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Abstract

We use transaction-level data to study changes in the concentration of US imports. Concentration has fallen in the typical industry, while it is stable by industry and origin country. The fall in concentration is driven by the extensive margin: the number of exporting firms has grown, and the number of exported products has fallen relatively more for top firms. Instead, average revenue per product of top firms has increased. At the industry level, top firms are converging, but top firms within country are diverging. Finally, higher concentration from an origin country is associated with a fall in prices, foreign entry and industry growth. These facts suggest that intensified competition in international markets coexists with growing concentration among national producers.

JEL-Codes: E230, F120, F140, L110, R120.

Keywords: superstar firms, concentration, US imports, firm heterogeneity, international trade.

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1 Introduction

We live in a superstar economy in which top firms command a disproportionate share of sales and wealth. A large number of papers have documented that the fraction of sales accrued by top firms and other concentration indexes have risen in most US sectors since the late 1990s. International evidence, albeit more sparse, indicates that concentration has grown in several OECD countries too. Large firms also dominate exports. In a sample of 32 mostly developing countries, the top five firms account on average for 30% of a county's total exports (Freund and Pierola, 2015). These observations have raised serious concerns that the growth of superstar firms may be synonymous of lower competition. The size of the phenomenon is so large that it is often the subject of media attention.[1] Yet, little is known to date on its causes and consequences.

The existing evidence points at growing concentration among *national* firms. However, companies from different countries compete in markets that are increasingly global. This is especially true in the manufacturing sector, where imports account for a sizable fraction of total domestic demand. For instance, import penetration in US manufacturing is around 30%, and it is significantly higher in high-tech industries. In global markets, stronger international competition and growing national concentration can coexist. In fact, leading models of international trade suggest that international competition causes reallocations towards top producers and may therefore increase concentration at the national level (e.g., Melitz, 2003, Melitz and Redding, 2014).

In this paper, we examine concentration in *international markets*. To this end, we use a unique transaction-level data set to study changes in the concentration of US seaborne imports between 2002 and 2012. Focusing on imports allows us to complement the picture arising from national production data. It enables us to document how firms from multiple countries compete in the world's largest global market.

We start by showing how concentration, measured by the share of seaborne imports that accrues to the four largest firms and by the Herfindahl-Hirschman index, has changed among firms selling in the US in the average 4-digit manufacturing industry. We contrast this with changes in concentration among firms from a single country of origin and among US producers. Our first main finding is that, while industry concentration among US firms has increased, concentration is stable among exporters from the average country of origin, and has fallen among exporters from all origin countries.

To understand why these trends differ at the country and industry level, we focus on the

[1] For instance, *The Economist* recently published a special report on the rise of giant companies (September 17, 2016). According to it, 10% of the world's public companies generate 80% of all profits, and the share of GDP generated by the Fortune 100 biggest American companies rose from about 33% of GDP in 1994 to 46% in 2013.

role of heterogeneity across origins. In particular, to get a sense of the geographical distribution of concentration, we draw maps showing which countries have affected competition in the US import market the most. This exercise reveals that industry concentration among exporters is lowest in Western Europe, South-East Asia, India and China, and has fallen especially in the latter two countries. We show that trends at the industry level are significantly driven by the low and falling levels of concentration in Asian countries, which command a large and growing share of US imports.

Next, we shed light on the firm-level determinants of changes in concentration. With the help of a simple structural model imposing minimal restrictions on the data, we dissect the observed variation in the sales share of the top-4 exporting firms into the contribution of the firm-level characteristics that we can extract from the data. We show that the most important factor in explaining the fall in concentration is the extensive margin. We observe a large increase in the number of firms that start exporting to the US in any industry. The extensive margin plays an important role also within firms. While all firms are shedding products, top firms are dropping proportionally more products than other firms.

On the contrary, the main force towards rising concentration is the intensive margin. Consistent with the view that top firms are breaking away from the pack, we show that the average revenue per product of top firms has grown significantly relative to the population average. This differential growth of top and non-top firms reflects important changes in the distribution of attributes across firm-products. In particular, our data allow us to identify quality-to-price ratios per firm-product as a synthetic measure of "appeal". Across products of top firms, appeal is converging, while it is diverging across all firms. Moreover, top firms in any industry are more different than the rest and more equal to each other than top firms from the same country of origin.

These findings paint a significantly different picture than the one arising from national-level studies. The sheer increase in the number of firms exporting to the US suggests that the overall level of competition may have intensified rather than fallen, even if the number of US entering firms has declined. Growing global competition is also consistent with the observed within-firm adjustments. As the total number of products increases, products per firm are falling, suggesting that firms are concentrating on core business to retain a competitive edge. Top firms, which are likely to be present in more markets and hence more exposed to global competition, are concentrating on their core business more than proportionally, rather than acquiring rapaciously new product lines. Moreover, the fall in heterogeneity at the top despite its overall increase suggests that top firms are dropping their marginal products at the same time as firms with below-average appeal are entering.

Finally, to shed more light on the hypothesis that intensified international competition may be accompanied by an increase in national concentration, we turn to regression analysis, which allows us to use alternative measures of concentration, add control variables, and explore different sources of variation in the data. Studying the correlates of the change in the sales share of the top-4 exporting firms and in the Herfindahl-Hirschman index across origins and industries, we find results suggesting that national concentration is not necessarily a sign of lack of competition. In particular, an increase in the concentration of exports from a single origin country is associated with a fall in prices, foreign entry, industry growth and a high demand elasticity. We show that these results are consistent with an increase in competition in models with heterogeneous firms and endogenous markups (e.g., Atkeson and Burstein, 2008, and Amiti, Itskhoki, and Konings, 2014, 2019). We also study how concentration correlates with technological characteristics and find evidence of growing concentration in industries with a declining labor share and a higher employment share of routine jobs in the US. This suggests that automation and labor-saving technologies may have contributed to consolidating the dominant position of top firms.

Before continuing, we mention briefly three important caveats that are discussed more in detail in the rest of paper. First, our data cover maritime trade only. While the analysis of this paper can be implemented on any subset of imports, and sea shipments are the largest component of world trade, we recognize that the results may not necessarily generalize to imports by land or air. Nevertheless, we show that our main facts are not driven by countries and industries for which seaborne trade is not a principal mode of export to the US. Second, we do not have data on the domestic sales of US firms. As a consequence, we cannot study concentration in the entire US market, but rather we focus on the import side and study concentration across different origins. Third, our data cover manufacturing industries only and hence cannot speak directly to the significant increase in concentration in non-traded sectors (e.g., Philippon, 2019, and Hsieh and Rossi-Hansberg, 2019).

This paper is related to the growing literature on the rise of national concentration. Several papers, including Autor et al. (2020), Barkai (2020), Covarrubias, Gutiérrez and Philippon (2019), and Gutiérrez and Philippon (2020), have documented the recent increase in concentration among US firms. All these papers study concentration among national firms using production data. Hence, they do not study how concentration has changed in any market. While it is understood that international competition is quantitatively important and has intensified in manufacturing, none of the above papers uses firm-level imports to study concentration among foreign firms. Freund and Sidhu (2017) is one of the first attempts at measuring global industrial concentration. Interestingly, they also find that global concentration has declined in most industries, but they do so combining national data. Hence, they study concentration among producers in the world, not in any destination market. Using firm-level data from the US Census, Amiti and Heise (2019) show that market concentration has been flat or falling when foreign imports are included and identify a causal effect of import competition on domestic market concentration and markups.[2] Our results on concentration of imports across origins is complementary to and entirely consistent with their findings.

Other papers have tried to measure changes in competition more directly by estimating markups. In particular, De Loecker and Eeckhout (2018), De Loecker, Eeckhout and Unger (2020), Hall (2018), and Diez, Leigh, and Tambunlertchai (2018) have documented an increase in average markups both in the US and in other countries.[3] However, this increase is partly explained, once again, by the growth of high-markup firms.[4] Other studies, such as Karabarbounis and Neiman (2018) and Anderson, Rebelo and Wong (2018) have found more mixed results. Our data do not contain enough information to estimate markups. Instead, we show evidence that concentration from one origin is positively correlated with measures of competition from other countries.

Rossi-Hansberg, Sarte and Trachter (2018) and Hsieh and Rossi-Hansberg (2019) study instead concentration in US local markets. They present evidence that US concentration, while growing at the national level, has actually been falling in local markets. They relate this to the advent of new technologies enabling firms to offer non-traded products at lower marginal costs in all markets. Their findings resonate well with ours. Nevertheless, they are entirely different. These papers still consider exclusively US firms, and focus on non-traded sectors, such as services, retail, and wholesale. While they correctly point out that markets in these sectors are local, many others are global, especially in manufacturing. Yet, all these papers share the insight that more competition in final markets, be it through trade or local production, can be associated with higher national concentration.

Finally, this paper is related to the large empirical literature on the role of firms, and especially superstar firms, in explaining trade flows.[5] In particular, we build on Redding and Weinsten (2017) and Bonfiglioli, Crinò and Gancia (2020), who decompose US imports into firm-level characteristics. In turn, these papers draw from seminal contributions aimed at identifying demand shifters as a determinant of sales, including Berry (1994), Khandelwal (2010), Feenstra and Romalis (2014), Hottman, Redding and Weinstein (2016) and Redding and Weinstein (2020). Beside developing the methodology, this literature has shown the quantitative importance of the distribution of demand shifters. Here, we are not interested in separating demand and supply factors determining a firm's appeal in a market. Rather, our contribution is to decompose the sales of top firms exporting to the US. None of the above-mentioned papers study concentration, nor do they relate it to international competition.

[2] Covarrubias, Gutiérrez and Philippon (2019) also show that the number of firms in Compustat data fell in response to Chinese import competition.

[3] See also Calligaris, Criscuolo and Marcolin (2018).

[4] Reallocations towards high-markup firms may actually imply lower monopoly distortions. See, for instance, Baqaee and Farhi (2020), Edmond, Midrigan and Xu (2018), and Epifani and Gancia (2011).

[5] See, for instance, Bernard et al. (2018), Freund and Pierola (2015), and Gaubert and Itskhoki (2021).

Many papers have shown that trade opportunities trigger reallocations in favor of top firms, thereby making firms more unequal and possibly raising national concentration (see, for instance, di Giovanni, Levchenko and Ranciere, 2011). These reallocations can also happen within firms. In particular, Bernard, Redding and Schott (2011) and Melitz, Mayer and Ottaviano (2014) show that trade liberalization and tougher competition cause multi-product firms to drop their least successful products and skew export sales towards the best performing products. They provide supportive evidence using US and French firm-level data, respectively. Our findings on how international concentration has changed among firms from multiple origins are fully consistent with the view proposed in these papers.[6]

The remainder of the paper is organized as follows. Section 2 provides a brief description of the data, and reports key statistics on concentration measures and on their evolution across firms from the same country of origin and industry, across all exporters to the US in the same industry, and across US firms. In Section 3, we implement a structural decomposition of the change in the concentration of US imports, as measured by the sales share of the top-4 firms in each country-industry and in each industry. Section 4 studies, by means of regressions informed by a simple theoretical framework, how changes in concentration at the country-industry level correlate with proxies for competitive pressure and other technological characteristics. Section 5 concludes. In the Appendix, we provide more details on the dataset and on the estimation of the elasticity of substitution that is needed to implement the structural decomposition, and report additional robustness checks.

2 Trends in Domestic and Import Concentration

2.1 Data

To perform our analysis, we use transaction-level data on US seaborne imports from the Piers database, as in Bonfiglioli, Crinò and Gancia (2020). Administered by IHS Markit, Piers contains the complete detail of the bill of lading of any shipment that is imported into the US by sea. IHS Markit collects the bills of lading filed with the US Customs, verifies and standardizes their information, and makes the resulting data available for sale. We purchased from IHS Markit information on the universe of seaborne manufacturing import transactions of the US, by exporting firm and product, in two years, 2002 and 2012. For each transaction, we know the complete name of the exporting firm, its country of origin, the exported product (according to the 6-digit level of the HS classification), the value (in US dollars) and the

[6] On the importance of the extensive margin in international trade, see Bonfiglioli, Crinò and Gancia (2020), Fernandes et al. (2018), and Hummels and Klenow (2005).

quantity (in kilograms) of the transaction.[7]

IHS Markit assigns to each transaction a HS code, which typically belongs to the first version of the HS classification (HS 1992).[8] We use a correspondence table developed by the World Integrated Trade Solutions to map each HS 6-digit product exported by a firm into a 4-digit SIC industry. The 4-digit level of industry aggregation strikes a balance between number and comparability of products. On the one hand, the structural decompositions presented in Section 3 require each industry to encompass sufficiently comparable products, which would call for the use of highly disaggregated industries. On the other hand, the Reverse-Weighting estimator (developed in Redding and Weinstein, 2016) that we use for estimating the elasticity of substitution in each industry rests on the set of firm-product pairs that are observed in both years (see Appendix B for details); identification therefore requires industries to be broad enough to encompass a sufficient number of continuing firm-products. In any case, the main trends in concentration documented in this paper are largely insensitive to the definition and level of aggregation of industries, as we discuss in the next section. Our final data set comprises 1,311,835 observations at the firm-product-year level. Firms belong to 366 4-digit SIC manufacturing industries and 104 origin countries spanning the five continents. Appendix A provides additional details about data construction and compares a number of moments obtained from Piers with those based on aggregate trade data from various sources.

We now discuss a number of advantages and limitations of the data. Three features of Piers are especially important for our analysis. First, access to Piers is not restricted and can be obtained by anyone, albeit at a fee. Second, all firms in Piers use the same export mode (by sea), which favors comparability. Third, Piers contains the full name of each firm, which allows to precisely identify companies exporting to the US by sea, thereby reducing the risk of over-counting them. These characteristics enable us to construct and compare concentration measures, and their underlying micro-level components, across virtually all countries in the world within the same destination market. At the same time, the fact that Piers only contains data on international trade transactions delimits the scope of our analysis in two ways. First, we do not analyze the non-tradable sectors. Second, because we do not have information on US sales by either domestic firms or affiliates of foreign multinationals, we do not study the overall evolution of concentration in the US manufacturing sector. Rather, we compare

[7]In the case of firms with multiple shipments (bills of lading) of the same product in a year, we purchased from IHS Markit information on the total value and quantity of these shipments across all bills of lading, but not the detailed information on each bill of lading, which would have been prohibitively expensive.

[8]A minority of product codes (98 out of 3,487 6-digit codes) belong to some subsequent revision of the HS classification issued over the period of our analysis. In the next section, we show that using a consistent product classification that excludes these 98 codes has no bearing on our main results.

Table 1: Import Penetration and Share of Seaborne Imports in Total Imports across US Manufacturing Sectors

	Import Penetration		Share of Seaborne Imports	
	Level (2011)	Change (2002-2011)	Level (2011)	Change (2002-2011)
	(1)	(2)	(3)	(4)
20 Food and kindred products	0.095	0.028	0.660	0.031
21 Tobacco products	0.020	0.004	0.783	0.051
22 Textile mill products	0.334	0.147	0.744	0.144
23 Apparel and other textile products	0.778	0.221	0.822	0.156
24 Lumber and wood products	0.138	-0.017	0.487	0.124
25 Furniture and fixtures	0.348	0.042	0.790	0.073
26 Paper and allied products	0.125	0.013	0.430	0.115
27 Printing and publishing	0.055	0.022	0.531	0.130
28 Chemical and allied products	0.256	0.068	0.376	0.063
29 Petroleum and coal products	0.111	0.015	0.952	0.009
30 Rubber and miscellaneous plastics products	0.262	0.112	0.652	0.091
31 Leather and leather products	0.952	0.098	0.771	0.018
32 Stone, clay and glass products	0.174	0.043	0.690	0.038
33 Primary metal industries	0.389	0.124	0.459	-0.028
34 Fabricated metal products	0.216	0.068	0.600	0.076
35 Industrial machinery and computer	0.467	0.116	0.441	0.000
36 Electronic and other electric equipment	0.560	0.094	0.295	0.006
37 Transportation equipment	0.316	-0.006	0.459	-0.007
38 Instruments and related products	0.341	0.089	0.213	-0.033
39 Miscellaneous manufacturing	0.775	0.260	0.379	-0.062
Manufacturing	0.279	0.032	0.494	0.039

Notes. Import penetration is the ratio of imports over absorption in the sector; absorption is defined as shipments plus imports minus exports. The share of seaborne imports is the ratio of seaborne imports over total imports in the sector. Sector-level imports and exports are computed using official trade data from US customs (Schott, 2008). Sector-level shipments data are sourced from the NBER Manufacturing Industry Database and are available up to the year 2011. Sectors are defined according to the 2-digit level of the Standard Industrial Classification (SIC).

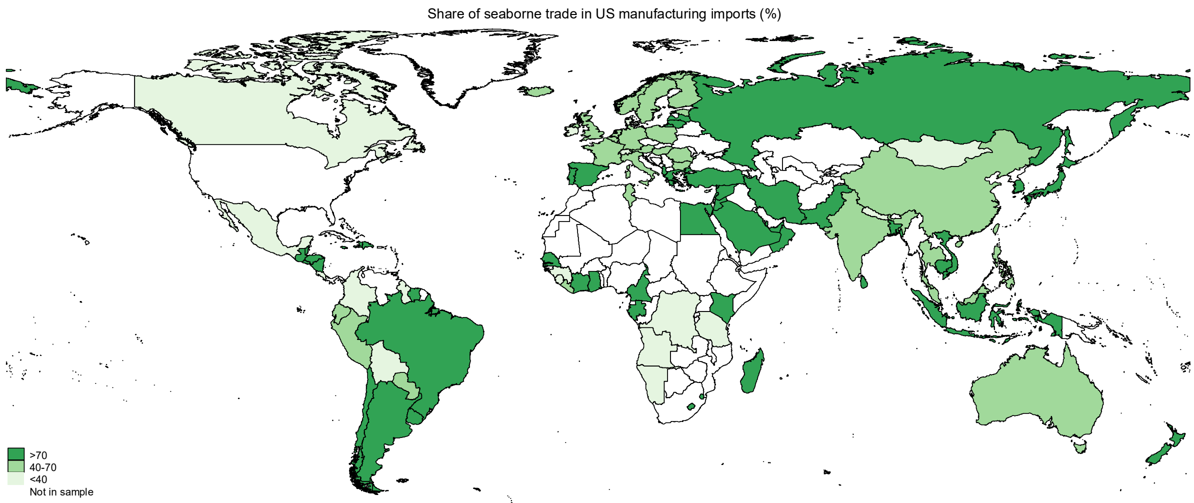
trends in concentration across manufacturing firms selling in the US market from different origin countries.

To have a sense of the fraction of total domestic demand for manufactures that is covered by imports in the US, Table 1 reports information on import penetration, both for manufacturing as a whole and for each 2-digit SIC manufacturing sector separately. Import penetration is the ratio of imports over domestic absorption, which is defined as shipments plus imports minus exports. Sector-level imports and exports are computed using official trade data from the US Customs (Schott, 2008), while sector-level shipments are sourced from the NBER Manufacturing Industry Database. Because shipments data are not available for the year 2012, we report statistics on import penetration for the 2002-2011 period. In manufacturing, imports account for 28% of total domestic demand in 2011. Import penetration is significantly higher than average not only in traditional sectors, such as textile, apparel, leather and furniture, but also in high-tech sectors, such as electronics, machinery and precision instruments. Import penetration has also increased over time, in all but two sectors. The widespread growth in import penetration suggests that competition among manufacturing firms in the US market has become increasingly global over the period of our analysis.

Another aspect of the data that is worth discussing is the fact that some of the firms in Piers could be trading companies rather than actual producers. The presence of intermediaries could complicate relating the observed distribution of exports across exporting firms to the distribution of revenues across producers. This issue is also discussed in Feenstra and Weinstein (2017), with reference to an earlier and more limited version of Piers. As shown by the authors, only 7.5% of US imports originate from foreign firms that have the words "trading," "exports," "imports" or variants of these words in their name. Consistent with this, we inspected the names of the top-10 exporting firms in each 2-digit manufacturing sector and found no trading company among them, suggesting that the majority of exports in our sample does indeed originate from actual producers.

Perhaps the most important caveat about our data, however, is the fact that Piers only contains shipments by sea, and thus excludes US imports occurring by air or land. This means that, strictly speaking, our results should be interpreted as applying to firms selling in the US by sea. At the same time, maritime trade is the main trade mode worldwide, accounting for over 70% of world trade by value and 80% by volume (UNCTAD, 2018). Seaborne trade is also the principal mode of importing goods into the US, with the share of seaborne imports in total US merchandise imports increasing from 46% in 2002 to 53% in 2012, according to official data from the US Customs. In Table 1, we provide further details on the importance of seaborne imports across manufacturing sectors. In manufacturing as a whole, imports by sea account for 49% of total US imports, and this share has risen by 4 percentage points over the period of our analysis. Seaborne imports also account for more than half of overall imports in the majority of manufacturing sectors, and this share has grown in sixteen out of twenty cases.

Figure 1 illustrates the importance of maritime trade with the US across countries. For each of the 104 countries in our sample, the figure shows the share of seaborne imports in total US manufacturing imports in 2012, based on official import data from the US Customs. Not surprisingly, seaborne trade is relatively unimportant for Canada and Mexico, whose firms mostly rely on land shipments to serve the neighboring US market. On the contrary, seaborne trade is the principal mode of serving the American market for the other main trading partners of the US. From 2002 to 2012, the share of seaborne imports into the US has increased from 62% to 64% for Germany, from 60% to 75% for South Korea and from 74% to 81% for Japan, while decreasing from 82% to 64% for China. More generally, seaborne imports represent 70% of total US manufacturing imports from the median country in our sample, and 85% of overall US imports for the median country-industry pair. In the next section, we further discuss the use of maritime import data and show that our main facts are



Source: Official customs data on US imports in 2012 (Schott, 2008). Darker colors indicate a higher share of seaborne trade in US manufacturing imports from a given country. Reported figures are computed across the 366 4-digit manufacturing industries included in the final sample. Only figures for the 104 origin countries considered in the analysis are displayed.

Figure 1: Share of Seaborne Trade in US Manufacturing Imports across Origin Countries

not driven by countries and industries for which seaborne trade is not a principal mode of export to the US.[9]

We close this section by providing some descriptive statistics on the composition of our final sample. These are reported in Table 2, separately for the two units of analysis considered in later sections: the country-industry-year triplet (panel a) and the industry-year pair (panel b). The former unit of analysis allows us to study concentration among firms exporting to the US in a given industry and year from the same origin country; the latter unit instead allows us to focus on concentration among firms exporting to the US in a given industry and year from all origins. The average triplet has 43 firms and 53 firm-products; the corresponding numbers for the average industry-year pair are 1,323 and 1,644. Regardless of the unit of analysis, the top-4 firms are significantly larger than the rest of firms: they produce more products (1.4 vs. 1.1 by triplet and 2.5 vs. 1.2 by industry-year) and sell more of each product on average ($6.5 vs. $1.2 million by triplet and $80 vs. $1.1 million by industry-year). Finally, multinational enterprises (MNEs), which are defined as firms exporting to the US from multiple origins within the same industry and year, account for 40% of exports in the average triplet and for roughly one third of exports in the average industry-year pair.

[9] See also Feenstra and Weinstein (2017) for the use of Piers to construct Herfindahl-Hirschman indexes for seaborne imports into the US across industries and origin countries. As discussed by the authors, the Herfindahl-Hirschman indexes based on seaborne transactions typically do not differ much from those based on all transactions (including land and air shipments) because the share of seaborne imports in total US imports is high for most countries and industries.

Table 2: Descriptive Statistics on Sample Composition

	Mean	Median	Std. Dev.
a) Statistics by country-industry-year			
N. of firm-products	53	8	315
N. of firms	43	7	249
N. of products per firm	1.1	1.0	0.2
Average exports per firm-product ($1000)	1191	203	11910
N. of products per firm, top-4 firms	1.4	1.0	1.2
Average exports per firm-product ($1000), top-4 firms	6479	743	75636
MNEs share of firms	0.32	0.25	0.22
MNEs share of exports	0.42	0.36	0.33
b) Statistics by industry-year			
N. of firm-products	1644	610	2981
N. of firms	1323	539	2347
N. of products per firm	1.2	1.1	0.2
Average exports per firm-product ($1000)	1132	582	2137
N. of products per firm, top-4 firms	2.4	1.5	3.1
Average exports per firm-product ($1000), top-4 firms	79854	16734	365700
MNEs share of firms	0.07	0.06	0.04
MNEs share of exports	0.32	0.27	0.21

Notes. The variables in panel a) are computed by country-industry-year triplet; reported statistics are mean, median and standard deviation calculated across triplets. The variables in panel b) are computed by industry-year pair; reported statistics are mean, median and standard deviation calculated across industry-years. The statistics on the top-4 firms refer to country-industry-year triplets (panel a) or industry-year pairs (panel b) with at least four firms exporting to the US. The statistics on multinational enterprises (MNEs) refer to country-industry-year triplets (panel a) or industry-year pairs (panel b) with at least one multinational firm exporting to the US. Industries are defined according to the 4-digit level of the Standard Industrial Classification (SIC).

2.2 Concentration Statistics

2.2.1 *Main Trends*

We use two measures of industry concentration: the share of US imports that is accrued by the four largest firms and the Herfindahl-Hirschman Index (HHI).[10] We compute the two measures both by industry, i.e., pooling firms exporting to the US from all origin countries, and by industry and country of origin. In the latter case, we treat MNEs' affiliates located in different countries as different firms, while we combine their sales when studying concentration at the industry level. For comparison, in this section, we also report the corresponding concentration measures computed among US firms, using data from COMPUSTAT.

Table 3 contains the main patterns in the data. It shows that the top-4 firms account for 79% of US imports in the average country-industry pair (panel a) and for 37% of US imports

[10] As discussed below, our main results are very similar if we use alternative measures of concentration, such as the share of sales that is accrued by the top-3 or top-5 firms.

Table 3: Baseline Evidence on Concentration

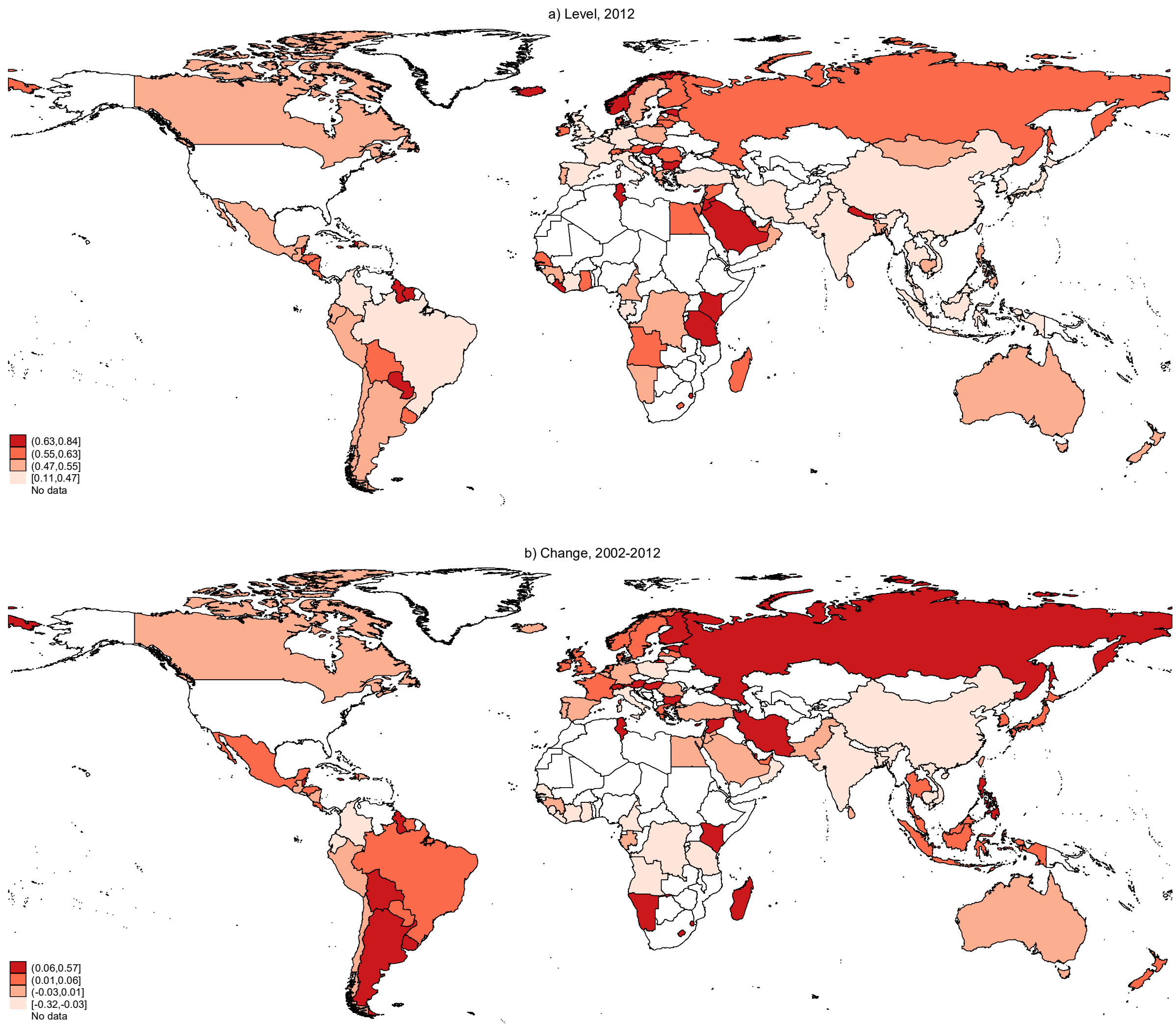
	Level (2012) Mean	Level (2012) Std. Dev.	Change (2002-2012) Mean	Change (2002-2012) Std. Dev.	Log Change (2002-2012) Mean	Log Change (2002-2012) Std. Dev.	% of Positive Changes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a) Piers: Statistics by country-industry							
Share of sales by the top-4 firms	0.795	0.213	-0.012	0.175	-0.033	0.301	0.470
Herfindahl-Hirschman index	0.461	0.295	0.011	0.280	-0.023	0.775	0.498
b) Piers: Statistics by industry							
Share of sales by the top-4 firms	0.372	0.230	-0.075	0.205	-0.296	0.587	0.338
Herfindahl-Hirschman index	0.091	0.129	-0.026	0.145	-0.548	1.175	0.317
c) Compustat: Statistics by industry							
Share of sales by the top-4 firms	0.879	0.150	0.049	0.091	0.062	0.126	0.696
Herfindahl-Hirschman index	0.548	0.297	0.128	0.186	0.274	0.393	0.727

Notes. The concentration measures presented in panel a) are computed by country-industry-year triplet using data from Piers. The concentration measures presented in panels b) and c) are computed by industry-year pair using data from Piers and Compustat, respectively. Columns (1)-(6) report simple averages and standard deviations calculated across country-industries (panel a) or industries (panels b and c). Column (7) reports the fraction of country-industries (panel a) or industries (panels b and c) with an increase in a given concentration measure over 2002-2012.

from all origin countries in the average industry (panel b). Interestingly, concentration among US firms in the average industry (panel c) is comparable to the concentration of US imports observed by country of origin (panel a). Table 3 also reports changes in the concentration measures between 2002 and 2012. Over the decade, concentration among firms exporting to the US from the same origin country barely changed. However, concentration among firms from all origin countries significantly decreased. In particular, the share of sales by the top-4 firms fell by 8 percentage points, or 0.30 log points. Conversely, as it is well known, the share of sales by the top-4 US firms has increased, by 5 percentage points on average. All these patterns hold when measuring concentration using the HHI, or when counting the fraction of industries or country-industries becoming more concentrated over the period. These statistics suggest that rising concentration among national firms can coexist with more competition in international markets. At the same time, these averages mask significant heterogeneity across country-industries or industries, as can be seen from the standard deviations reported in the table.

Our main goal is to dissect the changes in the concentration of US imports just documented. We begin by asking what drives the fall in concentration at the industry level even if there is no such trend by country of origin. One possibility is that the industry-level results are driven by some influential observations. Hence, to get a first sense of the role played by individual countries, we take a look at the geographical distribution of concentration among firms exporting to the US. In Figure 2, we draw world maps showing the average level of concentration and its change over time by country. Darker colors indicate a higher level of the HHI in 2012 (map a) or a larger increase in the HHI between 2002 and 2012 (map b). All figures are based on country-level arithmetic averages computed across 4-digit industries.

Some geographical patterns stand out. Focusing on levels, concentration in 2012 appears



Source: Piers (IHS Markit), US seaborne import data for 2002 and 2012. Darker colors indicate a higher level of the Herfindahl-Hirschman index of concentration in 2012 (map a) or a larger increase in the index between 2002 and 2012 (map b). All figures are country-level arithmetic averages computed across 4-digit industries.

Figure 2: Levels and Changes in the Herfindahl-Hirschman Index across Countries

Table 4: Additional Evidence on Concentration

	Level (2012)		Change (2002-2012)		Log Change (2002-2012)		% of Positive Changes
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a) No China and India							
Share of sales by the top-4 firms	0.453	0.234	-0.034	0.207	-0.132	0.502	0.417
Herfindahl-Hirschman index	0.132	0.171	-0.002	0.177	-0.227	1.079	0.401
b) No Asia and Pacific							
Share of sales by the top-4 firms	0.525	0.227	-0.030	0.198	-0.080	0.420	0.446
Herfindahl-Hirschman index	0.166	0.182	-0.005	0.180	-0.133	0.942	0.453
c) Countries exporting in both years							
Share of sales by the top-4 firms	0.380	0.242	-0.073	0.198	-0.294	0.587	0.346
Herfindahl-Hirschman index	0.103	0.156	-0.019	0.143	-0.530	1.168	0.326
d) Only top-4 firms in each triplet							
Share of sales by the top-4 firms	0.519	0.201	-0.081	0.213	-0.177	0.411	0.330
Herfindahl-Hirschman index	0.138	0.139	-0.041	0.170	-0.357	0.914	0.355
e) Unconsolidated MNEs							
Share of sales by the top-4 firms	0.364	0.230	-0.038	0.204	-0.169	0.577	0.382
Herfindahl-Hirschman index	0.087	0.126	-0.015	0.145	-0.297	1.127	0.380

Notes. All concentration measures are computed by industry-year pair using data from Piers. Columns (1)-(6) report simple averages and standard deviations calculated across industries. Column (7) reports the fraction of industries with an increase in a given concentration measure over 2002-2012. In panels a) and b), the concentration measures are computed after excluding firms exporting to the US from China and India and from all Asian and Pacific countries, respectively. In panel c), the concentration measures are computed using only firms from countries that exported to the US both in 2002 and in 2012 within a given industry. In panel d), the concentration measures are computed using only the top-4 firms in each country-industry-year triplet (or up to the top-3 firms for triplets with less than four firms). In panel e), the concentration measures are computed treating MNEs' affiliates located in different countries as different firms.

to be lower than average in Western Europe, India, China and some parts of South-East Asia. Conversely, concentration is higher than average in some parts of Eastern Europe, the Middle East and Russia. These cross-country patterns are broadly consistent with the evidence on the geographical distribution of markups reported in De Loecker and Eekhout (2020). Focusing on changes, concentration has grown in Latin America, Eastern Europe and Russia, and has fallen in China and India. These results are in line with Freund and Sidhu (2017), who stress the contribution of China and emerging markets to global competition using national data.

This preliminary look at the data suggests that the industry trends may be driven by the low and falling levels of concentration in Asian countries, which command a large and growing share of US imports. To better quantify the role of these countries, in panels a) and b) of Table 4, we re-compute the level and change in the two concentration measures by industry, after excluding from the sample firms exporting to the US from China and India and from all Asian and Pacific countries, respectively. Without these origin countries, the level of concentration in US imports would be higher and would have fallen by much less. For instance, without China and India, the share of the top-4 firms would have fallen by 0.13 log points instead of 0.30. In other words, these two countries alone account for more than half of the observed fall in concentration. Without all Asian and Pacific countries, the fall would have been a meager 0.08 log points, suggesting that all countries in the region have contributed to the trend. These are the most prominent examples of a more general pattern in the data: as we will show in Section 4, on average, concentration is lower and has fallen more in countries commanding a larger and growing share of US imports.

In the remaining panels of Table 4, we consider alternative explanations for the decline in industry concentration. One possibility is that the average number of countries serving the US market has increased over time. To see if this margin is quantitatively important, in panel c), we compute the two concentration measures using only firms from countries that exported to the US both in 2002 and in 2012 within a given industry. Results are almost unchanged, suggesting that exporters from new origin countries play a very marginal role. In panel d), we instead compute the two concentration measures by industry using the sub-sample consisting of only the top-4 firms in each country-industry-year triplet.[11] This exercise reveals that concentration is falling also among the top firms, which suggests that another reason for the fall in industry concentration is convergence among national champions. Finally, we study the role of MNEs, whose sales from different origins are consolidated in constructing our baseline concentration measures. To this end, in panel e), we build the two concentration measures treating MNEs' affiliates located in different countries as different firms. Unsurprisingly, when the sales of MNEs are not consolidated, the level of industry concentration is lower. More interestingly, in this case, the fall in industry concentration is also significantly smaller. This suggests that, contrary to some conventional wisdom, MNEs as a whole have contributed to the decline in concentration.

Finally, we study the heterogeneity in the levels and changes of the two concentration measures across 2-digit sectors. Tables 5 and 6 report the main patterns for the share of sales by the top-4 firms and for the HHI, respectively. Columns (3) and (4) confirm noticeable differences in trends. In a few sectors, concentration has actually increased. This is especially the case in sectors where the level of concentration is also particularly high, such as petroleum and coal products, and primary metal industries. On the other hand, concentration fell the most in sectors that are very competitive, such as apparel and other textile products, and furniture and fixtures. High-tech sectors, such as industrial machinery and computers, and instruments and related products, behave instead similarly to the average industry. These results highlight some divergence across sectors, especially between those dominated by few monopolists and those that are highly competitive. Despite these differences, the high standard deviations suggest the existence of significant heterogeneity also within 2-digit sectors.

[11] For triplets with less than four firms, we keep up to the top-3 firms.

Table 5: Share of Sales by the Top-4 Firms across Sectors

	Level (2012)		Change (2002-2012)		Log Change (2002-2012)		% of Positive
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Changes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
20 Food and kindred products	0.405	0.246	-0.055	0.193	-0.215	0.428	0.366
21 Tobacco products	0.472	0.116	-0.118	0.062	-0.212	0.075	0.000
22 Textile mill products	0.302	0.131	-0.056	0.176	-0.201	0.573	0.533
23 Apparel and other textile products	0.226	0.205	-0.147	0.221	-0.834	0.867	0.269
24 Lumber and wood products	0.453	0.298	-0.021	0.259	-0.191	0.691	0.538
25 Furniture and fixtures	0.248	0.160	-0.228	0.161	-0.753	0.415	0.000
26 Paper and allied products	0.368	0.258	-0.088	0.168	-0.297	0.497	0.357
27 Printing and publishing	0.329	0.333	-0.078	0.184	-0.436	0.520	0.200
28 Chemical and allied products	0.403	0.219	-0.059	0.258	-0.180	0.561	0.357
29 Petroleum and coal products	0.711	0.258	0.024	0.042	0.040	0.072	0.500
30 Rubber and miscellaneous plastics products	0.236	0.149	-0.089	0.141	-0.370	0.438	0.200
31 Leather and leather products	0.268	0.172	-0.064	0.226	-0.309	0.800	0.300
32 Stone, clay and glass products	0.418	0.279	-0.100	0.256	-0.347	0.669	0.304
33 Primary metal industries	0.475	0.226	0.060	0.254	0.095	0.682	0.615
34 Fabricated metal products	0.316	0.194	-0.117	0.210	-0.411	0.572	0.250
35 Industrial machinery and computer	0.365	0.203	-0.094	0.159	-0.298	0.449	0.256
36 Electronic and other electric equipment	0.403	0.199	-0.048	0.223	-0.178	0.564	0.412
37 Transportation equipment	0.573	0.255	0.029	0.180	-0.010	0.429	0.583
38 Instruments and related products	0.378	0.186	-0.086	0.126	-0.208	0.394	0.313
39 Miscellaneous manufacturing	0.330	0.210	-0.124	0.171	-0.416	0.523	0.176

Notes. The share of sales by the top-4 firms is computed separately for each 4-digit industry-year pair using data from Piers. Columns (1)-(6) report simple averages and standard deviations calculated across the 4-digit industries belonging to a given 2-digit sector. Column (7) reports the fraction of 4-digit industries within a 2-digit sector that are characterized by an increase in the share of sales by the top-4 firms over 2002-2012.

Table 6: Herfindahl-Hirschman Index across Sectors

	Level (2012)		Change (2002-2012)		Log Change (2002-2012)		% of Positive
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Changes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
20 Food and kindred products	0.100	0.120	-0.012	0.104	-0.387	0.814	0.286
21 Tobacco products	0.086	0.037	-0.033	0.027	-0.297	0.172	0.000
22 Textile mill products	0.047	0.037	-0.015	0.057	-0.345	1.005	0.467
23 Apparel and other textile products	0.045	0.072	-0.039	0.110	-1.581	1.741	0.231
24 Lumber and wood products	0.115	0.115	-0.008	0.168	-0.321	1.439	0.538
25 Furniture and fixtures	0.033	0.028	-0.090	0.137	-1.332	0.764	0.000
26 Paper and allied products	0.136	0.236	0.016	0.169	-0.458	0.998	0.333
27 Printing and publishing	0.082	0.151	0.011	0.109	-0.733	1.038	0.200
28 Chemical and allied products	0.094	0.116	-0.026	0.175	-0.355	1.240	0.357
29 Petroleum and coal products	0.329	0.286	0.028	0.129	0.146	0.435	0.500
30 Rubber and miscellaneous plastics products	0.031	0.036	-0.033	0.078	-0.744	0.760	0.200
31 Leather and leather products	0.043	0.050	-0.015	0.077	-0.580	1.490	0.300
32 Stone, clay and glass products	0.129	0.193	-0.025	0.183	-0.580	1.299	0.304
33 Primary metal industries	0.142	0.184	0.058	0.176	0.309	1.218	0.615
34 Fabricated metal products	0.058	0.071	-0.065	0.185	-0.752	1.134	0.250
35 Industrial machinery and computer	0.078	0.096	-0.055	0.137	-0.616	0.901	0.244
36 Electronic and other electric equipment	0.092	0.109	-0.018	0.152	-0.403	1.260	0.353
37 Transportation equipment	0.189	0.160	0.048	0.106	0.168	0.761	0.615
38 Instruments and related products	0.087	0.158	-0.068	0.105	-0.523	0.706	0.250
39 Miscellaneous manufacturing	0.073	0.107	-0.063	0.206	-0.806	1.232	0.235

Notes. The Herfindahl-Hirschman index is computed separately for each 4-digit industry-year pair using data from Piers. Columns (1)-(6) report simple averages and standard deviations calculated across the 4-digit industries belonging to a given 2-digit sector. Column (7) reports the fraction of 4-digit industries within a 2-digit sector that are characterized by an increase in the Herfindahl-Hirschman index over 2002-2012.

Table 7: Robustness Checks: Product Classification and Definition of Industries

	Level (2012)		Change (2002-2012)		Log Change (2002-2012)		% of Positive Changes
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a) <u>Excluding codes not in HS 1992 classification</u>							
Share of sales by the top-4 firms	0.369	0.228	-0.078	0.202	-0.302	0.583	0.332
Herfindahl-Hirschman index	0.089	0.128	-0.028	0.146	-0.562	1.168	0.314
b) <u>Alternative definition of industry: 3-digit SIC</u>							
Share of sales by the top-4 firms	0.300	0.216	-0.050	0.189	-0.321	0.678	0.289
Herfindahl-Hirschman index	0.068	0.121	0.004	0.100	-0.541	1.312	0.326
c) <u>Alternative definition of industry: 2-digit SIC</u>							
Share of sales by the top-4 firms	0.197	0.153	-0.048	0.149	-0.442	0.804	0.300
Herfindahl-Hirschman index	0.025	0.032	-0.007	0.036	-0.857	1.603	0.300
d) <u>Alternative definition of industry: 6-digit HS</u>							
Share of sales by the top-4 firms	0.614	0.252	-0.051	0.201	-0.129	0.414	0.394
Herfindahl-Hirschman index	0.258	0.259	-0.032	0.240	-0.247	0.949	0.402
e) <u>Alternative definition of industry: 4-digit HS</u>							
Share of sales by the top-4 firms	0.490	0.250	-0.056	0.195	-0.180	0.486	0.368
Herfindahl-Hirschman index	0.164	0.205	-0.026	0.187	-0.335	1.034	0.380
f) <u>Alternative definition of industry: 2-digit HS</u>							
Share of sales by the top-4 firms	0.301	0.205	-0.059	0.192	-0.314	0.653	0.337
Herfindahl-Hirschman index	0.067	0.126	-0.001	0.117	-0.559	1.329	0.344

Notes. The concentration measures are computed by industry-year using data from Piers. Columns (1)-(6) report simple averages and standard deviations calculated across industries. Column (7) reports the fraction of industries with an increase in a given concentration measure over 2002-2012. In panel a), the concentration measures are computed after excluding product codes that do not belong to the 1992 version of the HS classification. In panels b)-f), industries are defined according to the 3-digit level of the SIC classification, the 2-digit level of the SIC classification, the 6-digit level of the HS classification, the 4-digit level of the HS classification and the 2-digit level of the HS classification, respectively.

2.2.2 Robustness

We now study the robustness of the main trends discussed in the previous section, focusing on the fall in concentration at the industry level documented in panel b) of Table 3. A first set of concerns have to do with the product classification and the definition of industries. We address these concerns in Table 7. Regarding the product classification, one may worry that the fall in concentration could partially reflect the changes occurred in the HS classification between 2002 and 2012 (Pierce and Schott, 2012). We believe that classification changes are unlikely to have a major impact on our results, for two main reasons. First, the concentration statistics are computed using the total sales of each firm, i.e., after aggregating sales across individual products within each firm. Second, transactions in Piers are typically classified according to the first version of the HS classification, HS 1992, and only 98 out of 3,487 6-digit codes belong to subsequent revisions of the classification. Consistent with this, in panel a), we find that the concentration statistics, and their changes over time, are virtually unaffected if we re-compute them using a consistent product classification that excludes these 98 codes.

One may also worry that our evidence depends on the level of aggregation at which industries are defined. In panels b) and c), we therefore replicate the analysis using more aggregated sectors, defined at the 3- and 2-digit level of the SIC classification, respectively. The results are largely insensitive to the level of industry aggregation. A related concern is

Table 8: Robustness Checks: Measurement and Sample

	Level (2012)		Change (2002-2012)		Log Change (2002-2012)		% of Positive Changes
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a) Alternative definitions of top firms							
Share of sales by the top-3 firms	0.334	0.226	-0.072	0.211	-0.319	0.652	0.341
Share of sales by the top-5 firms	0.403	0.232	-0.081	0.199	-0.282	0.537	0.317
b) No Canada and Mexico							
Share of sales by the top-4 firms	0.366	0.226	-0.077	0.198	-0.302	0.574	0.324
Herfindahl-Hirschman index	0.086	0.124	-0.025	0.137	-0.558	1.136	0.301
c) No countries with small shares of seaborne trade							
Share of sales by the top-4 firms	0.369	0.226	-0.076	0.200	-0.296	0.580	0.313
Herfindahl-Hirschman index	0.088	0.126	-0.025	0.140	-0.547	1.156	0.307
d) No industries with small shares of seaborne trade							
Share of sales by the top-4 firms	0.342	0.220	-0.081	0.200	-0.339	0.615	0.320
Herfindahl-Hirschman index	0.076	0.110	-0.025	0.126	-0.627	1.208	0.301
e) No industries with large shares of imported inputs							
Share of sales by the top-4 firms	0.370	0.231	-0.078	0.206	-0.304	0.599	0.336
Herfindahl-Hirschman index	0.090	0.128	-0.025	0.142	-0.556	1.195	0.316
f) No countries with small market shares							
Share of sales by the top-4 firms	0.371	0.228	-0.077	0.205	-0.299	0.588	0.330
Herfindahl-Hirschman index	0.093	0.137	-0.026	0.148	-0.549	1.177	0.322
g) No countries with large market shares							
Share of sales by the top-4 firms	0.362	0.185	-0.059	0.160	-0.184	0.428	0.345
Herfindahl-Hirschman index	0.085	0.144	-0.017	0.136	-0.336	0.851	0.350

Notes. The concentration measures are computed by industry-year using data from Piers. Columns (1)-(6) report simple averages and standard deviations calculated across industries. Column (7) reports the fraction of industries with an increase in a given concentration measure over 2002-2012. In panel a), the concentration measures are the shares of sales by the top-3 or the top-5 firms. In panel b), the concentration measures are computed after excluding Canada and Mexico. In panel c), the concentration measures are computed after excluding countries for which the 2012 share of seaborne imports in total US manufacturing imports is below the 25th percentile of the distribution (i.e., the first group of countries in Figure 1). In panel d), the concentration measures are computed after excluding industries for which the 2012 share of seaborne imports in total US imports is below the 25th percentile. In panel e), the concentration measures are computed after excluding industries for which the average share of imports of parts and components in total US imports over 1972-2001 is above 25%. In panels f) and g), the concentration measures are computed after excluding countries whose market shares fall, respectively, below the 5th or above the 95th percentile of the distribution of market shares in a given industry and year.

that the baseline concentration statistics could be sensitive to the mapping between the HS and the SIC classification. To address this concern, in the remaining panels of Table 7, we define industries using the HS classification directly. In particular, we define an industry as a HS 6-digit code in panel d), a HS 4-digit code in panel e) and a HS 2-digit code in panel f). The baseline evidence is reassuringly preserved across the board.

A second set of concerns have to do with measurement and sample composition. As for measurement, one may worry that our baseline findings could not be robust across alternative concentration measures. While we have already shown that similar patterns hold both for the share of sales by the top-4 firms and for the HHI, in panel a) of Table 8, we document that the same conclusions obtain using the share of sales by the top-3 or top-5 firms as alternative concentration measures.[12]

Turning to sample composition, because Piers only includes transactions by sea, one concern is that the fall in concentration at the industry level could be driven by countries

[12] In untabulated results available upon request, we have re-computed the concentration statistics using import quantities rather than import values, both at the 4-digit SIC industry level and at the narrowest level of product detail allowed for by our data, the HS 6-digit level. The results are unchanged, suggesting that our main evidence is not driven by how we measure import flows.

or industries for which maritime trade is not a principal mode of serving the US market. To allay this concern, in panel b), we re-compute the concentration statistics after excluding Canada and Mexico. In panel c), we instead drop the whole set of countries for which the share of seaborne imports in total US manufacturing imports, based on official product-level data collected by the US Customs in 2012, is below the 25th percentile of the distribution (i.e., all countries in the first bin of Figure 1). In panel d), we exclude all industries for which the share of seaborne imports in total US imports, based on US Customs data for 2012, falls in the bottom quartile of the distribution. In all cases, we find no noteworthy change in the qualitative patterns and quantitative magnitudes of the results, suggesting that our baseline evidence is not driven by countries or industries for which seaborne trade constitutes a relatively smaller share of US imports.

Our data includes transactions involving not only final goods but also intermediate inputs, which constitute a significant share of total US imports, as shown by Antras (2003) and Bernard et al. (2010). In industries for which most imports reflect transactions between firms belonging to global value chains, using the observed distribution of import values to construct concentration measures could be problematic. In panel e), we therefore re-construct the concentration statistics after excluding industries in which US imports predominantly consist of intermediate inputs. We identify these industries as those for which imports of parts and components account for at least 25% of total US imports. Because Piers does not include information on related-party trade, we use industry-level data on imports of parts and components for the pre-sample 1972-2001 period from Schott (2004). The results are essentially unchanged, suggesting that the pattern documented in the previous section is unlikely to be driven by related-party trade reflecting firms' involvement in global value chains.

Finally, there may be concerns that our baseline evidence could be driven by few large or small countries. To allay this concern, in panels f) and g), we re-construct the concentration statistics on two sub-samples that exclude small and large countries, respectively. Small countries are those whose market shares fall below the 5th percentile of the distribution of market shares in a given industry and year; large countries are those whose market share fall above the 95th percentile of the distribution. In both cases, the results are close to those obtained on the whole sample. Overall, the robustness checks discussed in this section confirm that the fall in the concentration of US imports at the industry level is not an artifact of our choice of sample, its coverage, the definition and level of aggregation of products and industries, and measurement issues.

3 Decomposing Top Firms' Shares in US Imports

We now derive a simple decomposition that allows us to quantify the contribution of various firm-level characteristics to the observed changes in concentration, as measured by top firms' shares. Building on Hottman, Redding and Weinstein (2016), Redding and Weinsten (2017, 2020) and Bonfiglioli, Crinò and Gancia (2020), the characteristics that we can identify are the numbers of firms and products per firm, the average of a measure of "appeal" per firm-product and its heterogeneity across firm-products. Since the decomposition can be applied to any subset of firms, we will use it to study changes in concentration among foreign firms selling in the US market, both by country of origin and from all origin countries. Given that our data covers seaborne trade, our decompositions will be implemented on the subset of firms exporting to the US by sea.

3.1 A Structural Decomposition

Consider an industry i composed of differentiated varieties. Preferences over these varieties are:

$$C(i) = \left\{ \sum_{\omega \in \Omega_i} \left[\gamma(\omega) c\left(\omega\right) \right]^{(\sigma_i - 1)/\sigma_i} \right\}^{\sigma_i/(\sigma_i - 1)}, \quad \sigma_i > 1, \tag{1}$$

where $c\left(\omega\right)$ is the quantity consumed of variety $\omega \in \Omega_i$, and Ω_i denotes the set of varieties available for consumption in industry i; $\gamma(\omega)$ is a demand shifter sometimes interpreted as quality; and σ_i is the elasticity of substitution between varieties in industry i. Each variety is produced by a different firm; however, to make the model consistent with the data, a firm may produce more than one variety. Hence, ω refers to a firm-product pair. Denote by $p\left(\omega\right)$ the price of variety ω. Then, the minimum cost of one unit of the consumption basket $C(i)$ is given by the price index:

$$P(i) = \left[\sum_{\omega \in \Omega_i} \tilde{\gamma}\left(\omega\right)^{\sigma_i - 1} \right]^{1/(1-\sigma_i)}, \tag{2}$$

where $\tilde{\gamma}\left(\omega\right) \equiv \gamma(\omega)/p\left(\omega\right)$ is a synthetic measure of "appeal" of variety ω. Revenue from sales of a variety with appeal $\tilde{\gamma}$ is:

$$r\left(\omega\right) = \tilde{\gamma}(\omega)^{\sigma_i - 1} P(i)^{\sigma_i} C(i). \tag{3}$$

We use this model to decompose the share of top firms in US imports. Hence, $P(i)C(i)$ will be the value of US imports in industry i. We start by decomposing top firms' shares by industry and country of origin. Let $n^f(i, o)$ be the number of *firms* exporting to the US from country o in industry i. Let $n^p(i,o)$ be the number of *products per firm* and $\bar{r}(i,o)$ the *revenue per firm-product* from country o in industry i. Finally, we use the subscript *top* to denote the numbers of firms, products per firms and revenue per firm-product of the top $X \in \mathbb{N}$ firms from country o in industry i. By these definitions, the expenditure share of the top X exporters among all exporting firms from origin o is:

$$s_{top}(i,o) \equiv \frac{n^f_{top}(i,o) \cdot n^p_{top}(i,o) \cdot \bar{r}_{top}(i,o)}{n^f(i,o) \cdot n^p(i,o) \cdot \bar{r}(i,o)}, \tag{4}$$

where the denominator is total sales in industry i from country o and the numerator is the corresponding sales by top firms only. $s_{top}(i,o)$ measures concentration among exporters from a given country and industry. Equation (4) can immediately be used to decompose changes in the top firms' shares of US imports into an extensive margin (number of firms and products per firm) and an intensive margin (average revenue per firm-product):

$$\Delta \ln s_{top}(i,o) = -\Delta \ln n^f(i,o) + \Delta \ln n^p_{top}(i,o) - \Delta \ln n^p(i,o) + \Delta \ln \frac{\bar{r}_{top}(i,o)}{\bar{r}(i,o)}. \tag{5}$$

The advantage of the structural model is that it can be used to further decompose the intensive margin into firm-level characteristics, namely, the distribution of appeal. Consider $\bar{r}(i,o)$ first. From (3), we can express average revenue per firm-product as:

$$\ln \bar{r}(i,o) = \ln \mathbb{E}\left[\tilde{\gamma}(i,o)^{\sigma_i - 1}\right] + \ln A(i),$$

where $\mathbb{E}\left[\tilde{\gamma}(i,o)^{\sigma_i - 1}\right]$ is the arithmetic average of all $\tilde{\gamma}(\omega)^{\sigma_i - 1}$ sold from origin o in industry i and $A(i) = P(i)^{\sigma_i} C(i)$ captures demand conditions in industry i. Then, adding and subtracting $\ln \left\{\mathbb{E}\left[\tilde{\gamma}(i,o)\right]\right\}^{\sigma_i - 1}$ yields:

$$\ln \bar{r}(i,o) = \ln \left\{\mathbb{E}\left[\tilde{\gamma}(i,o)\right]\right\}^{\sigma_i - 1} + \ln \mathbb{E}\left[\frac{\tilde{\gamma}(i,o)^{\sigma_i - 1}}{\left\{\mathbb{E}\left[\tilde{\gamma}(i,o)\right]\right\}^{\sigma_i - 1}}\right] + \ln A(i). \tag{6}$$

This equation shows that exports per firm-product depend both on average appeal and on its dispersion. If $\sigma_i > 2$, sales are a convex function of $\tilde{\gamma}$, which implies that, by Jensen's inequality, $\bar{r}(i,o)$ is increasing in the dispersion of appeal holding constant the average. In this case, the reallocation of demand towards better firm-products is so strong as to increase total sales. An interesting implication is that in more "competitive" industries, i.e., where reallocation is strong enough, a high concentration at the top is associated with higher average sales.

Substituting $\tilde{\gamma}(\omega)$ from (3), we can express (6) in terms of σ_i and sales:

$$\ln \bar{r}(i,o) = \ln \left\{ \mathbb{E}\left[r(i,o)^{1/(\sigma_i-1)} \right] \right\}^{\sigma_i-1} + \ln \frac{\bar{r}(i,o)}{\left\{ \mathbb{E}\left[r(i,o)^{1/(\sigma_i-1)} \right] \right\}^{\sigma_i-1}}.$$

Taking differences:

$$\Delta \ln \bar{r}(i,o) = \Delta \ln \left\{ \mathbb{E}\left[[r(i,o)]^{1/(\sigma_i-1)} \right] \right\}^{\sigma_i-1} + \Delta \ln \frac{\bar{r}(i,o)}{\left\{ \mathbb{E}\left[[r(i,o)]^{1/(\sigma_i-1)} \right] \right\}^{\sigma_i-1}}. \tag{7}$$

Equation (7) decomposes the change in average revenues into two terms: the change in average appeal of firm-products and the change in its dispersion. The first term measures whether all firm-products are becoming better on average. The second term captures instead the role of differential growth in appeal within firm-products. Once again, if $\sigma_i > 2$, more dispersion in appeal leads to higher average sales, because the increase in demand for better-than-average firm-products is greater than the decrease in demand for the remaining ones.

Likewise, we can decompose average sales of top firms as follows:

$$\ln \bar{r}_{top}(i,o) = \ln \left\{ \mathbb{E}\left[[r_{top}(i,o)]^{1/(\sigma_i-1)} \right] \right\}^{\sigma_i-1} + \ln \frac{\bar{r}_{top}(i,o)}{\left\{ \mathbb{E}\left[[r_{top}(i,o)]^{1/(\sigma_i-1)} \right] \right\}^{\sigma_i-1}}.$$

Combining the two decompositions yields:

$$\begin{aligned} \Delta \ln \frac{\bar{r}_{top}(i,o)}{\bar{r}(i,o)} &= \Delta \ln \left\{ \mathbb{E}\left[r_{top}(i,o)^{1/\rho_i} \right] \right\}^{\rho_i} - \Delta \ln \left\{ \mathbb{E}\left[[r(i,o)]^{1/\rho_i} \right] \right\}^{\rho_i} \\ &\quad + \Delta \ln \frac{\bar{r}_{top}(i,o)}{\left\{ \mathbb{E}\left[r_{top}(i,o)^{1/\rho_i} \right] \right\}^{\rho_i}} - \Delta \ln \frac{\bar{r}(i,o)}{\left\{ \mathbb{E}\left[[r(i,o)]^{1/\rho_i} \right] \right\}^{\rho_i}}, \end{aligned} \tag{8}$$

where $\rho_i \equiv \sigma_i - 1$. Equation (8) shows how changes in the average and dispersion of appeal among the products of top and non-top firms affect concentration through the intensive margin. By removing the origin index o, we can immediately apply these decompositions also at the industry level, pooling firms from all origin countries.

Before proceeding, it is instructive to discuss similar decompositions of sales that have been proposed in the literature. Hottman, Redding and Weinstein (2016) use US barcode data to decompose the firm-size distribution into the contributions of costs, demand shifters, markups, and product scope. Redding and Weinstein (2017) use US import data to decompose the price indexes that determine comparative advantage across countries and sectors into the contributions of entry/exit, demand shifters and prices. These papers show that product scope, entry/exit and demand shifters explain a large fraction of the variation in the data, with a minor role for prices.[13] Building on these results, the decompositions in equations (5) and (8) allow us to assess how product scope, entry/exit and a single measure of appeal explain changes in concentration.[14]

3.2 Top Import Shares by Industry and Country

We now present the results of the decompositions in (5) and (8). As already noted, the decomposition of the intensive margin depends on the elasticity of substitution, σ_i. To check the sensitivity of the results to this parameter, we work with two different sets of estimates, both sourced from Bonfiglioli, Crinò and Gancia (2020) and based on the same micro data as in this paper. The main estimates are obtained by applying the Reverse-Weighting (RW) estimator proposed by Redding and Weinstein (2016). These estimates are identified out of time variation in prices and market shares for firm-products imported in both years, and are available for 259 industries. For robustness, we also use an alternative set of estimates, which are obtained by exploiting cross-industry variation in sales dispersion and are available for all industries. For the median industry in our sample, the estimated σ_i equals 3.54 for the RW estimator and 4.2 for the alternative method.[15] More details are reported in Appendix B.

Table 9 shows the decomposition of the change in the share of sales by the top-4 firms according to (5). Column (1) reports the variable to be explained, namely, the change in the log share of the top firms. The remaining columns display the contribution of each term on the right-hand side of (5), capturing the importance of the extensive margin, i.e., the number of firms and products per firm (columns 2-4), and of the intensive margin, i.e., the average revenue per firm-product by the top firms relative to all firms (column 5). Reported figures are simple averages, computed across all country-industry pairs (panel a) or across all industries (panels b and c). By construction, the contributions of the four components add up to the total change to be explained, as reported in the first column. Rows (1)-(3)-(5) refer to the sample of industries with non-missing values of the RW estimate of the elasticity of substitution; rows (2)-(4)-(6) refer instead to the full sample of industries. Since the decomposition in (5) does not make use of σ_i, the differences in results owe entirely to

[13] In particular, Hottman, Redding and Weinstein (2016) find that 50-70% of the variance in firm size can be attributed to differences in firm appeal, about 20-25% to differences in product scope, and less than 25% to cost. Redding and Weinstein (2017) find that around 50% of the cross-section (90% of the time-series) variation in comparative advantage is accounted for by variety and average demand/quality, with average prices contributing less than 10%.

[14] In Bonfiglioli, Crinò and Gancia (2020), we use the same data to decompose countries' market shares instead of concentration. The main findings of that paper, that firm heterogeneity is important for explaining average exports and why these are higher from richer and larger countries, are not directly related to the current analysis.

[15] All estimates satisfy the theoretical restriction $\sigma_i > 1$.

the different samples used.

Table 9 shows that the main factor explaining the fall in concentration in the US import market is the extensive margin. First, there is a large increase in the number of firms that start exporting to the US in a given industry ($-\Delta \ln n^f < 0$). Second, the extensive margin plays an important role also within firms. While all firms are shedding products ($-\Delta \ln n^p > 0$), top firms are dropping proportionally more products than other firms ($\Delta \ln n^p_{top} < \Delta \ln n^p$). Other things equal, the increase in the number of firms and the decrease in the relative number of products by the top firms would have commanded a pervasive fall in concentration. On the other hand, the intensive margin has worked in the opposite direction. The average sales per product of the top firms significantly grew relative to the rest of firms ($\Delta \ln \bar{r}_{top}/\bar{r} > 0$), pushing towards rising concentration. Interestingly, all these effects are stronger when focusing on concentration from all origins (panel b): entry is stronger, but so is divergence of top firm-products. However, when considering firms from a single origin (panel a), the opposite effects of the intensive and extensive margins almost exactly cancel out.

These results indicate that one reason for the fall in concentration in international markets is the sheer increase in the total number of exporting firms. The results also suggest, however, that these new exporters are likely to be small, thereby lowering the size of the average firm relative to the top firms. To neutralize this effect, we now decompose the share of sales by the top-4 firms over the top-100 firms (rather than all firms) in each industry. In this way, the extensive margin across firms is eliminated: $\Delta \ln n^f$ is equal to zero by construction. The results are reported in panel c). Interestingly, industry concentration is still falling significantly even among the top-100 firms, due to top firms losing products relative to their competitors. Sales per product of the top firms still grew relative to the rest of firms, albeit by a much smaller margin.

Consider next the decomposition of the intensive margin. Table 10 decomposes the relative sales per firm-product of the top firms, i.e., the figures reported in column (5) of Table 9, according to equation (8). As before, each number is the simple average of a given term on the right-hand side of (8), computed across all country-industry pairs (panel a) or across all industries (panels b and c). Hence, Table 10 decomposes the intensive margin into the contributions of average appeal (columns 2 and 3) and dispersion of appeal (columns 4 and 5). Rows (1)-(3)-(5) make use of the RW estimates of the elasticity of substitution, while rows (2)-(4)-(6) use the alternative estimates.

Columns (2) and (3) of Table 10 show the contribution of the change in the average appeal of top firm-products and of all firm-products, respectively. Column (2) shows that top firms are on average becoming better, i.e., the average appeal of their products is growing. On the other hand, column (3) shows that non-top firms are falling behind, i.e., their average appeal is shrinking. The latter effect is stronger than the former, although it is largely driven by the

Table 9: Decomposing the Change in the Share of Sales by the Top-4 Firms: Extensive vs. Intensive Margins

	(1)	(2)	(3)	(4)	(5)
	$\Delta \ln s_{top}$	$-\Delta \ln n^f$	$\Delta \ln n^p_{top}$	$-\Delta \ln n^p$	$\Delta \ln \frac{\bar{r}_{top}}{\bar{r}}$
a) Decomposition by country-industry					
1) RW estimate of the elasticity of substitution	-0.039	-0.279	-0.145	0.071	0.313
2) Alternative estimate of the elasticity of substitution	-0.033	-0.273	-0.147	0.072	0.314
b) Decomposition by industry					
3) RW estimate of the elasticity of substitution	-0.350	-0.776	-0.433	0.111	0.749
4) Alternative estimate of the elasticity of substitution	-0.296	-0.755	-0.429	0.105	0.783
c) Decomposition by industry, top-100 firms					
5) RW estimate of the elasticity of substitution	-0.236	0.000	-0.478	0.212	0.030
6) Alternative estimate of the elasticity of substitution	-0.215	0.000	-0.531	0.224	0.092

Notes: The table reports the decomposition of the change in the share of sales by the top-4 firms into the contributions of extensive and intensive margins. In panel a), the decomposition is performed separately by country-industry; reported statistics are simple averages of the individual components (labeled in the columns' headings) across country-industries. In panel b), the decomposition is performed separately by industry; reported statistics are simple averages of the individual components across industries. In panel c), the decomposition is performed separately by industry, using only the top-100 firms in each industry; reported statistics are simple averages of the individual components across industries. Rows (1), (3) and (5) refer to the sample of industries with non-missing values of the Reverse-Weighting estimate of the elasticity of substitution. Rows (2), (4) and (6) refer to the sample of industries with non-missing values of the alternative estimate of the elasticity of substitution (i.e., the whole sample of industries).

small size of new entrants. Consistent with this, panel c) shows that, once the entry margin is neutralized, the average appeal of the top-100 firms is actually growing rather than falling, but not as fast as the average appeal of the top-4 firms.

Finally, columns (4) and (5) show the contribution of the change in the dispersion of appeal among firm-products, for the top-4 firms and for all firms, respectively. Column (4) shows that the dispersion of appeal is actually falling among the top firms. This is consistent with the hypothesis that top firms are dropping their marginal products. On the other hand, column (5) shows that the dispersion of appeal is increasing among all firms, which is consistent with entry of below-average firms. Indeed, panel c) shows that, when the entry margin is neutralized by focusing on the top-100 firms, the dispersion of appeal falls also among all firms. The results are qualitatively similar across the two alternative estimates of the elasticity of substitution.

Similarly to existing decompositions of sales, these findings confirm the importance of entry/exit and product scope even for understanding concentration and are consistent with Bernard, Jensen, Redding and Schott (2018), who show that one reason for concentration is that the margins of firm participation in international markets are systematically correlated with one another.[16] However, they also show that while top firms are diverging from their

[16] For instance, large firms export to more markets, export more products, export more of each product to

Table 10: Decomposing the Change in the Relative Revenue of the Top-4 Firms: Average Appeal and Dispersion of Appeal

	(1)	(2)	(3)	(4)	(5)
	$\Delta \ln \frac{\bar{r}_{top}}{\bar{r}}$	$\Delta \ln \left\{\mathbb{E}\left[r_{top}^{1/\rho}\right]\right\}^{\rho}$	$-\Delta \ln\{\mathbb{E}[r^{1/\rho}]\}^{\rho}$	$\Delta \ln \frac{\bar{r}_{top}}{\left\{\mathbb{E}\left[r_{top}^{1/\rho}\right]\right\}^{\rho}}$	$-\Delta \ln \frac{\bar{r}}{\{\mathbb{E}[r^{1/\rho}]\}^{\rho}}$
a) Decomposition by country-industry					
1) RW estimate of the elasticity of substitution	0.313	0.174	0.272	-0.031	-0.102
2) Alternative estimate of the elasticity of substitution	0.314	0.223	0.312	-0.058	-0.163
b) Decomposition by industry					
3) RW estimate of the elasticity of substitution	0.749	0.354	0.630	-0.181	-0.053
4) Alternative estimate of the elasticity of substitution	0.783	0.532	0.624	-0.258	-0.115
c) Decomposition by industry, top-100 firms					
5) RW estimate of the elasticity of substitution	0.030	0.375	-0.297	-0.191	0.143
6) Alternative estimate of the elasticity of substitution	0.092	0.601	-0.397	-0.310	0.198

Notes: The table reports the decomposition of the change in the average revenue per firm-product by the top-4 firms relative to all firms (i.e., the intensive margin) into the contributions of average appeal and dispersion of appeal. In panel a), the decomposition is performed separately by country-industry; reported statistics are simple averages of the individual components (labeled in the columns' headings) across country-industries. In panel b), the decomposition is performed separately by industry; reported statistics are simple averages of the individual components across industries. In panel c), the decomposition is performed separately by industry, using only the top-100 firms in each industry; reported statistics are simple averages of the individual components across industries. Parameter ρ is equal to σ-1, where σ is the elasticity of substitution. In rows (1), (3) and (5), the individual components are computed using the Reverse-Weighting estimate of the elasticity of substitution; in rows (2), (4) and (6), they are computed using the alternative estimate of the elasticity of substitution.

national competitors and from marginal firms, they are increasingly more similar to each other at the global level. This latter result is novel in the literature and differs from the evidence on the role of firm heterogeneity in explaining sales. It is consistent with the view that more competition, as exemplified by massive entry, has been accompanied by the reallocation of sales towards top firms.

4 National Concentration and International Competition

In this section, we investigate the relationship between concentration at the country-industry level and international competition. We start by reviewing the main channels through which international competition may increase concentration of exports from a single origin in a simple model with granular firms. We then study, by means of regression analysis, the correlates of the change in the concentration of US imports at the country-industry level, and use the model to interpret the results.

4.1 Theoretical Framework

Consider an oligopolistic model with heterogeneous firms as in Atkeson and Burstein (2008), Amiti, Itskhoki and Konings (2014, 2019), and Gaubert and Itskhoki (2021).[17] Firms play

each market, import from more countries, import more inputs and import more of each input.

[17] We refer the reader to these papers for more details on the derivations.

a Bertrand-Nash game whereby the price of a variety ω, $p(\omega)$, is chosen so as to maximize profits in the destination market, taking as given the prices of all competitors. For simplicity, we restrict the analysis here to single-product firms. In equilibrium, the price is a markup over the marginal cost, and the markup is an inverse function of the perceived demand elasticity, $\epsilon(\omega)$:

$$p(\omega) = \frac{\epsilon(\omega)}{\epsilon(\omega) - 1} \frac{\tau(\omega) w(\omega)}{\varphi(\omega)}, \tag{9}$$

where the marginal cost comprises the cost of labor, $w(\omega)$, the unit labor requirement, $1/\varphi(\omega)$, and an iceberg trade cost, $\tau(\omega)$. Since firms are large, the perceived demand elasticity depends on the market share $s(\omega)$ captured by the variety:

$$\epsilon(\omega) = [1 - s(\omega)]\, \sigma_i + s(\omega)\alpha, \tag{10}$$

where $\alpha < \sigma_i$ is the elasticity of substitution across industries and

$$s(\omega) = \frac{[\gamma(\omega)/p(\omega)]^{\sigma_i - 1}}{\sum_{\omega \in \Omega_i} [\gamma(\omega)/p(\omega)]^{\sigma_i - 1}}. \tag{11}$$

Given the set of varieties in industry i, their marginal costs and demand shifters, conditions (9)-(10)-(11) form a system of equations with a unique solution.

Although there are no closed-form solutions, some important properties of the equilibrium can be characterized analytically. In particular, it can be shown that firms with better attributes, i.e., a combination of low marginal costs and a high $\gamma(\omega)$, capture larger market shares, charge higher markups, and make more profits. As in Atkeson and Burstein (2008), the elasticity of the markup with respect to the market share is an increasing function of the market share itself, as can be see from:

$$-\frac{d \ln \epsilon(\omega)}{d \ln s(\omega)} = \frac{s(\omega)\,(\sigma_i - \alpha)}{\sigma_i - s(\omega)\,(\sigma_i - \alpha)}. \tag{12}$$

This means that the markup charged by large firms react more to any change in their market share.[18]

Finally, consider the number of active firms. Assuming that there is a fixed cost of serving the market equal to $w(\omega)F(\omega)$, only firms with sufficiently good attributes will find it profitable to sell positive quantities. Specifically, for all $\omega \in \Omega_i$, the following condition must be satisfied:

$$\pi(\omega) = \frac{s(\omega)}{\epsilon(\omega)} P(i)^{1-\alpha_i} Y - w(\omega)F(\omega) \geq 0, \tag{13}$$

[18] Similarly, the markup elasticity with respect to the firm's own price and to the price of competitors is also increasing in the market share (see Amiti, Itskhoki and Konings, 2014, 2019).

where Y is total expenditure in the destination market. In a sequential entry game where firms with better attributes enter first, there exists a unique cutoff level such that all firms from a given origin with attributes $\gamma(\omega)\varphi(\omega)$ above this level serve the market.

We can now study the relationship between international competition and concentration among varieties from a given origin. If all firms from country o and industry i face the same trade and labor costs, then the market share of variety ω relative to other competitors from o is just a function of the distribution of the markups and attributes of these varieties:

$$\frac{s(\omega)}{\sum_{\omega\in\Omega_{io}} s(\omega)} = \frac{\left[\frac{\epsilon(\omega)-1}{\epsilon(\omega)}\frac{\gamma(\omega)}{\varphi(\omega)}\right]^{\sigma_i-1}}{\sum_{\omega\in\Omega_{io}}\left[\frac{\epsilon(\omega)-1}{\epsilon(\omega)}\frac{\gamma(\omega)}{\varphi(\omega)}\right]^{\sigma_i-1}}.$$

Consider the share of sales from o captured by the top firm as a measure of concentration. How does it depend on foreign competition? Keeping attributes constant, foreign competition can affect concentration from o through exit, i.e., a change in the set Ω_{io}, and the markups, $\epsilon(\omega)$. The first channel is the standard selection effect of trade. Even holding $\epsilon(\omega)$ constant, more international competition implies lower sales for any single firm, which, according to (13), will push the varieties with the worst attributes out of the market. The second channel is the pro-competitive effect of trade. Even holding constant the set of firms from o, the fall in market shares forces all firms to cut markups. However, (12) shows that top firms lower markups relatively more and hence are able to capture a larger share of total sales from o. Hence, as market shares in a destination fall, sales also become more concentrated.

4.2 Evidence

We now turn to the evidence and investigate the correlates of the change in the concentration of US imports at the country-industry level. In particular, we focus on the share of sales by the top-4 firms and on the HHI, and regress the change in either measure on a number of variables including the change in average prices per firm and proxies for competition both at the country-industry and at the industry level. This exercise complements our exact decompositions in various ways. It allows us to consider alternative measures of concentration, to compare alternative sources of variation and to shed more light on the hypothesis that intensified international competition may be accompanied by an increase in national concentration. We interpret the regression coefficients as conditional correlations highlighting the central tendencies in the data. We do not give these coefficients a causal interpretation, as causality may run either way and there could be third factors influencing both concentration and the covariates. However, we discuss how the findings compare to the predictions of the model.

Table 11: Correlates of Concentration: Share of Sales by the Top-4 Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ ln no. of firms	-0.201***	-0.215***	-0.221***	-0.217***	-0.223***	-0.190***	-0.189***
	[0.005]	[0.006]	[0.007]	[0.006]	[0.007]	[0.006]	[0.006]
Δ ln average price per firm	0.001	-0.005	-0.009**	-0.004	-0.008*	-0.010***	-0.010***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Initial ln share of sales by the top-4 firms	-0.306***	-0.321***	-0.333***	-0.319***	-0.334***	-0.491***	-0.492***
	[0.014]	[0.014]	[0.016]	[0.014]	[0.016]	[0.016]	[0.016]
Initial ln country share of US imports in the industry	-0.031***	-0.035***	-0.040***	-0.035***	-0.039***	-0.050***	-0.050***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Δ ln no. of firms from other countries		0.028***	0.032***	0.013	0.021**	0.281***	0.281***
		[0.008]	[0.009]	[0.009]	[0.010]	[0.096]	[0.096]
Δ ln industry share of total US imports		0.021***	0.026***	0.026***	0.030***		
		[0.005]	[0.006]	[0.005]	[0.006]		
Δ ln share of sales by top-4 firms in the industry		0.056***	0.067***	0.048***	0.058***		
		[0.006]	[0.007]	[0.006]	[0.007]		
ln elasticity of substitution (RW)			0.035***		0.035***		
			[0.006]		[0.006]		
Δ ln labor share in the industry				-0.017*	-0.034***		
				[0.009]	[0.011]		
ln routine intensity of the industry				0.063***	0.043***		
				[0.013]	[0.016]		
ln industry bulk weight x ln country distance from the US							0.010**
							[0.004]
Country FE	yes	yes	yes	yes	yes	yes	yes
Industry FE	no	no	no	no	no	yes	yes
Obs.	7044	7041	5349	6925	5304	7041	7041
R2	0.38	0.40	0.42	0.40	0.42	0.49	0.49

Notes. All regressions are estimated across country-industry pairs. The dependent variable is the change in the logarithm of the share of sales by the top-4 firms in a country-industry pair between 2002 and 2012. The labor share is defined as the ratio between total wage bill and value added. Routine intensity is defined as the share of routine-intensive occupations in the total number of hours worked. The bulk weight of an industry is the median weight-to-value ratio of US seaborne imports across the 6-digit HS codes belonging to the industry; the bulk weight of a 6-digit HS code is averaged between the years 2002 and 2012. The standard errors, reported in square brackets, are robust to heteroskedasticity. ***, **, *: denote significance at the 1%, 5%, and 10% level, respectively.

Table 11 reports the results for the share of US imports that is accrued by the top-4 firms. In column (1), we regress the 2002-2012 change in this concentration measure on a number of variables defined at the country-industry level. These are the changes in the number of exporting firms and in the average price per firm, the initial value of the concentration measure and the initial share of the country in US seaborne imports within the industry. All variables are computed from Piers and expressed in logarithms; all specifications include country fixed effects, in order to focus on cross-industry variation within countries and to control for country-specific characteristics that do not vary across industries, such as distance from the US and institutional quality. While the coefficient on the change in average prices is imprecisely estimated, the coefficients on the other variables are statistically significant at 1% level. As expected, the coefficient on the change in the number of firms confirms that concentration declines with entry. Further, concentration falls more in countries that capture a larger initial share of US imports in an industry, confirming the role of large origins in explaining the overall decline in concentration. The coefficient on the initial level of concentration, which is negative and precisely estimated, is consistent with the evidence in Gaubert and Itskhoki (2021) that sectors with stronger concentration at the top have a greater tendency for mean reversion.

The fact that concentration increases with exit is not informative about its correlation with competition. To search for evidence of pro-competitive effects, in the remaining columns, we start adding industry-level controls. In particular, in column (2), we add the change in the number of firms exporting to the US in an industry from other origin countries, the change in the share of the industry in US seaborne imports, and the change in the overall concentration of US imports in the industry, all computed from Piers. All coefficients are positive and highly statistically significant, suggesting that domestic concentration increases with entry of foreign competitors and in sectors that are expanding. These results are consistent with the pro-competitive effect described in the model: both foreign entry and industry growth are likely to indicate more competitive pressure, lower market shares for existing firms, and hence more concentrated sales. The positive coefficient on the change in concentration at the industry level indicates instead the existence of common trends across origins.

In column (3), we further control for the elasticity of substitution. Since estimates of this parameter are not available for all industries, some observations are dropped. Interestingly, we find that concentration increases more in sectors where varieties are better substitutes; moreover, the coefficient on the change in the average price per firm is now negative and precisely estimated, suggesting that growing concentration is associated with falling prices. These results are also consistent with the pro-competitive effect, which should lower markups and prices, and skew the distribution towards top firms, especially in industries with a high σ_i.

Next, we relate the change in concentration to technological characteristics of industries. As proxies for the diffusion of labor-saving technologies and automation, we include the change in the labor share and the routine intensity of the industry, both computed using US data.[19] The results are reported in columns (4) and (5); the only difference between the two columns is that the latter includes the elasticity of substitution among the covariates, while the former does not. In both columns, the change in concentration is negatively correlated with the change in the labor share. Moreover, both columns show that concentration increases relatively faster in more routine-intensive industries, which are more prone to automation. Since the two industry covariates are computed using US data, our estimates are less likely to

[19] The labor share of an industry is defined as the ratio between total wage bill and value added, and is computed using data from the NBER Manufacturing Industry Database. The routine intensity of an industry is defined as the share of routine-intensive occupations in the total number of hours worked in the industry. Routine intensive occupations are defined as in Autor and Dorn (2013) and identified using data on the task content of occupations provided by those authors. Information on the number of hours worked by industry and occupation is retrieved from the 5% extract of the 1990 US Census.

Table 12: Correlates of Concentration: Herfindahl-Hirschman Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ ln no. of firms	-0.464***	-0.488***	-0.487***	-0.489***	-0.489***	-0.443***	-0.442***
	[0.008]	[0.009]	[0.010]	[0.009]	[0.010]	[0.009]	[0.009]
Δ ln average price per firm	-0.001	-0.014*	-0.029***	-0.013*	-0.029***	-0.025***	-0.025***
	[0.008]	[0.007]	[0.009]	[0.008]	[0.009]	[0.007]	[0.007]
Initial ln Herfindahl-Hirschman index	-0.406***	-0.417***	-0.438***	-0.416***	-0.438***	-0.583***	-0.583***
	[0.009]	[0.009]	[0.011]	[0.009]	[0.011]	[0.011]	[0.011]
Initial ln country share of US imports in the industry	-0.077***	-0.086***	-0.094***	-0.085***	-0.093***	-0.111***	-0.110***
	[0.003]	[0.003]	[0.004]	[0.003]	[0.004]	[0.003]	[0.003]
Δ ln no. of firms from other countries		0.058***	0.052***	0.034**	0.037*	0.176	0.177
		[0.016]	[0.018]	[0.017]	[0.019]	[0.145]	[0.145]
Δ ln industry share of total US imports		0.056***	0.068***	0.062***	0.073***		
		[0.009]	[0.011]	[0.009]	[0.011]		
Δ ln Herfindahl-Hirschman index in the industry		0.056***	0.074***	0.049***	0.066***		
		[0.006]	[0.007]	[0.006]	[0.007]		
ln elasticity of substitution (RW)			0.103***		0.102***		
			[0.012]		[0.012]		
Δ ln labor share in the industry				-0.037**	-0.070***		
				[0.019]	[0.023]		
ln routine intensity of the industry				0.111***	0.061**		
				[0.026]	[0.030]		
ln industry bulk weight x ln country distance from the US							0.022**
							[0.009]
Country FE	yes	yes	yes	yes	yes	yes	yes
Industry FE	no	no	no	no	no	yes	yes
Obs.	9864	9857	7488	9702	7430	9857	9857
R2	0.43	0.45	0.47	0.45	0.47	0.53	0.53

Notes. All regressions are estimated across country-industry pairs. The dependent variable is the change in the logarithm of the Herfindahl-Hirschman index in a country-industry pair between 2002 and 2012. The labor share is defined as the ratio between total wage bill and value added. Routine intensity is defined as the share of routine-intensive occupations in the total number of hours worked. The bulk weight of an industry is the median weight-to-value ratio of US seaborne imports across the 6-digit HS codes belonging to the industry; the bulk weight of a 6-digit HS code is averaged between the years 2002 and 2012. The standard errors, reported in square brackets, are robust to heteroskedasticity. ***, **, *: denote significance at the 1%, 5%, and 10% level, respectively.

capture the effect of concentration on the labor share emphasized, for instance, in Autor et al. (2020). Rather, they are consistent with the view that automation, which is more prevalent among top firms, may also confer market power (see, for instance, Acemoglu, Lelarge and Restrepo, 2020, and Bonfiglioli et al. 2020).

In column (6), all industry-level variables are subsumed into industry fixed effects. This allows us to control for time-invariant heterogeneity across sectors, including differences in physical characteristics of products that may affect the cost and mode of transportation. The coefficients are all very precisely estimated and confirm that changes in concentration correlate negatively with changes in average prices per firm and in the number of competitors from the same origin country, as well as with the initial share of the country in US imports. Conversely, changes in concentration are positively associated with the entry of foreign competitors. Finally, in column (7), we add the interaction between the bulk weight of US seaborne imports in the industry and the distance of the country from the US.[20] This variable is a

[20] The bulk weight is the weight-to-value ratio. We use official product-level data from the US Customs to compute bulk weights of US seaborne imports for each 6-digit HS product in 2002 and 2012. Next, we

reasonably exogenous measure of country-industry trade costs. Consistent with the model, its positive and statistically significant coefficient confirms that concentration is higher in country-industries with a more limited access to the US market, where competition from foreign firms is likely to be tougher.[21]

The above evidence is confirmed by the results reported in Table 12, where we use the change in the HHI as the dependent variable. Since the HHI can be computed even for triplets with less than four firms, the number of observations is larger than in Table 11. Compared to the previous patterns, the evidence that a rise in concentration is associated with a fall in average prices is now stronger, as the price coefficient is precisely estimated in all specifications except the most parsimonious one, which excludes industry controls. More generally, Tables 11 and 12 provide a remarkably consistent picture, reassuring that none of the patterns discussed in this section depends on a specific measure of concentration.

In Appendix C, we report additional robustness checks on the results presented in Tables 11 and 12, focusing on the most complete specifications shown in columns (5) and (7). First, we re-estimate these specifications on a consistent sub-sample that excludes triplets with less than seven firms (the sample median). The results are similar to the baseline estimates, suggesting that granularity, which is likely to be relevant in small samples (see Gaubert and Itskhoki, 2021), is not a key determinant of the relationship between competition and concentration. Second, we report results for sub-samples that exclude: (i) Canada and Mexico; (ii) all countries for which the share of seaborne imports in total US manufacturing imports is below the 25th percentile of the distribution (i.e., all countries in the first bin of Figure 1); and (iii) all industries for which the share of seaborne imports in total US imports falls in the bottom quartile of the distribution. The results are similar to those obtained on the whole sample, suggesting that the pattern of correlations documented in this section is not driven by countries and industries for which seaborne trade is relatively unimportant. Finally, we show that the results are robust to excluding industries for which imports of parts and components account for at least 25% of total US imports, suggesting that trade in intermediates is not a key driver of the relationship between competition and concentration.

average the bulk weights across the two years for each product, and take the median of the resulting figures across all 6-digit HS codes belonging to a given 4-digit SIC industry. In column (7), the linear terms in bulk weight and distance are subsumed in the industry and country fixed effects, respectively.

[21] In the model, top firms have a lower pass-through of costs to prices. Hence, when facing higher trade costs, top sellers lower their markups relatively more, thereby gaining market shares compared to smaller firms from the same origin.

5 Conclusions

Much ink has been spilled on the recent increase in industrial concentration, raising concerns that the advent of giant companies may usher in an era of monopolies, growing profit shares and low economic dynamism. However, all existing evidence has been based on national data, which are not necessarily informative of the level of concentration in markets that are increasingly global. In this paper, we have documented for the first time what happened to concentration in the largest international market in the world, namely, the market of US imports. This has allowed us not only to complement national studies, but also to draw a comprehensive picture of how global firms from all countries compete in a single destination.

Our findings challenge the view that markets are becoming less competitive. The concentration of US imports has remained stable by country of origin while it has fallen significantly when pooling firms from all origins. To shed more light on this phenomenon, we have implemented a simple structural decomposition. One of the main factors behind falling concentration is the large increase in the number of firms and products exported to the US. Pushing in the opposite direction is the fact that sales per product by the top firms have increased relative to the average firm. Within firms, all exporters are dropping products, but top firms are doing it at a faster rate. We have also found evidence of national divergence versus global convergence among top firms.

These results seem consistent with the "superstar firm hypothesis", whereby increased concentration may be the result of markets being more competitive (Van Reenen, 2018, Amiti and Heise, 2019), and with the finding in Autor et al. (2020), according to which the industries that became more concentrated over our sample period were also those in which productivity increased the most.[22] Our results are also remarkably consistent with the reallocations predicted by leading models of international trade with heterogeneous multi-product firms (e.g., Melitz, 2003, Bernard, Redding and Schott, 2011). Hence, they suggest a possibly more benign view of concentration, at least for the manufacturing sector.

However, our results also show that firms are growing more and more unequal, a finding that resonates with recent evidence using very different data.[23] Some possible explanations for this widespread trend may include changes in innovation strategies (e.g., Bonfiglioli, Crinò and Gancia, 2018, 2019, Benhabib, Perla and Tonetti, 2017, König, Lorenz and Zilibotti, 2016, Dhingra, 2013), stronger sorting between firms, suppliers and workers (e.g., Bonfiglioli and Gancia, 2019, Song et al., 2019) or the uneven adoption of automation technologies (e.g., Acemoglu, Lelarge and Restrepo, 2020, Bonfiglioli et al. 2020 and Hubmer and Restrepo

[22] Covarrubias, Gutiérrez and Philippon (2019) call this "good concentration." They also show that import competition from China led to exit of US firms.

[23] See, for instance, Bonfiglioli, Crinò and Gancia (2018, 2019), Dunne et al. (2004), and Faggio, Salvanes and Van Reenen (2010).

(2021)). In turn, unequal growth at the firm level can potentially have adverse effects on labor market outcomes and the distribution of income. We therefore conclude that better understanding the causes and consequences of this process is an important question for future research.

Appendix A Additional Details about the Data

In this Appendix, we provide additional details about the data and compare a number of moments obtained from Piers with those based on aggregate trade data from various sources.

As mentioned in the main text, Piers contains the full name of each firm, thereby allowing us to precisely identify companies selling in the US by sea. A minority of firms (3% of the total) appear in Piers more than once with slightly different names, owing to minor record-keeping variations. We identify and consolidate these firms using a string matching algorithm. The latter computes the Levenshtein edit distance between all pairwise combinations of firm names sharing the same first character, normalizes the distance by the length of the longest string, and forms a match if the normalized edit distance is below a 5% threshold.

We perform a standard data cleaning to mitigate the risk of including transactions contaminated by reporting mistakes. In particular, we exclude firms with obvious inconsistencies in their names. We also exclude observations corresponding to firms with total exports to the US (across all products) below $1,000 in a given industry and year (4% of all firms), and to firms with extreme unit values for their products, defined as unit values falling above the top or below the bottom 0.01% of the distribution in a given year. Finally, we focus on country-industry-year triplets with at least two firm-products, as the dispersion terms of our structural decompositions are not defined for triplets with a single firm-product.

We now discuss how a number of moments obtained from Piers compare with those obtained from aggregate trade data. Regarding the number of firms exporting to the US, in Bonfiglioli, Crinò and Gancia (2020) we show that this number is particularly high for large Latin American countries, such as Brazil, and for European and South-East Asian countries, especially China. We also compare the number of foreign firms exporting to the US in our sample with the corresponding number reported in the World Bank Exporter Dynamics Database (EDD). The latter uses information on the universe of export transactions obtained from each country's government custom agency. We find that 34 out of the 48 countries covered by the EDD in 2012 were also part of our sample.[24] For the average or median country, the coverage rate of our sample equals 63% of the total number of exporting firms registered in the EDD. To benchmark this number, Kamal, Krizan and Monarch (2015) perform the same exercise for the restricted-access US Customs and Border Protection database, finding that it overshoots the number of foreign firms exporting to the US by 25% on average across countries.[25]

Finally, we have compared the unit values obtained from Piers with those for maritime

[24] Since our sample excludes firms selling less than $1,000 in the US, we have used the EDD statistics computed for firms with total exports above $1,000.

[25] Access to the US Customs and Border Protection is subject to strict requirements aimed at preserving confidentiality, which prevent us from using this database in our analysis.

trade based on official product-level data collected by the US Customs. A regression of the unit values in the Customs data on the unit values in Piers, run across origin countries and 6-digit products in 2002 and 2012, yields a coefficient of 0.836 (s.e. 0.003), with an R^2 of 0.58.

Appendix B Estimating The Elasticity of Substitution

In this Appendix, we provide details on the methods we use for estimating the elasticities of substitution employed in our decompositions. We first illustrate the Reverse-Weighting estimator developed by Redding and Weinstein (2016). Then, we move to the alternative approach that exploits differences in sales dispersion across industries. The presentation in this Appendix draws on Bonfiglioli, Crinò and Gancia (2020), from which the elasticities are sourced.

B.1 The Reverse-Weighting Estimator

Following Redding and Weinstein (2016), one can construct three equivalent expressions for the change in the price index of the basket of imported varieties in an industry between 2002 $(t-1)$ and 2012 (t). Using (2) and dropping the industry label to save on notation, these expressions read as follow:

$$\frac{P_t}{P_{t-1}} = \left(\frac{\lambda_{t,t-1}}{\lambda_{t-1,t}}\right)^{\frac{1}{\sigma-1}} \left\{ \sum_{\omega\in\Omega_{t,t-1}} s^*_{t-1}(\omega) \left[\frac{p_t(\omega)/\gamma_t(\omega)}{p_{t-1}(\omega)/\gamma_{t-1}(\omega)}\right]^{1-\sigma} \right\}^{\frac{1}{1-\sigma}}, \tag{A1}$$

$$\frac{P_t}{P_{t-1}} = \left(\frac{\lambda_{t,t-1}}{\lambda_{t-1,t}}\right)^{\frac{1}{\sigma-1}} \left\{ \sum_{\omega\in\Omega_{t,t-1}} s^*_{t}(\omega) \left[\frac{p_t(\omega)/\gamma_t(\omega)}{p_{t-1}(\omega)/\gamma_{t-1}(\omega)}\right]^{-(1-\sigma)} \right\}^{-\frac{1}{1-\sigma}}, \tag{A2}$$

$$\frac{P_t}{P_{t-1}} = \left(\frac{\lambda_{t,t-1}}{\lambda_{t-1,t}}\right)^{\frac{1}{\sigma-1}} \frac{\widetilde{P}^*_t}{\widetilde{P}^*_{t-1}} \left(\frac{\widetilde{S}^*_t}{\widetilde{S}^*_{t-1}}\right)^{\frac{1}{\sigma-1}}, \tag{A3}$$

where $\Omega_{t,t-1}$ denotes the set of varieties imported in both years (common varieties); $s^*(\omega)$ denotes the share of common variety ω in expenditure on all common varieties; $\widetilde{S}^*$ and $\widetilde{P}^*$ denote the geometric averages of $s^*(\omega)$ and $p(\omega)$, respectively, computed on common varieties; and $(\lambda_{t,t-1}/\lambda_{t-1,t})^{1/(\sigma-1)}$ is the variety-adjustment term, which adjusts the common varieties price index for entering and exiting varieties.

While the three ways of expressing the change in the price index are equivalent, the formulation in (A3) is the only one that exclusively depends on prices and expenditure shares, and not also on the demand shifter γ, i.e., this formulation is money-metric. Note also that the three expressions depend on the elasticity of substitution, σ. Hence, the idea behind the

RW estimator is to look for the value of σ that renders the three expressions for the change in the price index consistent with the same money-metric utility function.

Combining (A1)-(A3) and rearranging terms yields:

$$\Theta^{F}_{t-1,t}\left\{\sum_{\omega\in\Omega_{t,t-1}} s^{*}_{t-1}(\omega)\left[\frac{p_t(\omega)}{p_{t-1}(\omega)}\right]^{1-\sigma}\right\}^{\frac{1}{1-\sigma}} = \frac{\widetilde{P}^{*}_{t}}{\widetilde{P}^{*}_{t-1}}\left(\frac{\widetilde{S}^{*}_{t}}{\widetilde{S}^{*}_{t-1}}\right)^{\frac{1}{\sigma-1}}, \tag{A4}$$

$$\left(\Theta^{B}_{t,t-1}\right)^{-1}\left\{\sum_{\omega\in\Omega_{t,t-1}} s^{*}_{t}(\omega)\left[\frac{p_t(\omega)}{p_{t-1}(\omega)}\right]^{-(1-\sigma)}\right\}^{-\frac{1}{1-\sigma}} = \frac{\widetilde{P}^{*}_{t}}{\widetilde{P}^{*}_{t-1}}\left(\frac{\widetilde{S}^{*}_{t}}{\widetilde{S}^{*}_{t-1}}\right)^{\frac{1}{\sigma-1}}, \tag{A5}$$

where

$$\Theta^{F}_{t-1,t} \equiv \left\{\frac{\sum_{\omega\in\Omega_{t,t-1}} s^{*}_{t-1}(\omega)\left[\frac{p_t(\omega)}{p_{t-1}(\omega)}\right]^{1-\sigma}\left[\frac{\gamma_t(\omega)}{\gamma_{t-1}(\omega)}\right]^{\sigma-1}}{\sum_{\omega\in\Omega_{t,t-1}} s^{*}_{t-1}(\omega)\left[\frac{p_t(\omega)}{p_{t-1}(\omega)}\right]^{1-\sigma}}\right\}^{\frac{1}{1-\sigma}}, \tag{A6}$$

$$\Theta^{B}_{t,t-1} \equiv \left\{\frac{\sum_{\omega\in\Omega_{t,t-1}} s^{*}_{t}(\omega)\left[\frac{p_t(\omega)}{p_{t-1}(\omega)}\right]^{-(1-\sigma)}\left[\frac{\gamma_t(\omega)}{\gamma_{t-1}(\omega)}\right]^{-(\sigma-1)}}{\sum_{\omega\in\Omega_{t,t-1}} s^{*}_{t}(\omega)\left[\frac{p_t(\omega)}{p_{t-1}(\omega)}\right]^{-(1-\sigma)}}\right\}^{\frac{1}{1-\sigma}} \tag{A7}$$

are forward and backward aggregate demand shifters, respectively. These demand shifters summarize the impact of changes in the relative demand for individual varieties on the overall price index.

As shown by Redding and Weinstein (2016), identification of σ requires the following identifying assumption:

$$\Theta^{F}_{t-1,t} = \left(\Theta^{B}_{t,t-1}\right)^{-1} = 1. \tag{A8}$$

Consistent with the theoretical framework outlined in Section 3, (A8) implies that changes in relative demand cancel out across varieties, so that the aggregate demand shifters are both equal to 1. Using (A8) together with (A4) and (A5), one can construct a generalized method of moment estimator for σ. In particular, the following moment functions obtain:

$$M(\sigma) \equiv \begin{pmatrix} \frac{1}{1-\sigma}\ln\left\{\sum_{\omega\in\Omega_{t,t-1}} s^{*}_{t-1}(\omega)\left[\frac{p_t(\omega)}{p_{t-1}(\omega)}\right]^{1-\sigma}\right\} - \ln\left[\frac{\widetilde{P}^{*}_{t}}{\widetilde{P}^{*}_{t-1}}\left(\frac{\widetilde{S}^{*}_{t}}{\widetilde{S}^{*}_{t-1}}\right)^{\frac{1}{\sigma-1}}\right] \\ -\frac{1}{1-\sigma}\ln\left\{\sum_{\omega\in\Omega_{t,t-1}} s^{*}_{t}(\omega)\left[\frac{p_t(\omega)}{p_{t-1}(\omega)}\right]^{-(1-\sigma)}\right\} - \ln\left[\frac{\widetilde{P}^{*}_{t}}{\widetilde{P}^{*}_{t-1}}\left(\frac{\widetilde{S}^{*}_{t}}{\widetilde{S}^{*}_{t-1}}\right)^{\frac{1}{\sigma-1}}\right] \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}. \tag{A9}$$

The RW estimator $\hat{\sigma}$ solves:

$$\hat{\sigma} = \arg\min \left\{ M(\hat{\sigma})' \times \mathbb{I} \times M(\hat{\sigma}) \right\}, \tag{A10}$$

where $\mathbb{I}$ is the identity matrix. Weighting the two moment conditions by the identity matrix implies that the RW estimator minimizes the sum of squared deviations of the aggregate demand shifters from zero. Hence, the RW estimator selects the value of σ that minimizes the squared deviations of the forward and backward differences of the price index from a money-metric utility function.

B.2 Exploiting Variation in Sales Dispersion across Industries

As a robustness check on our main decompositions, in Tables 9 and 10, we use an alternative set of values of σ_i. To estimate them, we exploit the observed variation in sales dispersion across industries, building on the model's insight that a higher substitutability between varieties should generate more dispersion of sales for a given distribution of appeal.

To illustrate the approach, we start by using (3) to write:

$$\ln \mathbb{V}[\ln r_t(i,o)] = 2\ln(\sigma_i - 1) + \ln \mathbb{V}[\ln \tilde{\gamma}_t(i,o)], \tag{A11}$$

where $\mathbb{V}[\ln r_t(i,o)]$ and $\mathbb{V}[\ln \tilde{\gamma}_t(i,o)]$ denote the variance of log sales and log appeal, respectively, among varieties from country o in industry i and year t. This equation illustrates that a given dispersion of appeal, $\mathbb{V}[\ln \tilde{\gamma}_t(i,o)]$, translates into a larger dispersion of sales, $\mathbb{V}[\ln r_t(i,o)]$, in industries where varieties are more substitutable. If $\mathbb{V}[\ln \tilde{\gamma}_t(i,o)]$ was observed, one could estimate the structural parameter measuring the elasticity of substitution by first regressing $\ln \mathbb{V}[\ln r_t(i,o)]$ on $\ln \mathbb{V}[\ln \tilde{\gamma}_t(i,o)]$ and industry fixed effects, and then backing out the elasticities from the estimates of the fixed effects.

Unfortunately, $\mathbb{V}[\ln \tilde{\gamma}_t(i,o)]$ cannot be computed without an estimate of σ_i. Hence, we proxy for this term using observable variables that are known to be correlated with the dispersion of appeal. The first variable is the variance of log prices, $\mathbb{V}[\ln p_t(i,o)]$. While prices are just one component of $\tilde{\gamma}$, controlling for their variance would be sufficient to proxy for $\mathbb{V}[\ln \tilde{\gamma}_t(i,o)]$ if there was a one-to-one mapping between quality and prices, as in several models of endogenous quality. Indeed, an ample empirical evidence exists that prices are a good proxy for quality (see Hottman, Redding and Weinstein, 2016, Johnson, 2012). The second variable is the number of varieties from country o in industry i and year t, $N_t(i,o)$. Indeed, previous evidence shows that dispersion may systematically vary with the number of observations over which it is computed (Bonfiglioli, Crinò and Gancia, 2018, 2019). Finally, we control for country-time fixed effects, $\nu_t(o)$. The latter remove time-varying country characteristics that affect sales dispersion uniformly across industries, e.g., by systematically inducing some countries to specialize in high- or low-dispersion industries. Hence, we estimate the following specification:

$$\ln \mathbb{V}\left[\ln r_t\left(i,o\right)\right] = \alpha\left(i\right) + \nu_t\left(o\right) + \beta_1 \ln \mathbb{V}\left[\ln p_t\left(i,o\right)\right] + \beta_2 \ln N_t\left(i,o\right) + \varepsilon_t\left(i,o\right), \tag{A12}$$

where $\alpha\left(i\right)$ are industry fixed effects and $\varepsilon_t\left(i,o\right)$ is a error term. Using the estimates of $\alpha\left(i\right)$, we then solve for σ_i as $\sigma_i = \exp\left[\alpha\left(i\right)/2\right] + 1$ from (A11).

It is important to note that this approach does not identify the structural parameter measuring the elasticity of substitution, for two main reasons. First, the control variables included in (A12) are not perfect proxies for $\mathbb{V}\left[\ln \tilde{\gamma}_t\left(i,o\right)\right]$. Hence, part of the dispersion of appeal remains unobserved and ends up in the error term. If the unobserved component of $\mathbb{V}\left[\ln \tilde{\gamma}_t\left(i,o\right)\right]$ systematically varied across industries, the value of σ_i backed out from the industry fixed effects would not coincide with its structural counterpart. Second, even if the control variables were perfect proxies for $\mathbb{V}\left[\ln \tilde{\gamma}_t\left(i,o\right)\right]$, sales dispersion could depend on other industry characteristics that are not encompassed by our theoretical framework. In this case, the industry fixed effects would identify not just the elasticities of substitution but also these other industry-specific determinants of sales dispersion.

These are important caveats. Nevertheless, we believe it is useful to check how the results of our decompositions change when using this alternative approach. On the one hand, by absorbing the industry average, this approach allows us to isolate the cross-country variation in appeal; it is thus a way to study heterogeneity in appeal relative to other countries, rather than its absolute level. On the other hand, this alternative approach delivers estimates for all the 366 industries included in our sample, allowing us to check the results of our decompositions using the full sample size.

Appendix C Additional Robustness Checks

We report here additional robustness checks on the regression results discussed in Section 4. Table A1 shows results from specifications in which the dependent variable is the change in the share of sales by the top-4 firms in each country-industry pair. Table A2 contains results from the corresponding specifications using the change in the HHI as the dependent variable.

Table A1: Correlates of Concentration: Share of Sales by the Top-4 Firms - Alternative Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ ln no. of firms	-0.252***	-0.223***	-0.230***	-0.195***	-0.237***	-0.202***	-0.225***	-0.190***	-0.225***	-0.194***
	[0.011]	[0.010]	[0.007]	[0.006]	[0.007]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Δ ln average price per firm	-0.011	-0.012**	-0.009*	-0.011***	-0.012**	-0.013***	-0.008*	-0.008*	-0.009*	-0.012***
	[0.007]	[0.006]	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]
Initial ln share of sales by the top-4 firms	-0.364***	-0.518***	-0.331***	-0.490***	-0.323***	-0.487***	-0.343***	-0.486***	-0.322***	-0.480***
	[0.018]	[0.018]	[0.016]	[0.016]	[0.017]	[0.017]	[0.018]	[0.017]	[0.018]	[0.017]
Initial ln country share of US imports in the industry	-0.046***	-0.059***	-0.040***	-0.051***	-0.042***	-0.054***	-0.040***	-0.049***	-0.039***	-0.050***
	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Δ ln no. of firms from other countries	0.038***	0.082	0.024**	0.270***	0.026**	0.250***	0.015	0.240**	0.030***	0.353***
	[0.013]	[0.079]	[0.010]	[0.096]	[0.011]	[0.094]	[0.011]	[0.116]	[0.011]	[0.101]
Δ ln industry share of total US imports	0.040***		0.034***		0.034***		0.027***		0.027***	
	[0.007]		[0.006]		[0.006]		[0.007]		[0.006]	
Δ ln share of sales by top-4 firms in the industry	0.082***		0.065***		0.072***		0.059***		0.064***	
	[0.009]		[0.007]		[0.008]		[0.007]		[0.007]	
ln elasticity of substitution (RW)	0.050***		0.036***		0.037***		0.036***		0.026***	
	[0.008]		[0.006]		[0.006]		[0.007]		[0.006]	
Δ ln labor share in the industry	-0.030**		-0.034***		-0.030**		-0.045***		-0.053***	
	[0.015]		[0.011]		[0.012]		[0.012]		[0.012]	
ln routine intensity of the industry	0.042**		0.047***		0.050***		0.043**		0.038**	
	[0.021]		[0.016]		[0.017]		[0.017]		[0.017]	
ln industry bulk weight x ln country distance from the US		0.010*		0.012**		0.012**		0.016***		0.020***
		[0.006]		[0.005]		[0.006]		[0.005]		[0.005]
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	no	yes	no	yes	no	yes	no	yes	no	yes
Obs.	3956	5244	5137	6813	4642	6131	4457	5872	4274	5676
R2	0.42	0.50	0.42	0.49	0.43	0.50	0.43	0.49	0.42	0.49
Sample	Country-industry-years with 7+ firms		No Canada and Mexico		No countries with small shares of seaborne trade		No industries with small shares of seaborne trade		No industries with large shares of imported inputs	

Notes. All regressions are estimated across country-industry pairs. The dependent variable is the change in the logarithm of the share of sales by the top-4 firms in a country-industry pair between 2002 and 2012. The labor share is defined as the ratio between total wage bill and value added. Routine intensity is defined as the share of routine-intensive occupations in the total number of hours worked. The bulk weight of an industry is the median weight-to-value ratio of US seaborne imports across the 6-digit HS codes belonging to the industry; the bulk weight of a 6-digit HS code is averaged between the years 2002 and 2012. Columns (1) and (2) exclude country-industry pairs with less than seven firms in a given year. Columns (3) and (4) exclude Canada and Mexico. Columns (5) and (6) exclude countries for which the 2012 share of seaborne imports in total US manufacturing imports is below the 25th percentile of the distribution (i.e., the first group of countries in Figure 1). Columns (7) and (8) exclude industries for which the 2012 share of seaborne imports in total US imports is below the 25th percentile. Columns (9) and (10) exclude industries for which the average share of imports of parts and components in total US imports over 1972-2001 is above 25%. The standard errors, reported in square brackets, are robust to heteroskedasticity. ***, **, *: denote significance at the 1%, 5%, and 10% level, respectively.

Table A2: Correlates of Concentration: Herfindahl-Hirschman Index - Alternative Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ ln no. of firms	-0.525***	-0.468***	-0.498***	-0.450***	-0.507***	-0.460***	-0.496***	-0.443***	-0.493***	-0.453***
	[0.025]	[0.025]	[0.010]	[0.009]	[0.011]	[0.010]	[0.011]	[0.010]	[0.011]	[0.010]
Δ ln average price per firm	-0.037**	-0.040**	-0.028***	-0.026***	-0.031***	-0.028***	-0.027***	-0.021***	-0.025**	-0.024***
	[0.018]	[0.016]	[0.009]	[0.008]	[0.010]	[0.008]	[0.009]	[0.008]	[0.010]	[0.008]
Initial ln Herfindahl-Hirschman index	-0.505***	-0.632***	-0.436***	-0.583***	-0.431***	-0.581***	-0.440***	-0.576***	-0.434***	-0.573***
	[0.016]	[0.016]	[0.011]	[0.011]	[0.011]	[0.011]	[0.012]	[0.012]	[0.012]	[0.012]
Initial ln country share of US imports in the industry	-0.116***	-0.139***	-0.094***	-0.112***	-0.098***	-0.119***	-0.094***	-0.109***	-0.094***	-0.111***
	[0.007]	[0.007]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Δ ln no. of firms from other countries	0.088***	-0.019	0.040**	0.157	0.041**	0.138	0.032	0.080	0.061***	0.270*
	[0.032]	[0.153]	[0.019]	[0.144]	[0.021]	[0.141]	[0.022]	[0.178]	[0.021]	[0.153]
Δ ln industry share of total US imports	0.101***		0.081***		0.079***		0.067***		0.066***	
	[0.019]		[0.011]		[0.012]		[0.012]		[0.012]	
Δ ln Herfindahl-Hirschman index in the industry	0.110***		0.074***		0.080***		0.068***		0.071***	
	[0.012]		[0.007]		[0.008]		[0.008]		[0.008]	
ln elasticity of substitution (RW)	0.136***		0.104***		0.108***		0.097***		0.084***	
	[0.021]		[0.012]		[0.013]		[0.014]		[0.013]	
Δ ln labor share in the industry	-0.063*		-0.066***		-0.059**		-0.097***		-0.110***	
	[0.036]		[0.024]		[0.026]		[0.026]		[0.025]	
ln routine intensity of the industry	0.059		0.071**		0.088***		0.061*		0.046	
	[0.050]		[0.031]		[0.033]		[0.032]		[0.032]	
ln industry bulk weight x ln country distance from the US		0.032*		0.024**		0.026**		0.034***		0.038***
		[0.017]		[0.011]		[0.012]		[0.010]		[0.010]
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	no	yes	no	yes	no	yes	no	yes	no	yes
Obs.	3956	5244	7174	9511	6353	8403	6193	8122	6008	7976
R2	0.42	0.49	0.47	0.53	0.47	0.53	0.48	0.53	0.47	0.53
Sample	Country-industry-years with 7+ firms		No Canada and Mexico		No countries with small shares of seaborne trade		No industries with small shares of seaborne trade		No industries with large shares of imported inputs	

Notes. All regressions are estimated across country-industry pairs. The dependent variable is the change in the logarithm of the Herfindahl-Hirschman index in a country-industry pair between 2002 and 2012. The labor share is defined as the ratio between total wage bill and value added. Routine intensity is defined as the share of routine-intensive occupations in the total number of hours worked. The bulk weight of an industry is the median weight-to-value ratio of US seaborne imports across the 6-digit HS codes belonging to the industry; the bulk weight of a 6-digit HS code is averaged between the years 2002 and 2012. Clumns (1) and (2) exclude country-industry pairs with less than seven firms in a given year. Columns (3) and (4) exclude Canada and Mexico. Columns (5) and (6) exclude countries for which the 2012 share of seaborne imports in total US manufacturing imports is below the 25th percentile of the distribution (i.e., the first group of countries in Figure 1). Columns (7) and (8) exclude industries for which the 2012 share of seaborne imports in total US imports is below the 25th percentile. Columns (9) and (10) exclude industries for which the average share of imports of parts and components in total US imports over 1972-2001 is above 25%. The standard errors, reported in square brackets, are robust to heteroskedasticity. ***, **, *: denote significance at the 1%, 5%, and 10% level, respectively.

References

[1] Acemoglu, Daron, Claire Lelarge and Pascual Restrepo (2020). "Competing with Robots: Firm-Level Evidence from France," *American Economic Association, Papers and Proceedings*, 110, 383–388.

[2] Amiti, Mary and Sebastian Heise (2019). "U.S. Market Concentration and Globalization," *Mimeo.*

[3] Amiti, Mary, Oleg Itskhoki and Jozef Konings (2014). "Importers, Exporters, and Exchange Rate Disconnect," *American Economic Review* 104, 1942–1978.

[4] Amiti, Mary, Oleg Itskhoki and Jozef Konings (2019). "International Shocks, Variable Markups, and Domestic Prices," *Review of Economic Studies*, 86, 2356–2402.

[5] Anderson, Eric, Sergio Rebelo and Arlene Wong (2018). "Markups Across Space and Time," *NBER Working Paper No. 24434.*

[6] Antras, Pol (2003). "Firms, Contracts and Trade Structure," *Quarterly Journal of Economics*, 118, 1375–1418.

[7] Atkeson, Andrew and Ariel Burstein (2008). "Pricing to Market, Trade Costs, and International Relative Prices," *American Economic Review*, 98, 1998–2031.

[8] Autor, David and David Dorn (2013). "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market," *American Economic Review*, 103, 1553–1597.

[9] Autor, David, David Dorn, Lawrence Katz, Christina Patterson and John Van Reenen (2020). "The Fall of the Labor Share and the Rise of Superstar Firms," *Quarterly Journal of Economics*, 135, 645–709.

[10] Baqaee, David and Emmanuel Farhi (2020). "Productivity and Misallocation in General Equilibrium," *Quarterly Journal of Economics*, 135, 105–163.

[11] Barkai, Simcha (2020). "Declining Labor and Capital Shares," *Journal of Finance*, 75, 2421–2463.

[12] Benhabib, Jess, Jesse Perla and Christopher Tonetti (2017). "Reconciling Models of Diffusion and Innovation: A Theory of the Productivity Distribution and Technology Frontier," *NBER Working Paper No. 23095.*

[13] Bernard, Andrew, Bradford Jensen, Stephen Redding and Peter Schott (2010). "Intra-Firm Trade and Product Contractability," *American Economic Review, Papers and Proceedings*, 100, 444–448.

[14] Bernard, Andrew, Bradford Jensen, Stephen Redding and Peter Schott (2018). "Global Firms," *Journal of Economic Literature*, 56, 565–619.

[15] Bernard, Andrew, Stephen Redding and Peter Schott (2011). "Multiproduct Firms and Trade Liberalization," *Quarterly Journal of Economics*, 126, 1271–1318.

[16] Berry, Steven (1994). "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, 25, 242–262.

[17] Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger and Gino Gancia (2020). "Robot Imports and Firm-Level Outcomes," *CEPR Discussion Paper No. 14593.*

[18] Bonfiglioli, Alessandra, Rosario Crinò and Gino Gancia (2018). "Betting on Exports: Trade and Endogenous Heterogeneity," *Economic Journal*, 128, 612–651.

[19] Bonfiglioli, Alessandra, Rosario Crinò and Gino Gancia (2019). "Trade, Finance and Endogenous Heterogeneity," *Journal of the European Economic Association*, 17, 79–130.

[20] Bonfiglioli, Alessandra, Rosario Crinò and Gino Gancia (2020). "Firms and Economic Performance: A View from Trade," *CEPR Discussion Paper No. 12829.*

[21] Bonfiglioli, Alessandra and Gino Gancia (2019). "Heterogeneity, Selection and Labor Market Disparities," *Review of Economic Dynamics,* 31, 305–325.

[22] Calligaris, Sara, Chiara Criscuolo and Luca Marcolin (2018). "Mark-Ups in the Digital Era," *OECD Science, Technology and Industry Working Paper No. 2018/10.*

[23] Covarrubias, Matias, Germán Gutiérrez and Thomas Philippon (2019). "From Good to Bad Concentration? U.S. Industries over the Past 30 Years," *NBER Macroeconomics Annual*, 34, 1–46.

[24] De Loecker, Jan and Jan Eeckhout (2018). "Global Market Power," *NBER Working Paper No. 24768.*

[25] De Loecker, Jan, Jan Eeckhout and Gabriel Unger (2020). "The Rise of Market Power and the Macroeconomic Implications," *Quarterly Journal of Economics*, 135, 561–644.

[26] Dhingra, Swati (2013). "Trading Away Wide Brands for Cheap Brands," *American Economic Review*, 103, 2554–2584.

[27] Diez, Federico, Daniel Leigh and Suchanan Tambunlertchai (2018). "Global Market Power and its Macroeconomic Implications," *IMF Working Paper No. 18/137.*

[28] di Giovanni, Julian, Andrei Levchenko and Romain Ranciere (2011). "Power Laws in Firm Size and Openness to Trade: Measurement and Implications," *Journal of International Economics*, 85, 42–52.

[29] Dunne, Timothy, Lucia Foster, John Haltiwanger and Kenneth Troske (2004). "Wage and Productivity Dispersion in US Manufacturing: The Role of Computer Investments," *Journal of Labor Economics*, 22, 397–429.

[30] Edmond, Chris, Virgiliu Midrigan and Daniel Yi Xu (2018). "How Costly are Markups?" *NBER Working Paper No. 24800.*

[31] Epifani, Paolo and Gino Gancia (2011). "Trade, Markup Heterogeneity and Misallocations," *Journal of International Economics*, 83, 1–13.

[32] Faggio, Giulia, Kjell Salvanes and John Van Reenen (2010). "The Evolution of Inequality in Productivity and Wages: Panel Data Evidence," *Industrial and Corporate Change*, 19, 1919–1951.

[33] Feenstra, Robert and John Romalis (2014). "International Prices and Endogenous Quality," *Quarterly Journal of Economics*, 129, 477–527.

[34] Feenstra, Robert and David Weinstein (2017). "Globalization, Competition, and U.S. Welfare," *Journal of Political Economy*, 125, 1041–1074.

[35] Fernandes, Ana, Peter Klenow, Sergii Meleshchuk, Martha Denisse Pierola and Andres Rodriguez-Clare (2018). "The Intensive Margin in Trade," *NBER Working Paper No. 25195*.

[36] Freund, Caroline and Martha Denisse Pierola (2015). "Export Superstars," *Review of Economics and Statistics*, 97, 1023–1032.

[37] Freund, Caroline and Dario Sidhu (2017). "Global Competition and the Rise of China," *PIIE Working Paper No. 17-3*.

[38] Gaubert, Cecile and Oleg Itskhoki (2021). "Granular Comparative Advantage," *Journal of Political Economy*, forthcoming.

[39] Gutierrez, German and Thomas Philippon (2020). "How European Markets Became Free: A Study of Institutional Drift," *NBER Working Paper No. 24700*.

[40] Hall, Robert (2018). "New Evidence on the Markup of Prices Over Marginal Costs and the Role of Mega-Firms in the US Economy," *NBER Working Paper No. 24574*.

[41] Hottman, Colin, Stephen Redding and David Weinstein (2016). "Quantifying the Sources of Firm Heterogeneity," *Quarterly Journal of Economics*, 131, 1291–1364.

[42] Hsieh, Chang-Tai and Esteban Rossi-Hansberg (2019). "The Industrial Revolution in Services," *NBER Working Paper No. 25968*.

[43] Hubmer, Joachim and Pascual Restrepo (2021). "Not a Typical Firm: The Joint Dynamics of Firms, Labor Shares, and Capital-Labor Substitution," *mimeo Boston University*.

[44] Hummels, David and Peter Klenow (2005). "The Variety and Quality of a Nation's Exports," *American Economic Review*, 95, 704–723.

[45] Johnson, Robert (2012). "Trade and Prices with Heterogeneous Firms," *Journal of International Economics*, 86, 43–56.

[46] Kamal, Fariha, C.J. Krizan and Ryan Monarch (2015). "Identifying Foreign Suppliers in U.S. Merchandise Import Transactions," *Board of Governors of the Federal Reserve System - International Finance Discussion Paper No. 1142*.

[47] Karabarbounis, Loukas and Brent Neiman (2018). "Accounting for Factorless Income," *NBER Macroeconomics Annual*, 33, 167–228.

[48] Khandelwal, Amit (2010). "The Long and Short (of) Quality Ladders," *Review of Economic Studies*, 77, 1450–1476.

[49] König, Michael, Jan Lorenz and Fabrizio Zilibotti (2016). "Innovation vs. Imitation and the Evolution of Productivity Distributions," *Theoretical Economics*, 11, 1053–1102.

[50] Melitz, Marc (2003). "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71, 1695–1725.

[51] Melitz, Marc, Thierry Mayer and Gianmarco Ottaviano (2014). "Market Size, Competition, and the Product Mix of Exporters," *American Economic Review*, 104, 495–536.

[52] Melitz, Marc and Stephen Redding (2014). "Heterogeneous Firms and Trade," in *Handbook of International Economics* (Gopinath, Helpman and Rogoff, eds.), Volume 4, 1–54, Elsevier.

[53] Philippon, Thomas (2019). *The Great Reversal: How America Gave Up on Free Markets*, Cambridge MA: Harvard University Press.

[54] Pierce, Justin and Peter Schott (2012). "Concording US Harmonized System Categories Over Time," *Journal of Official Statistics*, 28, 53–68.

[55] Redding, Stephen and David Weinstein (2016). "A Unified Approach to Aggregate Price and Welfare Measurement," *NBER Working Paper No. 22479.*

[56] Redding, Stephen and David Weinstein (2017). "Accounting for Trade Patterns," *CEPR Discussion Paper No. 13459.*

[57] Redding, Stephen and David Weinstein (2020). "Measuring Aggregate Price Indexes with Taste Shocks: Theory and Evidence for CES Preferences," *Quarterly Journal of Economics*, 135, 503–560.

[58] Rossi-Hansberg, Esteban, Pierre-Daniel Sarte and Nicholas Trachter (2018). "Diverging Trends in National and Local Concentration," *CEPR Discussion Paper No. 13174.*

[59] Schott, Peter (2004). "Across-Product versus Within-Product Specialization in International Trade," *Quarterly Journal of Economics,* 119, 647–678.

[60] Schott, Peter (2008). "The Relative Sophistication of Chinese Exports," *Economic Policy*, 23, 6–49.

[61] Song, Jae, David Price, Fatih Guvenen, Nicholas Bloom and Till von Wachter (2019). "Firming Up Inequality," *Quarterly Journal of Economics*, 134, 1–50.

[62] UNCTAD (2018). *Review of Maritime Transport*, New York: United Nations Publications.

[63] Van Reenen, John (2018). "Increasing Differences between Firms: Market Power and the Macro-Economy," *CEP Discussion Paper No. 1576.*