada and Mexico. In June and August of 2018, the United States imposed 25% additional duty on $50 billion worth of Chinese exports related to China's "Made in China 2025" industrial policy. China responded with 25% additional tariffs on the same amount of U.S. products, notably agricultural products such as soybeans (Zhang, 2020).

In September 2018, the United Stated raised tariffs by 10% on $200 billion worth of products from China and China retaliated with 5–10% tariffs on $60 billion worth of products from the United States. After the negotiation between China and the United States broke down, the 10% tariffs applied by the United States on $200 billion worth of Chinese goods increased to 25% in June 2019, and China's tariffs on $60 billion worth of U.S. exports increased to 5–25%. In September 2019, the United States increased tariffs by 15% on the first batch of products from a list of $300 billion worth of Chinese exports and China responded by increasing tariffs on the first batch of products from a list of $75 worth of billion U.S. exports (Wong & Koty, 2020).

In January 2020, the United States and China signed the phase one trade deal which reduces the first batch of the $300/$75 billion tariffs by half, and suspends the second batch of the $300/$75 billion tariffs as well as the 5% tariff increase on $250 billion worth of Chinese export threatened by the United States (Bown & Kolb, 2020).

We construct three relevant scenarios with different tariff increases:

Scenario 1: Steel-aluminum Tariff increases due to the U.S. steel and aluminum tariffs and retaliatory tariffs from China, the EU, India, and Turkey. U.S. tariffs on Mexico and Canada, and corresponding retaliatory tariffs have been removed, reflecting the results of later negotiations.

Scenario 2: March 2020 Tariff increases in scenario 1 and additional tariff increases between the United States and China, including the $50 billion round, the $200 billion/$60 billion round, and the first wave of the $300/$75 billion round tariff increases (reduced by half). This is the scenario after the phase one trade deal which became effective in February 2020.

Scenario 3: Full tariffs Cumulative tariff increases in scenario 1 and 2, and scheduled tariff increases on $250 billion Chinese products from 25% to 30%, and the full first wave and the second wave of the $300/$75 billion round tariffs. This represents a reversion of the phase one trade deal and the implementation of threatened tariffs.[9]

[9] China's retaliation for the additional 5% tariff $250 billion worth of Chinese exports has not been announced yet and is not included. Also, the model does not include the scattered exemptions or China's purchase commitment in the phase one trade deal. In addition, our analysis does not consider the renegotiated NAFTA, also known as the United-States- Mexico–Canada Agreement. However, since the new NAFTA largely maintains tariff-free trade in most goods, we expect it to have little impact at the aggregate level.

2.3. Data processing

Tariff increases listed above are collected from original government announcements, using up-to-date chronicles as guidance (Bown & Kolb, 2020; Wong & Koty, 2020). The raw tariff increases, mostly at the HS8 code level, are aggregated to the HS6 level by simple averaging, then merged to 2016 trade flow data as reported by the United States from the UN Comtrade database.[10] A concordance between six-digit HS codes and GTAP codes is conducted by the authors using existing concordances. Specifically, the 2017 HS6 code is first cross-walked to 2007 HS6 using a concordance from UN Trade Statistics; then the 2007 HS6 codes are preliminarily cross-walked to GTAP codes using a concordance from World Integrated Trade Solution. After the preliminary matching, HS6 codes that are not matched by the WITS concordance go through additional rounds of matching based on corresponding HS4 codes and commodity description. Original tariff increase data, HS6-level data, GTAP-sector level data, documents and data processing codes are freely available for download (Li, 2020).

3. Results and reports

3.1. Trade-weighted tariff increases

We first report, in Table 1 and Appendix Table A.1, the trade-weighted cumulative tariff increases in different scenarios. We omit the tariff increases for Scenario 1: Steel-aluminum because they are minor compared the other two scenarios. The tariff lists of both countries contain products with little trade volume, highlighting the importance of using trade-weighted tariff increases. The trade-weighted average U.S. tariff increase on Chinese exports is about 18.6% by March 2020 and by 30.4% in the full tariffs scenario. The corresponding Chinese retaliations increase trade weighted tariffs by 18.9% by March 2020 and by 23.3% in the full tariff scenario. In the full tariffs scenario, China's retaliation will be lower than the U.S. tariffs both in trade weighted tariff increase and in the amount of trade affected.

In March 2020 after the phase one trade deal, among important Chinese products with more than 5% share of China–U.S. export, ‘Other machinery and equipment’ took the hardest hit (38.1%), followed by ‘Electronic equipment’ (18.5%) and ‘Chemical rubber and plastic products (17.4%).’ In the full tariffs scenario where the phase one trade deal is reverted, tariffs on important Chinese exports to the United States will be above 20% across the board, with tariffs on “Other machinery and equipment” and “Electronic equipment” raised to as high as 47.9% and 31.7%. Among important U.S. exports to China with more than 5% export share, “Motor vehicles and parts,” “Oil seeds” (mostly soybeans,) and “Other machinery and equipment” experience the highest tariff increases after the phase one trade deal. Notably, China's tariff increases on certain import commodities (e.g. “Other transport equipment” and “Chemical, rubber and plastic products”) are modest, possibly reflecting China's dependence on certain products from the United States. If the phase one trade deal is reverted, China's tariffs on “Motor vehicles and parts” from the United States increase by another 9.0%.

3.2. Welfare analysis

This section reports percentage changes in overall welfare across countries (Fig. 1) for the three scenarios.[11] Overall, the steel and aluminum tariffs have minor effects on welfare compared to the full-blown trade disputes between the United States and China. With the tariffs after the phase one trade deal as of March 2020, welfare in the United States decreases by 0.2% and welfare in China decreases by 1.7%. In the full tariffs scenario, China's welfare loss will further reach 2.4% and U.S. welfare loss will become 0.4%. All other countries and regions in this study, especially major exporters of manufactured goods to the United States, gain from the trade disputes between the United States and China. Malaysia, Mexico, and Taiwan gaining 0.9%, 0.8%, and 0.7% of welfare respectively under scenario 2, are the largest winners in the U.S.–China trade war. Thailand and other Southeast Asian countries are among the major beneficiaries as well.

Given the scale of the trade distortion, the estimated welfare impacts seem modest. One reason is that the sizable tariffs are limited to U.S.–China trade. Trade diversion to and from other countries substantially offsets the impacts. The results are also consistent with high optimal tariffs—a well-known suspicious feature of Armington models.[12] The tariff increases generate beneficial terms-of-trade impacts that help to offset the adverse welfare impacts.

Error bars are included in Fig. 1 to illustrate the range of results when we increase and decrease the trade elasticities by two standard deviations, as reported in their original estimation (Hertel et al., 2007). Deviations from the central trade elasticities has little impact on the welfare impacts, but does play a role in the sectoral responses reported below. Using the Trade elasticities reported in Ossa (2015) which are in general smaller than the elasticities estimated by Hertel et al. (2007), we obtain somewhat lower welfare impacts, with 1.6% welfare decrease for China and 0.2% welfare decrease for the United

[10] Using simple average of HS8 may create overestimation, because HS8 codes are only observed if there is a tariff increase. However, as tariff increases spread to more commodities, it is less of a concern.

[11] See Appendix Table A.2 for the level of benchmark household consumption, which is the base for the percentage changes in welfare.

[12] See Brown (1987), Balistreri and Markusen (2009), and Balistreri and Rutherford (2013) for a critiques of the Armington structure and implied optimal tariffs. In fact, for China Balistreri and Rutherford (2013) show that the qualitative welfare impact of a marginal move away from observed tariffs is sensitive to the particular trade structure: Armington (1969) versus Melitz (2003).

Table 1
Trade-weighted tariff increases (%).

	$E_{cn,us}$	US tariffs on China		$E_{us,cn}$	China's tariffs on US	
		Mar. 2020	Full		Mar. 2020	Full
Electronic equipment	46.3	18.5	31.7	17.6	12.7	16.0
Other transport equipment	0.9	18.9	24.2	13.4	10.0	14.9
Chemical, rubber and plastic products	7.1	17.4	27.4	13.2	12.6	14.4
Motor vehicles and parts	2.3	24.7	29.6	10.7	34.2	43.2
Oil seeds	0.0	25.0	30.0	10.5	29.0	33.2
Other machinery and equipment	8.2	38.1	47.9	7.7	14.0	17.5
Non-ferrous metals	0.9	20.7	30.0	4.7	29.0	33.5
Paper and paper products	1.1	17.8	26.8	3.3	15.2	19.7
Other manufacturing	8.2	12.4	24.3	2.2	17.5	20.8
Petroleum and coke	0.1	45.5	55.5	1.7	25.4	28.4
Other mining	0.1	24.8	29.8	1.4	19.7	20.4
Other food	1.2	24.0	30.7	1.4	25.1	30.6
Other animal products	0.1	24.1	32.3	1.2	11.9	20.3
Beverages and tobacco products	0.0	11.2	18.9	1.1	26.0	31.5
Other grains	0.0	25.0	30.0	1.1	24.9	34.9
Lumber	0.9	6.9	9.2	1.0	17.7	22.7
Fabricated metal products	3.4	20.8	29.4	0.9	17.7	21.8
Textiles	2.8	11.2	25.3	0.9	11.8	14.4
Forestry	0.0	26.4	35.2	0.9	6.6	9.1
Plant fibres	0.0	25.9	31.8	0.8	25.0	30.0
Other meat	0.0	31.7	43.4	0.7	51.9	56.7
Non-metallic minerals	1.4	17.5	26.2	0.6	14.9	17.8
Iron and steel	0.9	28.5	35.0	0.5	23.4	23.8
Milk	0.0	12.6	19.4	0.4	25.4	26.1
Leather	5.7	13.0	28.2	0.4	17.2	24.3
Vegetable and fruit	0.1	27.6	40.4	0.3	41.1	45.6
Other crops	0.1	19.9	28.0	0.3	22.2	30.6
Coal	0.0	25.0	30.0	0.3	27.5	29.9
Fishing	0.0	13.9	19.7	0.2	0.8	1.0
Vegetable oils	0.0	20.5	26.1	0.2	22.7	30.3
Wheat	0.0	25.0	30.0	0.1	24.3	34.3
Wearing apparel	8.1	9.5	21.0	0.1	24.1	25.9
Sugar	0.0	23.5	34.2	0.1	11.3	16.1
Cattle meat	0.0	32.5	45.0	0.1	55.0	60.0
Gas distribution	0.0	25.0	30.0	0.0	25.0	25.0
Electricity	0.0	25.0	30.0	0.0	0.0	0.0
Cattle	0.0	21.4	26.9	0.0	0.1	0.1
Wool	0.0	25.0	30.0	0.0	24.7	25.4
Oil	0.0	25.0	30.0	0.0	2.5	5.0
Raw milk	0.0	0.0	0.0	0.0	0.0	0.0
Processed rice	0.0	25.0	30.0	0.0	25.0	25.0
Cane and beet	0.0	10.8	20.0	0.0	6.7	10.0
Paddy rice	0.0	7.5	15.0	0.0	25.0	25.0
Weighted average		18.6	30.4		18.9	23.3
Total value of exports ($billion)	452.0			182.5		

Note: The tariff increases are from the trade war database by Li (2020). $E_{cn,us}$ represents the commodity's share in Chinese exports to the United States. $E_{us,cn}$ represents the commodity's share in U.S. exports to China. Trade flow shares are calculated based on 2014 data in the GTAP 10 database. See Appendix Table A.1 for baseline tariff rates.

States under scenario 2 (results available upon request). This is typical in a perfect competition CGE model considering substantial tariff increases. In models with many goods, factors, policy instruments, and trade partners the basic Ramsey intuition (from the study of public economics) dominates: We find smaller welfare losses when the tax shock is applied to goods with lower relative elasticities. Of course, this is an empirical result from a relatively complex model and not a general theoretic proposition.[13]

[13] There are simple theoretic environments where it can be shown that welfare impacts increase with smaller trade elasticities. The very influential environment considered by Arkolakis, Costinot, and Rodríguez-Clare (2012) is a good example. While these simplified models may adopt an Armington structure it is important to point out that the overall model and trade shocks examined are quite different. There are many sectors and many elasticities in our model interacting with a number of dissimilar tax and tariff rates. When the Armington elasticities are reduced in our experiment they are reduced relative to other elasticities used to parameterize production technologies and preferences in the GTAPinGAMS framework. In Arkolakis et al. (2012) there is only one elasticity for one sector, so the Ramsey intuition is irrelevant. Arkolakis et al. (2012) state clearly (p.99) that in their Armington environment "welfare changes . . . only depend on terms-of-trade changes." In contrast, in our model there are a number of empirically important general-equilibrium reallocations induced by the trade war, where we have different tariff changes across different goods traded among a limited set of countries. This is the value of using a CGE model in this context relative to a simple model.

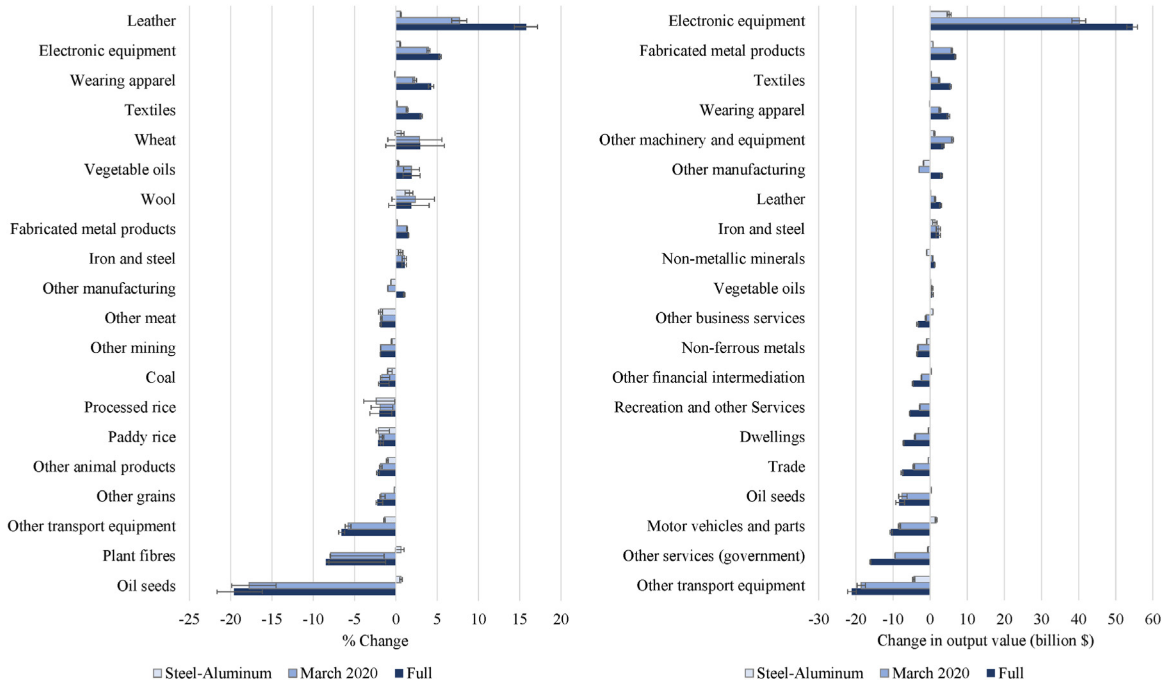

Fig. 2. US revenue changes (% and $B) by sector (top 10 winners and losers).

3.3. Sectoral impacts in the United States and China

While welfare change is essential for aggregate policy decisions, there are important distributional impacts that cleave with import-competing and exporting sectors. In this section, we present changes in revenue by sector. Figs. 2 and 3 present the major sectoral impacts for the United States and China (see Appendix Table A.3 for baseline revenues). We present the results in both percentage and absolute change ($Billion) to reveal the importance of the trade dispute to the individual sector and the economy as a whole. The first-order effect of a tariff increase is to depress revenue in exporting sectors and increase revenue in import-competing sectors that are targeted. These impacts explain the revenue growth of the U.S. "Iron and steel" sector under steel and aluminum tariffs (Fig. 2). It can also explain the decline in the U.S. "Oil Seeds" sector under China's retaliatory tariffs. Similarly, in scenarios 2 sizeable tariffs on Chinese electronic products boost the U.S. "Electronic equipment" sector by $40.2 billion dollars or 4.0% and suppress the corresponding sector in China by $70.4 billion or 3.0%. We also highlight second-order effects that operate through upstream and downstream sectors. For example, in the United States the "Other transportation equipment") sector suffers a loss from the steel and aluminum tariffs due to higher input costs, and the "Construction" and "Trade" sectors in China suffer significant revenue reductions.

If the U.S. policy goal is to protect certain domestic industries, such as electronic equipment, and to constraint the growth of corresponding industries in China, then the overall effect of the trade war is consistent with the policy intentions. However, the relative magnitudes of the impacts are limited due to trade diversions. Also, China's retaliations and unintended second-order effects create cost for other industries. For China, the negative impacts of the trade war are spread across many sectors, suggesting that a balanced, as opposed to targeted, approach is required to mitigate the trade war impacts.

3.4. The pattern of trade

In Tables 2 and 3 we report the percent change in trade flows. Major shifts in trade patterns are mostly focused on the United States and China. With cumulative tariff increases as of March 2020, exports from China to the United States fall by 52.3%, and exports from the United States to China fall by 49.3%.[14] We show significant trade diversion as total Chinese exports fall by only 4.9%, with major penetration into the EU (+8.0%), Canadian (+10.2%), and Mexican (10.8%) markets. While the U.S. intent is to promote trade surplus the trade disruptions have the opposite effect, with total export decreasing more than total import. With additional tariffs in scenario 3, exports from China to the United States will decrease by 72.8%, and exports from the United States to China decreases by 54.8%.

[14] With low (high) Armington elasticities, China's exports to the United States fall by 50.5% (53.9%) and exports from the United States to China fall by 45.5% (52.1%).

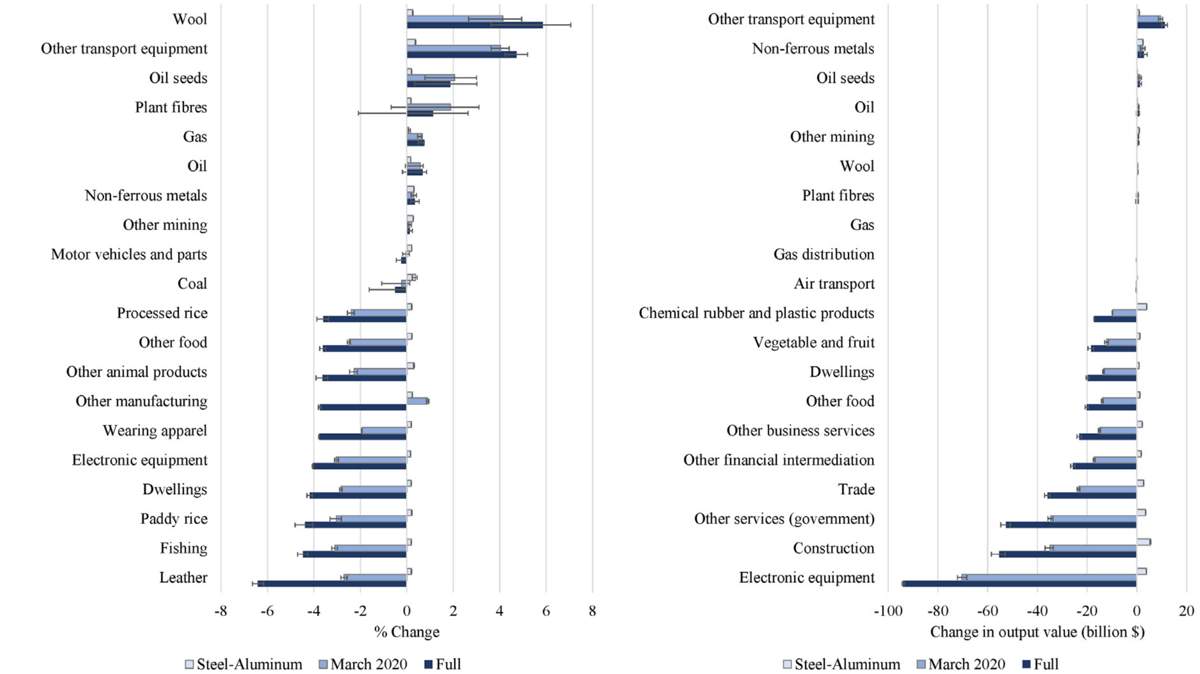

Fig. 3. China revenue changes (% and $B) by sector (top 10 winners and losers).

Table 2
Change in the pattern of international trade with EU and North American countries (%).

Exporter	Importer							
	U.S.	China	EU	Canada	Mexico	Rest of world	Total exports	Total imports
U.S.		−1.2	−1.7	−2.9	−0.9	0.7	−0.8	−0.4
		−49.3	−2.2	−2.8	−0.8	−0.4	−5.8	−4.0
		−54.8	−3.0	−3.2	−1.2	−1.5	−7.0	−4.9
China	−0.8		0.4	1.1	0.1	0.3	0.1	0.1
	−52.3		8.0	10.2	10.8	6.3	−4.0	−4.9
	−72.8		11.4	14.5	15.7	9.1	−5.4	−6.5
EU	−1.2	0.3	0.3	1.2	0.3	0.2	0.2	0.2
	5.7	0.3	−0.1	2.0	1.6	−0.7	0.3	0.2
	9.1	−1.0	−0.4	2.3	2.1	−1.2	0.2	0.1
Canada	−2.0	1.0	1.1		2.2	1.0	−1.0	−0.9
	0.7	2.2	−1.2		0.2	−1.7	0.2	0.1
	1.6	0.7	−2.2		−0.3	−2.8	0.4	0.3
Mexico	−0.6	0.3	0.4	0.5		0.4	−0.3	−0.3
	5.8	−5.1	−5.7	−5.7		−6.6	2.2	2.0
	8.4	−8.4	−8.4	−8.5		−9.8	3.1	2.8
Rest of world	1.0	0.2	0.3	1.3	0.5	0.2	0.3	0.3
	9.3	−0.6	−0.2	1.6	1.5	−0.7	0.6	0.5
	14.0	−1.8	−0.6	1.7	1.9	−1.2	0.6	0.5

Note: The change in trade flows are calculated using 2014 data in the GTAP 10 database. See Appendix Table A.4 for baseline trade flow values.

Table 3 shows percent change in trade flows for major Asian trading partners of the United States or China, including Japan, South Korea, Southeast Asia. It shows that Asian countries in general saw significant increases in exports to the United States due to the ongoing U.S.–China trade war, with South Korean exports to the United States rising over 17.5% in the March 2020 tariff scenario with the phase one deal, mainly benefiting from the trade diversion from the electronic equipment sector. In contrast, the Southeast Asian countries and Japan saw 7.9% and 4.7% increases in their exports to China under the same scenario. However, most Asian countries experience modest setbacks in their exports to China, while Chinese exports to all Asian countries roughly increase by 3–4% under the March 2020 tariff scenario, again reflecting the diversion of exports originally destined to the United States.

Table 3
Change in the pattern of international trade with Asian countries (%).

Exporter	Importer							Total export	Total import
	U.S.	China	Japan	S. Korea	SE Asia	Rest of Asia	Rest of world		
U.S.		−1.2	0.9	1.1	0.9	0.0	−1.1	−0.8	−0.4
		−49.3	−0.1	−0.3	−0.2	−1.5	−1.6	−5.8	−4.0
		−54.8	−1.3	−1.6	−1.3	−2.7	−2.2	−7.0	−4.9
China	−0.8		0.2	0.5	0.2	0.2	0.4	0.1	0.1
	−52.3		6.0	6.5	6.5	6.0	7.9	−4.0	−4.9
	−72.8		8.4	9.0	9.4	8.6	11.3	−5.4	−6.5
Japan	−1.2	0.4		0.9	0.3	0.2	0.6	0.2	0.2
	10.1	−1.0		−1.0	−1.4	−1.5	−0.2	0.8	0.7
	14.6	−2.5		−1.9	−2.0	−2.1	−0.5	0.9	0.6
South Korea	11.4	−0.5	−0.4		−0.4	−0.5	−0.1	1.0	0.7
	24.5	−1.9	−1.9		−1.9	−2.3	−0.8	1.3	1.0
	30.1	−3.3	−2.6		−2.6	−3.0	−1.1	1.3	0.9
Southeast Asia	−0.2	0.3	0.1	0.4	0.2	0.2	0.3	0.2	0.2
	16.3	−1.5	−1.8	−1.3	−1.0	−1.5	−0.7	0.7	0.7
	26.2	−3.4	−3.0	−2.4	−1.8	−2.4	−1.5	0.9	0.8
Rest of Asia	−1.3	0.3	0.2	0.5	0.3	0.3	0.4	0.2	0.2
	4.5	−1.1	−0.4	−0.1	−0.3	−0.4	0.1	0.2	0.2
	8.2	−2.2	−0.7	−0.5	−0.7	−0.8	−0.2	0.2	0.1
Rest of world	−0.7	0.3	0.1	0.8	0.1	0.2	0.3	0.2	0.2
	4.6	0.9	−0.8	0.0	−0.6	−0.9	−0.2	0.4	0.4
	7.0	−0.1	−1.3	−0.6	−0.9	−1.4	−0.6	0.4	0.3

Note: The change in trade flows are calculated using 2014 data in the GTAP 10 database. See Appendix Table A.5 for baseline trade flow values.

The significant trade diversion effects shown in Tables 2 and 3 vary by sector and have important policy implications. Here we provide two examples of sectoral-level pattern of trade changes.[15] Agricultural products such as soybeans and meat products are one of the hallmark products of U.S. exports to China. Our results show that even with the phase one trade deal, China has strong and strategic incentives to diversify away from the United States and seek products by U.S. competitors, including soybeans from Brazil and pork products from Europe (He, Hayes, & Zhang, 2020). The effects of these trade diversions are amplified by better connections between Europe and China due to the Belt and Road Initiative, and China's increasing number of free-trade-agreement partners such as Chile (Zhang, 2020). In contrast, electronic equipment represents one of the most important Chinese exports to the United States, and the declines in Chinese electronic equipment are largely filled by South Korea, Japan and Southeast Asian countries. A long-term disruption of the U.S.–China trade relations could lead to relocations of export-orienting sectors such as electronic equipment from China to other Asian countries, especially South Korea.

4. Conclusion and discussion

This paper introduces a data source for the tariff increases resulting from the recent trade disputes and documents the impacts of these tariffs using a standard off-the-shelf general-equilibrium simulation model. We find modest impacts on overall welfare, but large impacts on sectoral revenue and the pattern of international trade.

The welfare impacts estimated in this study (−1.7% for China and −0.2% for the United States by March 2020) are comparable to those of previous significant trade events. For example, the welfare impacts of China's WTO accession is estimated to be 1.24% by Li and Zhai (2000) and 2.2% by Ianchovichina and Martin (2004). Similarly, for China's WTO accession, Chen and Ravallion (2004) estimated a 1.5% increase in China's mean income, and Wang (2003) estimated a 2.9% increase in China's cumulative GDP by 2010. For other major trade agreements, papers reviewed by Francois (2000) find the WTO agreements in the Uruguay round increase China's welfare by −0.2% to 1.7%, and U.S. welfare by 0.1–0.9%. Ballard and Cheong (1997) estimated that the establishment of a Pacific free trade area including China and the United States would increase China's welfare by 1.4% and U.S. welfare by 0.13%. Results from this paper demonstrate that the U.S.–China trade war is among the most significant trade events in recent history. A caveat to this comparison is that, unlike the above-mentioned long-term trade agreements, the trade war tariffs could be temporary. The results of this study should be interpreted as the potential long-run impacts if the tariffs were to persist. Future studies should consider the dynamic effects of temporary tariffs.

Key limitations of the GTAPinGAMS model that we employ include parametric and structural uncertainty. In order to look at some preliminary parametric sensitivities we present results based on alternative trade elasticities. We leave an exploration of structural sensitivity for future research. Significant progress has been made in the adoption of advanced trade structures in a computational setting. In fact, the recent work of Balistreri and Tarr (2018), Costinot and Rodríguez-Clare (2014), and Balistreri, Hillberry, and Rutherford (2011) suggest considerable differences across models that consider trade induced variety and productivity adjustments.

[15] The results on the pattern of trade changes at each sectoral level are not shown for brevity, but they are available from the authors upon request.

While the standard GTAPinGAMS model provides a useful benchmark, it has limitations. For example, foreign direct investment (FDI) is not represented in the model. In other words, the model used in this study does not distinguish between domestic and foreign ownership. In reality, the trade war does affect FDI: the direct effect of the trade war is to raise the regulatory hurdles and restrict FDI between the United States and China; the indirect effect is to change the incentives for foreign investors, thus reshaping the global FDI flow. The changes in FDI will have dynamic effects on economic growth. Since the standard GTAPinGAMS model is static, it does not capture these effects. It is our hope that the tariff database presented in this paper can facilitate future studies with more sophisticated models considering international industrial organization and the inherent dynamics of trade.

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Appendix A. Additional tables

Table A.1
Baseline tariffs (%).

	Chinese tariff		U.S. tariff	
	U.S.	Rest of world	China	Rest of world
Beverages and tobacco products	6.0	13.6	5.0	5.4
Cane and beet	0.0	0.4	0.0	0.0
Cattle meat	19.0	13.5	0.0	1.9
Coal	0.0	0.3	0.0	0.0
Chemical rubber and plastic products	6.0	4.2	3.4	1.6
Oil	6.0	1.1	0.0	0.0
Cattle	2.0	3.9	0.0	0.2
Electronic equipment	1.8	3.1	0.4	0.5
Electricity	0.0	0.0	0.0	0.0
Fabricated metal products	8.0	6.6	2.0	1.3
Forestry	0.0	2.7	0.0	0.4
Fishing	9.0	8.5	0.0	0.1
Other grains	1.0	1.4	0.0	0.6
Iron and steel	4.0	2.7	1.0	0.4
Leather	8.0	7.1	13.0	9.0
Lumber	0.0	2.4	3.0	1.8
Milk	6.0	11.0	19.0	10.0
Motor vehicles and parts	23.0	9.3	1.0	0.9
Non-ferrous metals	1.0	1.2	3.0	1.3
Non-metallic minerals	10.0	8.8	5.0	2.8
Other animal products	6.0	7.7	0.0	0.8
Other crops	6.0	7.1	1.0	1.1
Other food	10.0	7.7	3.0	2.3
Petroleum and coke	3.0	3.0	1.0	1.0
Other machinery and equipment	5.0	4.9	1.0	0.6
Other manufacturing	6.0	5.8	1.0	0.7
Other mining	0.0	0.7	0.0	0.0
Other meat	11.0	13.4	3.0	2.5
Oil seeds	3.0	5.4	0.0	0.1
Other transport equipment	3.0	4.4	3.0	1.1
Processed rice	1.0	0.9	5.0	2.6
Paddy rice	1.0	0.8	0.0	0.6
Plant fibres	1.0	2.0	0.0	0.5
Paper and paper products	1.0	3.1	0.0	0.5
Sugar	11.0	16.4	15.0	11.4
Textiles	7.0	6.1	7.0	5.5
Veg and fruit	11.0	10.4	1.0	1.7
Vegetable oils	11.0	8.8	2.0	1.8
Wearing apparel	15.0	13.4	12.0	10.3
Wheat	1.0	1.2	1.0	1.0
Wool	2.0	3.7	1.0	1.9

Note: This table reports baseline tariffs in the GTAP 10 database for year 2014. The tariff on the rest of world is the simple average of all regions in this study.

Table A.2
Baseline welfare ($billion).

	Baseline	Steel–Aluminum	March 2020	Full
China	3940.5	−0.7	−68.1	−93.2
USA	11,992.1	−3.5	−28.6	−50.1
Rest of Southeast Asia	56.4	0.0	0.2	0.3
Singapore	143.5	0.0	0.2	0.3
Philippines	221.1	0.0	0.4	0.5
Hong Kong	191.0	0.0	0.4	0.6
Rest of South Asia	431.8	0.0	0.4	0.7
Indonesia	511.7	0.1	0.7	1.1
India	1233.8	−0.2	0.7	1.4
Russia	1080.5	−0.2	0.9	1.4
Thailand	217.3	0.0	1.0	1.4
Australia	790.2	0.5	1.0	1.3
Taiwan	214.3	0.0	1.3	1.7
Viet Nam	147.4	0.0	1.3	2.4
Malaysia	170.2	0.0	1.3	1.9
South Korea	717.6	−1.1	1.4	2.1
Brazil	1508.8	0.2	2.0	2.4
Canada	1024.5	−0.8	2.0	2.9
Rest of Asia	2120.5	−0.5	2.2	3.8
Japan	2706.5	0.0	4.1	5.2
Rest of World	3731.9	0.5	4.1	5.9
Mexico	894.4	0.1	6.7	9.6
EU	11,487.1	0.7	11.2	15.2

Note: This table reports baseline welfare (aggregate consumption) in the GTAP 10 database for year 2014, as well as the absolution welfare changes caused by the additional tariffs.

Table A.3
Baseline sector revenues ($billion).

	China				U.S.			
	Baseline	SA	March 2020	Full	Baseline	SA	March 2020	Full
Air transport	72	0.1	−0.2	−0.4	288	0.4	0.3	−0.1
Beverages and tobacco products	274	0.6	−5.7	−8.7	167	−0.8	−1.6	−1.9
Cane and beet	61	0.1	−1.4	−2.1	2	0.0	0.0	0.0
Communications	536	1.1	−8.9	−13.6	1054	0.3	−0.2	−1.0
Cattle meat	35	0.1	−0.6	−1.1	132	−0.1	0.0	0.0
Construction	2515	5.4	−35.0	−55.3	2140	0.5	0.6	0.5
Coal	203	0.8	−0.4	−1.0	73	−0.7	−1.3	−1.4
Chemical rubber and plastic products	2084	3.9	−9.8	−17.1	1140	2.6	0.2	0.3
Oil	121	0.2	0.7	0.8	299	0.7	0.2	−0.3
Cattle	85	0.2	−1.6	−3.0	73	−0.1	−0.2	−0.3
Dwellings	460	0.9	−13.4	−19.7	1722	−0.5	−4.1	−7.2
Electronic equipment	2252	3.8	−70.4	−94.0	1054	5.1	40.2	54.6
Electricity	481	1.1	−5.9	−9.0	442	−0.4	−1.0	−1.5
Fabricated metal products	579	1.5	−9.1	−11.6	443	0.8	5.9	6.8
Forestry	71	0.1	0.1	−0.4	30	0.0	−0.4	−0.5
Fishing	146	0.3	−4.7	−6.7	7	0.0	0.0	0.0
Gas	2	0.0	0.0	0.0	41	0.0	0.0	0.0
Gas distribution	6	0.0	−0.1	−0.2	101	0.1	0.0	−0.1
Other grains	107	0.2	−1.5	−2.6	50	−0.1	−0.9	−1.1
Iron and steel	1303	2.6	−7.7	−10.7	221	1.3	2.3	2.3
Insurance	103	0.2	−1.7	−2.5	680	0.2	−0.9	−2.1
Leather	187	0.4	−5.2	−12.3	19	0.1	1.4	2.8
Lumber	218	0.4	−1.8	−4.9	349	−0.2	0.4	0.4
Milk	56	0.1	−1.0	−1.6	117	−0.4	−0.9	−1.1
Motor vehicles and parts	879	1.9	−0.2	−2.0	713	1.6	−8.3	−10.5
Non-ferrous metals	789	2.4	2.4	2.7	195	−0.9	−3.3	−3.5
Non-metallic minerals	834	1.8	−10.8	−16.6	177	−0.9	0.7	1.2
Other animal products	259	0.8	−6.0	−9.6	73	−0.8	−1.4	−1.6
Other business services	1082	2.1	−15.0	−23.1	2414	0.8	−1.1	−3.3
Other crops	32	0.1	−0.3	−0.5	12	0.0	0.1	0.0
Other food	543	1.2	−13.8	−20.1	431	−1.3	−1.5	−2.2
Other financial intermediation	892	1.7	−17.1	−25.7	1883	0.3	−2.3	−4.6
Petroleum and coke	617	1.1	−1.7	−3.1	684	1.0	−0.9	−1.9
Other machinery and equipment	1262	3.2	−14.6	−11.7	708	1.1	6.1	3.5
Other manufacturing	327	0.8	2.9	−12.1	304	−1.8	−3.0	3.1
Other mining	328	0.9	0.4	0.4	56	−0.3	−1.0	−1.1

Table A.3 (*Continued*)

	China				U.S.			
	Baseline	SA	March 2020	Full	Baseline	SA	March 2020	Full
Other meat	193	1.0	−4.0	−6.7	104	−2.0	−1.9	−2.0
Oil seeds	60	0.1	1.2	1.1	35	0.3	−7.6	−8.3
Other services (government)	1768	3.5	−34.6	−52.6	5190	−0.6	−9.4	−16.1
Other transport equipment	246	0.9	9.5	11.2	302	−4.4	−18.6	−21.1
Other transport	851	1.7	−11.0	−17.1	755	0.4	−0.6	−1.4
Processed rice	146	0.3	−3.6	−5.4	3	−0.1	−0.1	−0.1
Paddy rice	85	0.2	−2.6	−3.8	3	−0.1	−0.1	−0.1
Plant fibres	20	0.0	0.4	0.2	6	0.0	−0.5	−0.5
Paper and paper products	326	0.6	−2.6	−4.4	427	−0.3	−1.0	−1.0
Raw milk	24	0.1	−0.5	−0.8	47	−0.1	−0.6	−0.7
Recreation and other services	422	0.8	−8.7	−13.0	1555	0.0	−2.8	−5.5
Sugar	18	0.1	−0.2	−0.4	21	0.0	0.0	0.0
Textiles	750	1.4	−4.3	−14.2	181	0.3	2.5	5.5
Trade	1326	2.7	−23.4	−35.9	3593	−0.5	−4.4	−7.5
Veg and fruit	499	1.2	−12.1	−18.4	66	−0.4	−0.2	−0.2
Vegetable oils	116	0.2	−1.4	−2.3	28	0.1	0.5	0.5
Wearing apparel	428	0.9	−8.4	−16.4	118	−0.1	2.6	4.9
Wheat	46	0.1	−0.7	−1.2	11	0.1	0.3	0.3
Wool	7	0.0	0.3	0.4	0	0.0	0.0	0.0
Water transport	111	0.2	−1.5	−2.2	75	0.0	−0.2	−0.3
Water	169	0.3	−2.6	−3.9	354	−0.1	−0.7	−1.2

Note: This table reports baseline sector revenues in the GTAP 10 database for year 2014, as well as the absolution revenue changes caused by the additional tariffs.

Table A.4
Baseline trade flow with EU and North American countries ($billion).

Exporter	Importer						Total export	Total import
	U.S.	China	EU	Canada	Mexico	Rest of world		
U.S.		183	519	281	222	764	1969	2538
China	452		487	63	79	1340	2419	1995
EU	584	393	4529	93	47	1762	7409	7296
Canada	337	27	60		10	78	512	558
Mexico	286	11	30	27		57	411	431
Rest of world	879	1381	1670	95	74	3669	7768	7670

Note: This table reports baseline trade-flows in the GTAP 10 database for year 2014.

Table A.5
Baseline trade flow with Asian countries ($billion).

Exporter	Importer							Total export	Total import
	U.S.	China	Japan	S. Korea	SE Asia	Rest of Asia	Rest of world		
U.S.		183	89	60	102	195	1341	1969	2538
China	452		192	112	269	393	1001	2419	1995
Japan	136	225		57	114	111	223	867	876
South Korea	72	193	37		78	80	171	631	586
SE Asa	149	221	120	53	247	174	386	1350	1338
Rest of Asia	283	418	172	134	209	510	845	2571	2385
Rest of world	1447	756	266	170	319	922	6802	10,681	10,770

Note: This table reports baseline trade-flows in the GTAP 10 database for year 2014.

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