Product Mix and Firm Productivity Responses to Trade Competition*

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Abstract

We document how demand shocks in export markets lead French multi-product exporters to re-allocate the mix of products sold in those destinations. In response to positive demand shocks, those French firms skew their export sales towards their best-performing products; and also extend the range of products sold to that market. We develop a theoretical model of multi-product firms and derive the specific demand conditions needed to generate these product-mix reallocations. These demand conditions are associated with endogenous price elasticities that satisfy Marshall's Second Law of Demand (the price elasticity of demand decreases with consumption). Under these demand conditions, our theoretical model highlights how the increased competition from demand shocks in export markets – and the induced product mix reallocations – induce productivity changes within the firm. We then empirically test for this connection between the demand shocks and the productivity of multi-product firms exporting to those destinations. We find that the effect of those demand shocks on productivity is substantial – and explain an important share of aggregate productivity fluctuations for French manufacturing.

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1 Introduction

Ever since Krugman (1980), the C.E.S./monopolistic competition model has been the workhorse model of new trade theory. It combines intra-industry trade, imperfect competition, and returns-to-scale in a general equilibrium setting; and it has been extended in myriads of directions (with much of this research still ongoing). However, this very tractable analytical framework has a major drawback: it cannot be used to investigate "competitive" effects of trade. Price elasticities for all goods are constant, and there can be no markup responses to the trading environment.

In order to analyze competitive effects (response of markups to trade, market size, and geography), trade theory in parallel has developed models with endogenous price elasticities. Maintaining monopolistic competition in general equilibrium, an early approach followed by Dixit and Stiglitz (1977, section II: "Variable Elasticity Case") and Krugman (1979) has been to consider preferences featuring Marshall's Second Law of Demand (MSLD) – according to which the price elasticity of demand falls with quantity consumed.[1] These models then predict pro-competitive effects of trade: Falling markups in response to trade integration, as highlighted by Krugman (1979).[2] The welfare gains from these pro-competitive effects are further amplified when firms are heterogeneous. Dhingra and Morrow (2019) show that the pro-competitive reallocations generate an additional channel that magnify the welfare gains from any given trade liberalization.[3]

These models have also played a crucial role in explaining aggregate empirical patterns that are incompatible with the workhorse C.E.S./monopolistic competition model: Incomplete pass-through of cost shocks to prices and pricing to market (most prominently for the adjustment to exchange rate shocks; see Burstein and Gopinath, 2014, for a recent survey); Increasing trade elasticities with lower trade volumes;[4] And tougher selection (and higher firm turnover rates) in larger markets.[5] At

[1]Marshall (1936, Book 3, Chapter 4, Section 2) argues that this is normal behavior of demand: "The elasticity of demand is great for high prices, and great, or at least considerable, for medium prices; but it declines as the price falls; and gradually fades away if the fall goes so far that satiety level is reached. This rule appears to hold with regard to nearly all commodities and with regard to the demand of every class;[...]". We thank Peter Neary for bringing this terminology to our attention.

[2]Pro-competitive effects of trade have also been extensively studied using oligopoly models. These models also feature endogenous price elasticities, and further share many similar equilibrium properties with monopolistic competition/MSLD models.

[3]The contribution of these reallocations to welfare are first-order whereas they are second-order in the C.E.S. case (because the market equilibrium is then efficient). Arkolakis et al. (2018) also analyze the gains from trade in models with endogenous markups. They focus on the measurement of those gains as a function of the trade volume generated by a given trade liberalization.

[4]See Novy (2013) and Arkolakis et al. (2018). Novy (2013) uses translog preferences, which satisfy MSLD; Arkolakis et al. (2018) use a general family of preferences with endogenous price elasticities and estimate coefficients that validate MSLD.

[5]See Syverson (2004), Campbell and Hopenhayn (2005), and Asplund and Nocke (2006). MSLD is sufficient for the induced maximized profit function to exhibit all the properties postulated by Asplund and Nocke (2006) in order to

the microeconomic level, there is a long literature documenting a strong positive correlation between firm/plant/product performance and markups; and how those markups and associated pass-through rates respond to trade shocks.[6] In our theory section, we describe how all these empirical patterns are intrinsically linked to MSLD and thus cannot be reconciled with C.E.S./monopolistic competition.

The first contribution of our paper is to derive new testable implications of MSLD using sales data at the finest level of disaggregation (by market, firm, and product). In contrast, the other microeconomic ways of testing for MSLD entail substantially more onerous data requirements. Data on firm-product prices or quantities (which are typically very noisy) are needed in order to estimate the shape of demand directly. And the recovery/estimation of marginal cost shocks to measure markups entails additional functional form assumptions for demand and/or production.[7] In this paper we develop and implement a new complementary methodology for testing MSLD based on trade-induced reallocations across products (measured in terms of changes in revenue shares) and their impact on firm productivity. In so doing, we introduce a flexible theoretical framework with general additive separable preferences and multi-product firms to highlight how certain properties of demand – which relate to the curvature of demand and marginal revenue curves underpinning MSLD – are crucial in generating predictions for reallocations that are consistent with the data. Empirically, we show that the reallocations induced by destination-level trade shocks are quantitatively important at the level of the firm (aggregating across destinations). Thus they have the potential to influence firm-level productivity (as confirmed by our theoretical model). Our second contribution is to document a very large impact of those trade shocks on multi-product firm productivity.

The emphasis on multi-product firms is crucial. Measuring the direct impact of trade on reallocations across firms is a very hard task. On the one hand, shocks that affect trade are also likely to affect the distribution of market shares across firms. On the other hand, changes in market shares across firms likely reflect many technological factors (not related to reallocations). Looking at reallocations across products within firms obviates many of these problems. Recent theoretical models of multi-product firms highlight how trade induces a similar pattern of reallocations within

explain the empirical relationship between market size and firm turnover that they document (in a dynamic setting).

[6] See De Loecker et al. (2016) and Dhyne et al. (2017) for recent evidence on the strong positive correlation between product-level markups and performance (within firms); there is also a long literature estimating this correlation at the firm-level. Berman, Martin and Mayer (2012), Li, Ma and Xu (2015), Amiti, Itskoki, and Konings (2014), and Chatterjee, Dix-Carneiro, and Vichyanond (2013) all find evidence of incomplete pass-through at the producer level.

[7] See DeLoecker and Goldberg (2014) for a survey of this literature and a discussion of these data and functional form requirements. One significant exception is the work by Atkin et al. (2015) who directly obtain markup information via a firm survey. They also find a very strong positive correlation between firm size and markups.

firms as it does across firms (see the recent survey by Bernard et al, 2018b). Our theoretical model fits within this literature. In order to focus on the impact of competition on within-firm product reallocations and productivity, we abstract from economies of scope (across products) and cannibalization effects (see Bernard et al, 2011, Dhingra, 2013, Eckel and Neary, 2010, Nocke and Yeaple, 2014). In our empirical work, we directly check that such firm-wide interactions do not affect our main results on product reallocations.

On the empirical side, measuring reallocations within multi-product firms has several advantages: Trade shocks that are exogenous to individual firms can be identified much more easily than at a higher level of aggregation; Controls for any technology changes at the firm-level are also possible; and reallocations can be measured for the same set of narrowly defined products sold by the same firm across destinations or over time. In addition, impediments to factor reallocations are likely to be substantially higher across firms than across product lines within firms. Moreover, multi-product firms dominate world production and trade flows.

For all these reasons, reallocations within multi-product firms have the potential to generate large changes in aggregate productivity. We find very strong empirical confirmation for this link between trade shocks in export markets (which induce the reallocations) and productivity for multi-product French exporters. Although we measure firm productivity using deflated sales (value-added), we recover the changes in *real* productivity at the industry and aggregate level using the observed changes in firm-level employment. We show counter-factual predictions for the impact of the trade shocks on real output per worker at the industry-level. This impact is very large: between 1995-2005, the trade shocks account for a 1 percent yearly average increase in French manufacturing productivity.

Our paper is also related to the empirical literature on trade-induced reallocations. In a previous paper, Mayer, Melitz and Ottaviano (2014), we investigated the mechanics of product reallocations within multi-product firms across export destination markets. We used the term 'skewness' to refer to the concentration of the export market shares of different products in any destination and showed that this skewness consistently varied with destination characteristics such as GDP and geography: French firms sold relatively more of their best performing products in bigger, more centrally-located destinations (where competition from other exporters and domestic producers is tougher). Baldwin and Gu (2009), Bernard, Redding and Schott (2011), and Iacovone and Javorcik (2010) analyze similar reallocations over time for Canada, Mexico, and the United States following CUSFTA/NAFTA liberalization. They find that multi-product firms in all three countries reduced the number of products they produce following liberalization. Baldwin and Gu (2009) and Bernard, Redding and Schott (2011) further report that CUSFTA induced a significant increase in the skewness of production across products. Iacovone and Javorcik (2010) separately measure the skewness of Mexican firms' export sales to the United States. They report an increase in this skewness following NAFTA: They show that Mexican firms expanded their exports of their better performing products (higher market shares) significantly more than those for their worse performing exported products during the period of trade expansion from $1994-2003$. Relative to these papers (including our previous one), a significant innovation in our current paper is to directly connect the evidence on trade-induced reallocations to the empirical validity of MSLD and to measure the impact of those reallocations on firm-level productivity.

These findings have important consequences for the nascent literature analyzing the increasing concentration of market share amongst industry-leading firms (see Autor et al. 2020 for a recent example). Our model explains how rising concentration may not stem from changes in competition regimes (linked to anti-trust policies) but can alternatively come from demand-side growth, including access to new or growing export markets.

The rest of the paper is organized as follows. Section 2 introduces our dataset on French exporters and provides novel evidence on reallocations over time with a special emphasis on the skewness effect. It shows that positive demand shocks in any given destination market induce French exporters to skew their product level export sales to that destination towards their best performing products. These demand shocks also lead to strong positive responses in both the intensive and extensive margins of export sales to that destination. Section 3 introduces our flexible theoretical framework with multi-product firms and shows how MSLD can rationalize this empirical evidence (along with the prior evidence we just described). It also shows how MSLD implies that positive demand shocks engender increases in multi-product firm productivity as firms reallocate market and labor shares toward better performing products. Sections 4 and 5 take these predictions to the data and measure large responses in multi-product firm productivity to demand shocks in export markets.

2 Reallocations Over Time

We now document how changes *within* a destination market over time induce a similar pattern of reallocations as the ones we previously described (holding across destinations). More specifically, we show that demand shocks in any given destination market induce firms to skew their product level export sales to that destination towards their best performing products. In terms of first moments, we show that these demand shocks also lead to strong positive responses in both the intensive and extensive margins of export sales to that destination.

2.1 Data

We measure firm-product-destination export sales using French customs data spanning the period 1995-2005. All firms operating in the French metropolitan territory must report their export sales according to the following criteria: Exports to each EU destination whenever within-EU exports exceeds 100,000 Euros;[8] and exports to non-EU country whenever exports to that destination exceeds 1,000 Euros or a ton. Despite these limitations, the database is nearly comprehensive. For instance, in 2005, 103,220 firms report exports across 234 destination countries (or territories) for 9873 products. This represents data on over 2.2 million shipments.

We restrict our analysis to firms whose main activity is classified as manufacturing to ensure that firms take part in the production of the goods they export.[9] This leaves us with data covering more than a million shipments by firms across all manufacturing sectors.[10]

Matched balance-sheet data provide us with information on variables that are needed to assess firm productivity such as turnover, value added, employment, investment, raw material use and capital. However, we can only measure product reallocations in terms of sales in export markets as the breakdown of sales across products for the domestic market is not available to us. We will have to take this into account in designing our estimation strategy. The balance-sheet data we have access to comes in two sources where the official identification number of the firm can be matched with customs information. The first source is the EAE, produced by the national statistical institute, and exhaustive for manufacturing firms with size exceeding 20 employees. The second is BRN, which comes from tax authorities, and includes a broader coverage of firms, since it is based on the firm's legal tax regime and a relatively low sales threshold. Whenever firm data is available from both

[8]If this threshold is not met, firms can choose to report under a simplified scheme without supplying separate EU export destinations. However, in practice, many firms under the threshold report their exports by destination. During our sample period, the threshold increased from 38,050 Euros (250,000 French Francs) to 100,000 Euros in 2001. We have checked that all our results are robust to using only the 1996-2001 subsample (a sample period that also features a more stable product classification schedule; See Pierce and Schott, 2012).

[9]Some large distributors such as Carrefour account for a disproportionate number of annual export shipments. The online appendix to this paper replicates our main empirical results for the set of firms with wholesale or retail trade as their main activity (except the ones on productivity, which is notoriously more difficult to measure for those firms). Results are very comparable to the ones regarding manufacturing.

[10]In a robustness check, we also drop observations for firms that report an affiliate abroad. This avoids the issue that multinational firms may substitute exports of some of their best performing products with affiliate production in the destination country (affecting our measurement of product reallocations). Results are quantitatively very similar in all regressions.

sources, we give precedence to the EAE data (which is more closely monitored by the statistical authorities).[11] Table 1 provides some descriptive statistics relevant to the match between customs and balance sheet data. The overall match is not perfect but covers between 88 and 95 percent of the total value of French exports. The match with firms declaring manufacturing as their main activity is still very good although there is a clear trend of declining quality of match, particularly after 2000. This is also visible in the aggregate growth rate of exports in our sample (column 5) that overall provide a quite good match of the overall exports growth rate in column (4), but deteriorating over time. Our investigations suggest that the increasing propensity of large French manufacturers to declare their main activity as retail or some other service activity might provide part of that explanation.[12] Overall our matched dataset is very comparable to recent papers using the same primary sources as in by Eaton et al. (2011), Berman et al. (2012) or di Giovanni et al. (2014) for instance.

Table 1: Aggregate Exports, Production, Employment, and Productivity

	Exports								
	Value	Share		Growth Rate		VA	Emp.	VA/Emp.	
Year	B Eur	Match	Mfg	Full	Mfg	B Eur	M work.	K Eur	Growth
1995	211.3	94.9	74.0			177.1	2.903	61.0	
1996	219.6	93.5	73.2	3.9	2.8	178.6	2.918	61.2	0.3
1997	252.7	92.8	72.6	15.1	14.2	188.0	2.899	64.8	6.0
1998	267.1	92.0	72.1	5.7	4.9	193.3	2.914	66.3	2.3
1999	277.5	91.1	71.7	3.9	3.3	198.9	2.870	69.3	4.5
2000	319.4	90.8	71.9	15.1	15.4	209.5	2.924	71.6	3.4
2001	324.6	89.9	69.0	1.6	-2.3	199.4	2.932	68.0	-5.1
2002	321.7	90.4	68.4	-0.9	-1.8	198.0	2.865	69.1	1.7
2003	314.3	90.4	65.3	-2.3	-6.7	187.3	2.633	71.1	2.9
2004	335.0	88.4	64.6	6.6	5.4	193.2	2.577	75.0	5.4
2005	350.8	88.0	62.9	4.7	1.9	194.9	2.505	77.8	3.8

Column (1): Total value of exports from customs data. Column (2): Export share of firms matched with balance-sheet data from BRN/EAE. Column (3): Export share of matched firms with main activity classified as manufacturing. Columns (4) and (5): Export growth rates for customs data and subset of manufacturing firms. Columns (6) to (8): Aggregate value added, employment, and their ratio for the subset of manufacturing firms. Column (9): Growth rate of labor productivity from previous column.

[11]The correlations between variables reported both in EAE and BRN (value added, employment, exports, capital stock) are very high: between .91 and .99 in all cases.

[12]This is another reason why we check all our results against the early 1996-2001 sub-sample.

2.2 Measuring Export Demand Shocks

Consider a firm i exporting a number of products s in industry I to destination d in year t. We measure industries (I) at the 3-digit ISIC level (35 different classifications across French manufacturing). We consider several measures of demand shocks that affect this export flow. At the most aggregate level we use the variation in GDP in d, $\log \mathrm{GDP}_{d,t}$. At the industry level I, we use total imports into d *excluding* French exports, $\log M_{d,t}^{I}$. We can also use our detailed product-level shipment data to construct a firm i-specific demand shock:

$$\text{log trade shock}_{i,d,t}^{I} \equiv \overline{\log M_{d,t}^{s}} \quad \text{for all products } s \in I \text{ exported by firm } i \text{ to } d \text{ in year } t_0, \tag{1}$$

where $M_{d,t}^{s}$ represents total imports into d (again, excluding French exports) for product s and the overline represents the (unweighted) mean. For world trade, the finest level of product level of aggregation is the HS-6 level (from UN-COMTRADE and CEPII-BACI)[13], which is more aggregated than our NC8 classification for French exports (roughly 5,300 HS products per year versus 10,000 NC8 products per year). The construction of the last trade shock is very similar to the one for the industry level imports $\log M_{d,t}^{I}$, except that we only use imports into d for the precise product categories that firm i exports to d.[14] In order to ensure that this demand shock is exogenous to the firm, we use the set of products exported by the firm in its first export year in our sample (1995, or later if the firm starts exporting later on in our sample), and then exclude this year from our subsequent analysis. Note that we use an un-weighted average so that the shocks for all exported products s (within an industry I) are represented proportionately.[15]

For all of these demand shocks $X_t = \mathrm{GDP}_{d,t}, M_{d,t}^{I},\ M_{d,t}^{s}$, we compute the first difference as the Davis-Haltiwanger growth rate: $\tilde{\Delta} X_t \equiv (X_t - X_{t-1}) / (.5X_t + .5X_{t-1})$. This measure of the first difference preserves observations when the shock switches from 0 to a positive number, and ranges between -2 and 2. This is mostly relevant for our measure of the firm-specific trade shock, where the product-level imports into d, $M_{d,t}^{s}$ can often switch between 0 and positive values. Whenever $X_{t-1}, X_t > 0$, $\tilde{\Delta} X_t$ is monotonic in $\Delta \log X_t$ and approximately linear for typical growth

[13] See Gaulier and Zignago (2010).

[14] There is a one-to-many matching between the NC8 and HS6 product classifications, so every NC8 product is assigned a unique HS6 classification. We use the same $M_{d,t}^{s}$ data for any NC8 product s within the same HS6 classification.

[15] Thus, positive idiosyncratic demand shocks to high market-share products (which mechanically contribute to increase the skewness of product sales) are given the same weight as positive idiosyncratic shocks to low market-share products (which mechanically contribute to decrease the skewness of product sales); and vice-versa for negative shocks.

rates ($|\Delta \log X_t| < 2$).[16] We thus obtain our three measures of demand shocks in first differences: $\tilde{\Delta}\text{GDP}_{d,t}, \tilde{\Delta}M^I_{d,t}$, $\overline{\tilde{\Delta}M^s_{d,t}}$. From here on out, we refer to these three shocks, respectively, as GDP shock, trade shock – ISIC, and trade shock. Note that this last firm-level shock, $\overline{\tilde{\Delta}M^s_{d,t}}$, represents the un-weighted average of the growth rates for all products exported by the firm in $t-1$.

2.3 The Impact of Demand Shocks on Trade Margins and Skewness

Before focusing on the effects of the demand shocks on the skewness of export sales, we first show how the demand shocks affect firm export sales at the intensive and extensive margins (the first moments of the distribution of product export sales). Table 2 reports how our three demand shocks (in first differences) affect changes in firm exports to destination d in ISIC I (so each observation represents a firm-destination-ISIC combination). We decompose the firm's export response to each shock into an intensive margin (average exports per product) and an extensive margin (number of exported products). We clearly see how all three demand shocks induce very strong (and highly significant) positive responses for both margins. This confirms that our demand shocks capture important changes in the local demand faced by French exporters.[17]

Table 2: Demand Shocks and Local Exports

Dependent Variable	$\Delta \log$ Exports per Product			$\Delta \log$ # Products Exported		
$\tilde{\Delta}$ GDP Shock	0.493^a			0.149^a		
	(0.048)			(0.016)		
$\tilde{\Delta}$ trade shock		0.277^a			0.076^a	
		(0.009)			(0.004)	
$\tilde{\Delta}$ trade shock - ISIC			0.039^a			0.014^a
			(0.005)			(0.002)
Observations	401575	407520	407520	401575	407520	407520

Standard errors in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$. All regressions include year dummies, and standard errors clustered at the level relevant for the variable of interest: destination country for columns (1) and (4), firm-destination for columns (2) and (5) and ISIC-destination for columns (3) and (6).

We now investigate the consequences of those demand shocks for the skewness of export sales

[16]Switching to first difference growth rates measured as $\Delta \log X_t$ (and dropping products with zero trade in the trade shock average) does not materially affect any of our results.

[17]Specifications using the log levels of the shocks and firm-destination-ISIC fixed-effects yield similar results. Other specifications including the three covariates show that those demand shocks are different enough to be estimated jointly while each keeping its positive sign and statistical significance. We also have experimented with the addition of a control for a worldwide shock (aggregated from the destination-specific shocks using the firm's prior year export shares). This captures firm-wide scale effects that are not specific to any particular destination. The effect of this additional control on the destination-specific coefficient is negligible, thus confirming that worldwide shocks do not influence the coefficients presented in Table 2.

(independent of the level of product sales). In Mayer, Melitz and Ottaviano (2014), we focused on those effects in the cross-section across destinations. Here, we examine the response of skewness within a destination over time using our new demand shocks. In order to avoid capturing effects driven by income shocks which could affect the demand for quality, we focus on the trade shocks and add income per capita as a control. We rely on the Theil index as our measure of skewness due to its aggregation properties:[18] We will later aggregate the export responses at the destination-ISIC level up to the firm-level – in order to generate predictions for firm-level productivity. Thus, our measure of skewness for the distribution of firm i's exports to destination d in industry I, $x^s_{i,d,t}$, is the Theil index (computed over all N^I_{idt} products s that firm i exports to d in year t):

$$T^I_{i,d,t} \equiv \frac{1}{N^I_{idt}} \sum_{s \in I} \frac{x^s_{i,d,t}}{\bar{x}^I_{idt}} \log\left(\frac{x^s_{i,d,t}}{\bar{x}^I_{idt}}\right), \quad \bar{x}^I_{idt} \equiv \frac{\sum_{s\in I} x^s_{idt}}{N^I_{idt}}. \tag{2}$$

Table 3 reports regressions of this skewness measure on both export demand shocks at the firm-destination-ISIC level. In the first two columns, we use a specification in (log) levels (FE), and use firm-destination-ISIC fixed effects to isolate the variation over time. In the next two columns, we return to our specification in first differences (FD). In the last two columns we add the firm-destination-ISIC fixed effects to this specification in first differences (FD-FE). This controls for any trend growth rate in our demand shocks over time. All specifications include a control for income per capita (not reported). Across all three specifications, we see that positive export demand shocks induce a highly significant increase in the skewness of firm export sales to a destination.[19]

Table 3 focuses on the contemporaneous response of skewness to the demand shocks. In Figure 1, we show the dynamic response of skewness by including two years of leads and lags for the demand shocks. The figure shows the regression coefficients for each lead and lag along with its 95% confidence interval. This regression framework requires us to drop the first and last two years in our sample in order to measure the response of skewness 2 years before and after the demand shock. This is why our contemporaneous coefficients (along the vertical dotted line) are different

[18] As we do throughout the paper, we use skewness as an index of inequality for the distribution of product sales. This is distinct from the statistical definition of skewness as a measure of asymmetry. Hence, all of our empirical measures for skewness will be based on entropy indices (such as the Theil and Atkinson inequality measures).

[19] Just as we did for the impact of the destination-specific trade shocks on the first moment of exports (extensive and intensive margins), we experimented with the addition of controls for firm-wide global shocks. One control for global scale effects is the same worldwide trade shock that we used as a control in Table 2. Another control for firm-wide product interactions (such as complementarities in production) is a measure of skewness based on global (to the world) exports, based again on the Theil index (this global index is described in greater detail section 5). The effects of these additional global controls on the destination-specific coefficients are negligible, thus confirming that worldwide shocks – including production complementarities – do not influence the coefficients presented in Table 3.

Table 3: Demand shocks and local skewness

Dependent Variable	$T^I_{i,d,t}$	$T^I_{i,d,t}$	$\Delta T^I_{i,d,t}$			
Specification	FE	FE	FD	FD	FD-FE	FD-FE
log trade shock	0.048^a					
	(0.003)					
log trade shock - ISIC		0.001^a				
		(0.000)				
$\tilde{\Delta}$ trade shock			0.038^a		0.034^a	
			(0.004)		(0.005)	
$\tilde{\Delta}$ trade shock - ISIC				0.007^a		0.006^a
				(0.002)		(0.002)
Observations	450620	450620	401541	401541	375033	375033

Standard errors in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$. FE refers to firm-destination-ISIC fixed effects. All regressions include year dummies, with standard errors clustered at the level relevant for the variable of interest: Firm-destination for trade shock and ISIC-destination for trade shock - ISIC. All regressions include a control for income per capita shocks in the destination country.

than those reported in Table 3.[20] Figure 1 shows that there are no significant pre-trends associated with the response of skewness to the demand shock. The bulk of the response is contemporaneous, and remains significant for only a single year following the shock.

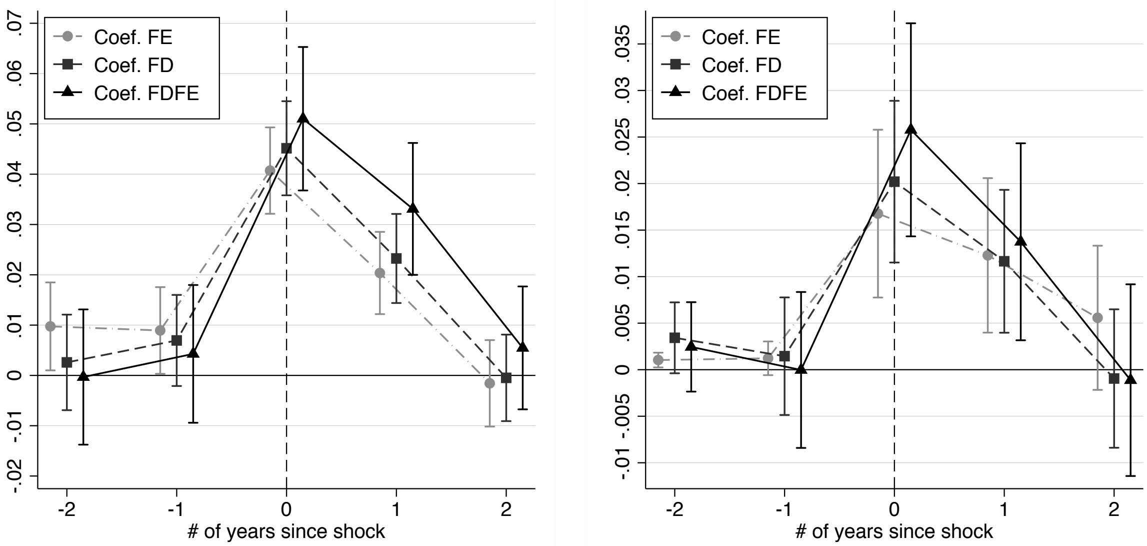
We now return to the contemporaneous response of skewness and investigate its robustness to alternate measurement methods. The first column of Table 4 replicates the FD-FE specifications from 3 using our Theil measure for skewness. This is our most demanding specification. Each entry in Table 4 represents a separate regression with the same additional controls that we previously described. The next three columns of Table 4 explore alternative measures of skewness using the Atkinson index. This index was developed to allow for greater flexibility in quantifying the contribution of different parts of the distribution to overall inequality. It is defined as:

$$A^{I,\eta}_{i,d,t} \equiv \begin{cases} 1 - \frac{1}{\bar{x}^I_{idt}} \left[\frac{1}{N^I_{idt}} \sum_{s \in I} (x^s_{idt})^{1-\eta} \right]^{\frac{1}{1-\eta}}, \quad \bar{x}^I_{idt} \equiv \frac{\sum_{s \in I} x^s_{idt}}{N^I_{idt}}, & \text{for } 0 \leq \eta \neq 1 \\ 1 - \frac{1}{\bar{x}^I_{idt}} \left[\prod_{s \in I} x^s_{idt} \right]^{\frac{1}{N^I_{idt}}}, & \text{for } \eta = 1 \end{cases} \tag{3}$$

The parameter η is often called the inequality aversion parameter as higher values put more weight on the low end of the distribution. When η gets close to 0, more weight is given to high values, in our case to the firm's best performing products. As η increases, more weight is given to the distribution of the firm's worse performing products relative to the best performing ones. This

[20] The differences are most notable for the ISIC trade shock: the coefficients are substantially larger once we drop those first and last 2 years from our sample.

Figure 1: Demand shocks and local skewness - leads and lags



(a) trade shock

(b) trade shock - ISIC

Atkinson index is also equal to one minus the ratio of the generalized (C.E.S.) mean over the arithmetic mean. Different values of η provide different special cases of the generalized mean: with $\eta = 2$, it is the harmonic mean, whereas with $\eta = 1$ it is the geometric mean. In the limit, when $\eta = 0$, it is the arithmetic mean, in which case there can never be any inequality ($A^{I,\eta}_{i,d,t} \equiv 0$ for any distribution of product sales x^s_{idt}). Table 4 reproduces our skewness results for a wide range of inequality parameters η, starting with a low value of $\eta = .5$ along with the special cases of $\eta = 1$ and $\eta = 2$.[21] Those results, reported in columns (2-4), clearly show that the effect of the demand shocks on skewness do not rely on the Theil functional form nor on a specific weighing scheme for the Atkinson index.

All the skewness measures so far in Table 4 combine changes to both the intensive product mix margin (the relative sales of different products exported in both $t-1$ and t), and the extensive margin (products sold in one period but not the other). In the next set of columns, we isolate the skewness response that is driven only by the intensive product mix margin. To do this, we recompute the same skewness measures on the restricted subset of products that are exported in both $t-1$ and t (denoted by $\bar{T}$ and $\bar{A}$). Results using these intensive margin skewness measures are reported in the following 4 columns of Table 4. Across all those different skewness metrics, there remains a positive and significant (beyond the 1% level) response of skewness at the intensive

[21]This range of parameters is also consistent with that advocated by Atkinson and Brandolini (2010) for the evaluation of income inequality.

Table 4: Skewness and Shocks: Robustness

					Intensive Margin Only			
RHS	$\Delta T^{I}_{i,d,t}$	$\Delta A^{I,.5}_{i,d,t}$	$\Delta A^{I,1}_{i,d,t}$	$\Delta A^{I,2}_{i,d,t}$	$\Delta \bar{T}^{I}_{i,d,t}$	$\Delta \bar{A}^{I,.5}_{i,d,t}$	$\Delta \bar{A}^{I,1}_{i,d,t}$	$\Delta \bar{A}^{I,2}_{i,d,t}$
$\tilde{\Delta}$ trade Shock	0.034^{a}	0.014^{a}	0.019^{a}	0.018^{a}	0.013^{a}	0.007^{a}	0.010^{a}	0.009^{a}
	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
$\tilde{\Delta}$ trade Shock - ISIC	0.006^{a}	0.003^{a}	0.004^{a}	0.004^{a}	0.005^{a}	0.002^{a}	0.004^{a}	0.004^{a}
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)

Notes: This table presents the results of individual regressions where the columns give the LHS and the rows give the RHS variables. FE refers to firm-destination-ISIC fixed effects. All regressions include a control for income per capita shocks in the destination country and year dummies. Standard errors clustered at the level relevant for the variable of interest: Firm-destination for trade shock and ISIC-destination for trade shock - ISIC.

margin: within a constant set of exported products, positive demand shocks skew market shares towards better performing products.

3 Theoretical Framework

In the previous section we documented the pattern of product reallocations in response to demand shocks in export markets. We now develop a theoretical model of multi-product firms that highlights the specific demand conditions needed to generate this pattern. These demand conditions imply MSLD and generate all of the micro-level evidence on firm/product selections, prices, and markups presented in the introduction. In particular, those demand conditions highlight how demand shocks lead to changes in competition for exporters in those markets (which lead to the observed reallocations). Those reallocations, in turn, generate changes in firm productivity. We directly investigate the empirical connection between demand shocks and productivity in the following sections.

Our theoretical model contributes to the growing literature emphasizing demand systems with variable price elasticities for models of monopolistic competition, such as Zhelebodko et al. (2012), Bertoletti and Epifani (2014), Fabinger and Weyl (2014), Mrazova and Neary (2017), and Parenti, Ushchev, and Thisse (2017). Our main point of departure relative to those papers is that we seek to connect the demand conditions on variable elasticities (and MSLD) directly to the evidence on the product reallocations that we document; and our additional goal of empirically connecting those to firm-level productivity. In this spirit, our paper is most closely related to Arkolakis et al. (2018) and Asplund and Nocke (2006), who also directly connect their theoretical modeling of endogenous markups with empirical moments: Arkolakis et al. (2018) focus on the implications for the welfare gains from trade; and Asplund and Nocke (2006) focus on the implications for firm turnover in a dynamic setting.

We use the same class of separable preferences as Zhelebodko et al. (2012) which allow for both MSLD and non-MSLD demand. We then show how the restriction to the MSLD subset is both necessary and sufficient for consistency with the empirical evidence. We first start with the same closed economy setup as Zhelebodko et al. (2012) but then extend the model to incorporate multi-product firms and asymmetric countries in an open-economy.

3.1 Closed Economy

To better highlight the role played by the properties of the demand system, we initially start with a closed economy and analyze the impact of demand shocks on product reallocations. We then develop an open economy version of our model that meshes more closely with our empirical setup. We show how demand shocks in an export market induce very similar product reallocations as in the closed economy (but for exporters to that market). We develop both a general equilibrium (with a single differentiated good sector for the whole economy) and a partial equilibrium version focusing on a single sector among many in the economy. In the latter, we also introduce a short-run version where entry is restricted (general equilibrium is inherently a long-run scenario). We show how demand shocks induce the same skewness pattern in all of these modeling alternatives. This highlights the critical role of the demand system in shaping the pattern of reallocations.

Multi-Product Production with Additive Separable Utility

We consider a sector with a single productive factor, labor. We will distinguish between two scenarios. The first is the standard general equilibrium (GE) setup with a single sector. The exogenous labor endowment L indexes both the number of workers L^w (with inelastic supply) and consumers L^c. The endogenous wage is set to one by choosing labor as the *numeraire*. Aggregate expenditures are then given by the exogenous labor endowment. In our partial equilibrium (PE) scenario, we focus on the sector as a small part of the economy. We take the number of consumers L^c as well as their individual expenditures on the sector's output as exogenously given. The supply of labor L^w to the sector is perfectly elastic at an exogenous economy-wide wage. We choose units so that both this wage and the exogenous expenditure per-consumer is equal to 1. This involves a normalization for the measure of consumers L^c and the choice of labor as *numeraire*: Aggregate accounting then implies that this normalized number of consumers L^c represents a fraction of the labor endowment

L.[22] In both scenarios, we model a demand shock as an increase in the number of consumers L^c. This increases aggregate expenditures one-for-one, given our assumptions of unitary consumer income. In our GE scenario, this increase is associated with a proportional increase in labor supplied L^w. In our PE scenario, the labor supply response is left unrestricted, isolating the demand-side effects.

In both scenarios each consumer's utility is assumed to be additively separable over a continuum of imperfectly substitutable products indexed by $i \in [0, M]$ where M is the measure of products available. The representative consumer then solves the following utility maximization problem:

$$\max_{q_i \geq 0} \int_0^M u(q_i) di \text{ s.t. } \int_0^M p_i q_i di = 1,$$

where $u(q_i)$ is the sub-utility associated with the consumption of q_i units of product i. We assume that this sub-utility exhibits the following properties:

$$\textbf{(A1)}\ u(0) = 0;\ u'(q_i) > 0 \text{ and } u''(q_i) < 0 \text{ for } q_i \geq 0.$$

The first order condition for the consumer's problem determines the *inverse* residual demand function (per consumer):

$$p(q_i) = \frac{u'(q_i)}{\lambda}, \tag{4}$$

where $\lambda = \int_0^M u'(q_i) q_i di > 0$ is the marginal utility of income. Given our assumption of separable preferences, this marginal utility of income λ is the unique endogenous aggregate demand shifter: Higher λ shifts all residual demand curves *inward*; we refer to this as an increase in competition for a given level of market demand L^c. Concavity of $u(q_i)$ ensures that the chosen consumption level from (4) also satisfies the second order condition for the consumer's problem. This residual demand curve (4) is associated with a marginal revenue curve

$$\phi(q_i) = \frac{u'(q_i) + u''(q_i) q_i}{\lambda}. \tag{5}$$

[22] As we will restrict our analysis to additively separable preferences – which are non-homothetic – changes in consumer income will have different effects than changes in the number of consumers L^c. We focus on this functional form for tractability and do not wish to emphasize its properties for income elasticities. As first highlighted by Deaton and Muellbauer (1980), additively separable preferences imply a specific relationship between price and income elasticities. We emphasize the properties of demand for those price elasticities. Thus, we analyze changes in the number of consumers L^c holding their income fixed. This is akin to indexing the preferences to a given reference income level.

Let $\varepsilon_p(q_i) \equiv -p'(q_i)q_i/p(q_i)$ and $\varepsilon_\phi(q_i) \equiv -\phi'(q_i)q_i/\phi(q_i)$ denote the elasticities of inverse demand and marginal revenue. Thus $\varepsilon_p(q_i) \geq 0$ is the inverse price elasticity of demand (less than 1 for elastic demand). Although the demand and marginal revenue curves are residual (they depend on λ), their elasticities are nonetheless independent of λ. These preferences nest the C.E.S. case where the elasticities $\varepsilon_p(q_i)$ and $\varepsilon_\phi(q_i)$ are constant; using the additively separable functional form for C.E.S., the marginal utility of income λ is then an inverse monotone function of the C.E.S. price index.

Products are supplied by firms that may be single- or multi-product. Market structure is monopolistically competitive as in Mayer, Melitz and Ottaviano (2014): each product is supplied by a single firm and each firm supplies a countable number of products (among the continuum of consumed products). Technology exhibits increasing returns to scale associated with a fixed overhead cost, along with a constant marginal cost of production. We assume that the fixed cost f is common for all products while the marginal cost v (variety level cost) is heterogeneous. For a given firm, products are indexed in increasing order m of marginal cost from a 'core product' indexed by $m = 0$. Firm entry incurs a sunk cost f^e. After this cost is incurred, entrants randomly draw the marginal cost for their core product from a common continuous differentiable distribution $\Gamma(c)$ with support over $[0, \infty)$; we refer to this cost draw as the firm's core competency.[23] This gives an entrant the exclusive blueprint used to produce a countable range of additional products indexed by the integer m (potentially zero) at marginal cost $v(m, c) \equiv cz(m)$ with $z(0) = 1$ and $z'(m) > 0$.[24]

Product-Level Performance and Selection

A firm owning the blueprint for product i with marginal cost v and facing demand conditions λ chooses the optimal output per consumer $q(v, \lambda)$ to maximize total product-level profits $L^c [p(q_i)q_i - vq_i] - f$, so long as those profits are non-negative; or does not produce product i otherwise.[25] The first order condition whenever production occurs equalizes marginal revenue with marginal cost:

$$\phi(q(v, \lambda)) = v. \tag{6}$$

[23]This assumption of infinite support is made for simplicity in order to rule out the possibility of an equilibrium without any firm selection. We could also introduce an upper-bound cost draw so long as this upper-bound is high enough that the equilibrium features selection (some firms do not produce).

[24]The assumption $z'(m) > 0$ will generate the within-firm ranking of products discussed in the introduction. In the limit case when $z'(m)$ is infinite, all firms only produce a single product.

[25]As we have assumed that any firm's set of products is of measure zero relative to the set of available products M, there is no product inter-dependence in the firm's pricing/output decision (no cannibalization).

In order to ensure that the solution to this maximization problem exists (for at least some $v > 0$) and is unique, we further restrict our choice of preferences to satisfy:

$$\textbf{(A2)}\ 2u''(q_i) + u'''(q_i)q_i < 0.$$

This assumption ensures that marginal revenue $\phi(q_i)$ is decreasing for all output levels and positive for at least some output levels. This ensures elastic demand along a top portion of the demand curve.

The profit maximizing price associated with the output choice (6) can be written in terms of the chosen markup $\mu(q_i) \equiv 1/\left(1 - \varepsilon_p(q_i)\right)$:

$$p(q(v,\lambda)) = \mu(q(v,\lambda))v. \tag{7}$$

Those output and price choices are associated with the following product-level revenues and operating profits *per-consumer*:

$$r(v,\lambda) = p(q(v,\lambda))q(v,\lambda) \qquad \text{and} \qquad \pi(v,\lambda) = \left[p(q(v,\lambda)) - v\right] q(v,\lambda).$$

Total product-level sales are then given by $L^c r(v,\lambda)$ while total product net profits are $L^c \pi(v,\lambda) - f$. Using the first order condition for profit maximization (6) and our derivations for marginal revenue (5) and markup (7), the elasticities for all these product-level performance measures can be written in term of the elasticities of demand and marginal revenue:

$$\begin{aligned}
\varepsilon_{q,v} &= -\frac{1}{\varepsilon_\phi}, & \varepsilon_{r,v} &= -\frac{1-\varepsilon_p}{\varepsilon_\phi}, & \varepsilon_{\pi,v} &= -\frac{1-\varepsilon_p}{\varepsilon_p}, \\
\varepsilon_{q,\lambda} &= -\frac{1}{\varepsilon_\phi}, & \varepsilon_{r,\lambda} &= -\frac{1-\varepsilon_p}{\varepsilon_\phi} - 1, & \varepsilon_{\pi,\lambda} &= -\frac{1}{\varepsilon_p},
\end{aligned} \tag{8}$$

where we use the elasticity notation $\varepsilon_{g,x}$ to denote the elasticity of the function g with respect to x. All of the elasticities with respect to the product marginal cost v are negative, indicating that lower marginal cost is associated with higher output, sales, and profit (both operating and net). As expected, an increase in competition λ (for any given level of market demand L^c) will result in lower output, sales, and profit for all products.

Since operating profit is monotonic in a product's marginal cost v, the production decision associated with non-negative net profit will lead to a unique cutoff cost level $\hat{v}$ satisfying

$$\pi(\hat{v}, \lambda)L^c = f. \tag{9}$$

All products with cost $v \leq \hat{v}$ will be produced. Since $v(0, c) = c$ (recall that $v(m, c) = cz(m); z(0) = 1$) any firm with core competency $c \leq \hat{v}$ will produce at least its core ($m = 0$) product. Thus, $\hat{c} = \hat{v}$ will be the firm-level survival cutoff. Those surviving firms (with $c \leq \hat{c}$) will produce $M(c) = \max\{m \mid cz(m) \leq \hat{v}\}$ *additional* products (potentially none, and then $M(c) = 0$) and earn firm-level net profits:

$$\Pi(c, \lambda) = \sum_{m=0}^{M(c)} \left[\pi\left(cz(m), \lambda\right) L^c - f\right].$$

Since $\varepsilon_{\pi,v}$ and $\varepsilon_{\pi,\lambda}$ are both negative, increases in competition λ – holding market demand L^c constant – will be associated with lower cutoffs $\hat{v} = \hat{c}$. Tougher competition thus leads to tougher selection: the least productive firms exit and all surviving firms shed (weakly) their worst performing products.

Free Entry in the Long-Run

In the long-run when entry is unrestricted, the expected profit of the prospective entrants adjusts to match the sunk cost:

$$\int_0^{\hat{c}} \Pi(c, \lambda) d\Gamma(c) = \sum_{m=0}^{\infty} \left\{ \int_0^{\hat{c}/z(m)} \left[\pi\left(cz(m), \lambda\right) L^c - f\right] d\Gamma(c) \right\} = f^e. \tag{10}$$

This free entry condition, along with the zero cutoff profit condition (9) jointly determine the equilibrium cutoffs $\hat{v} = \hat{c}$ along with the competition level λ. The number of entrants N^e is then determined by the consumer's budget constraint:

$$N^e \left\{ \sum_{m=0}^{\infty} \left[\int_0^{\hat{c}/z(m)} r(cz(m), \lambda) d\Gamma(c) \right] \right\} = 1. \tag{11}$$

These conditions hold in both our GE and PE scenarios.

Since labor is the unique factor and *numeraire*, we can convert the firms' costs (both per-unit production costs and the fixed costs) into employment. Aggregating over all firms yields the aggregate labor demanded:

$$L^w = N^e \left(f^e + \sum_{m=0}^{\infty} \left\{ \int_0^{\widehat{c}/z(m)} \left[cz(m)q\left(cz(m), \lambda\right) L^c + f \right] d\Gamma(c) \right\} \right)$$

As the free entry condition (10) entails no ex-ante aggregate profits (aggregate revenue is equal to the payments to all workers, including those employed to cover the entry costs), this aggregate labor demand L^w will be equal to the number of consumers L^c. This ensures labor market clearing in our GE scenario. In our PE scenario, this implies that the endogenous labor supply adjusts so that it equalizes the normalized number of consumers (recall that this is an exogenous fraction of the economy-wide labor endowment).[26]

In these long-run scenarios, the impact of an increase in demand L^c on the cutoffs will depend on some further assumptions on demand, which we discuss in detail following the introduction of our short-run scenario. However, we note that the impact for the level of competition λ is unambiguous: higher demand leads to increases in competition λ.[27]

Short-Run Scenario

We now consider an alternative short-run situation in which the number of incumbents is fixed at $\bar{N}$ in the PE scenario (with the same exogenous distribution of core competencies $\Gamma(c)$). In this case, free entry (10) no longer holds: firms with core competencies below the profit cutoff in (9) produce while the remaining firms shut-down. However, the budget constraint (11) still holds with the exogenous number of incumbents $\bar{N}$ now replacing the endogenous number of entrants N^e. Together with the zero cutoff profit (9), those two conditions jointly determine the endogenous cutoffs $\hat{v} = \hat{c}$ and competition level λ.

As was the case in the long-run scenarios with free-entry, an increase in demand L^c must lead to an increase in competition λ.[28] However, the response of the cutoffs is now unambiguous: the

[26]This sector-level adjustment for labor supply is very similar to the case of C.E.S. product differentiation within sectors and Cobb-Douglas preferences across sectors. In the latter case, the sector's labor supply adjusts so that it is equal (as a fraction of the aggregate labor endowment) to the exogenous Cobb-Douglas expenditure share for the sector. See Melitz and Redding (2014) for an example of those preferences with firm heterogeneity.

[27]Competition λ must strictly increase for the free entry condition to hold. If λ decreased (even weakly), then net profit for a given variety $\pi(v, \lambda)L^c - f$ should strictly increase (given $dL^c > 0$ and $\varepsilon_{\pi,\lambda} < 0$). The cutoffs $\hat{v} = \hat{c}$ must then strictly increase (given 9); along with the average firm profit (the left-hand-side) in the free-entry condition (10). Thus, this condition could not hold if λ weakly decreased.

[28]Competition λ must strictly increase in order to satisfy the budget constraint (11) with a fixed number of incumbents. As we argued in a previous footnote (27), λ weakly decreasing would imply a strict increase in the cutoffs $\hat{v} = \hat{c}$. This would entail both a strict increase in the number of products consumed as well as a weak increase in expenditures per-product $r(v, \lambda)$ for each consumer (recall that $\varepsilon_{r,\lambda} < 0$). This would necessarily violate the

increase in demand must raise profits for all products (given their cost v) since there is no induced response in entry; leading to an increase in the cutoffs $\hat{v} = \hat{c}$.[29] In this short-run scenario, it is the production of these new varieties (previously unprofitable) that generates the increased competition. In the long run, the increased competition is driven by the entry of new firms (and the varieties they produce).

Curvature of Demand

Up to now, we have placed very few restrictions on the shape of the residual demand curves that the firms face, other than the conditions (A1)-(A2) needed to ensure a unique monopolistic competition equilibrium. In particular, the rates of change of the elasticities of residual demand and marginal revenue (the signs of $\varepsilon_p'(q_i)$ and $\varepsilon_\phi'(q_i)$) were left unrestricted. We now show how further restrictions on those rates of change (or alternatively the curvature of demand and marginal revenue) are intrinsically tied to product-level reallocations – in addition to their better known consequences for prices, markups and pass-through. After we develop the open economy version of our model in the next section, we highlight the reverse connection from the pattern of product reallocations we documented in Section 2 back to their necessary conditions for demand. Throughout, we assume that conditions (A1)-(A2) hold in our monopolistic competition equilibrium. Thus, a *necessary* condition for an empirical pattern is an *additional* condition that must hold (to generate that empirical prediction) *conditional* on those initial assumptions.

The further restrictions on the shapes of demand and marginal revenue are both related to MSLD:

$$\textbf{(MSLD)}\ \varepsilon_p'(q_i) > 0 \text{ for } q_i \geq 0 \qquad \text{and} \qquad \textbf{(MSLD')}\ \varepsilon_\phi'(q_i) > 0 \text{ for } q_i \geq 0.$$

Figure 2 depicts a log-log graph of the inverse demand and marginal revenue curves satisfying those restrictions. Under (MSLD) demand becomes more inelastic with consumption.[30] It is a necessary

consumer's budget constraint.

[29]Note that with a fixed number of incumbents, the budget constraint (11) implies an increasing relationship between the cutoff $\hat{c}$ and the level of competition λ (which reduces product-level revenues $r(v, \lambda)$ for all products).

[30](MSLD) is equivalent to the assumption by Arkolakis et al. (2018) that the demand function of any product is log-concave in log-prices. In the terminology of Mrazova and Neary (2017) it defines the "sub-convex" case demand case. In the terminology of Zhelobodko et al (2012), this class of preferences exhibits increasing "relative love of variety" (RLV) as consumers care more about variety when their consumption level is higher. In the terminology of Kimball (1995), this class of preferences exhibits a positive superelasticity of demand. Bertoletti and Epifani (2014) refer to this case as "decreasing elasticity of substitution". The "Adjustable pass-through" (APT) class of demand functions proposed by Fabinger and Weyl (2012) also satisfies (MSLD). Mrazova and Neary (2019) show that when demand is weakly "super-convex" (the opposite case to MSLD: $\varepsilon_p'(q_i) \leq 0$), then the firm profit function is supermodular in marginal cost and a multiplicative cost-shifter. This relationship is both necessary and sufficient when considering log-supermodularity of the operating profit function. And conversely, (MSLD) is necessary and sufficient

and sufficient condition for better performing products (lower v) to have higher markups and for tougher competition (higher λ) to lower markups for any given product (given a cost v).[31] Thus, the evidence discussed in the introduction linking better product and firm performance to higher markups implies that (MSLD) must hold. It is also consistent with the estimates of Arkolakis et al. (2018) for bilateral trade demand. In our model with monopolistic competition, (MSLD) is also equivalent to an alternate condition that the pass-through elasticity from marginal cost to price $\theta \equiv \partial \ln p(q(v,\lambda))/\partial \ln v = \varepsilon_p/\varepsilon_\phi$ is less than 1 (see appendix A for proof). Thus, the vast empirical evidence on incomplete pass-through (see the survey by Burstein and Gopinath, 2014) also requires this demand condition (MSLD). Most importantly, we will show that (MSLD) is a necessary condition for the evidence we documented on product reallocations for French exporters. This provides an independent confirmation for this demand condition that does not rely on the (very noisy) measurement of product prices and the estimation of markups (or alternatively marginal costs).

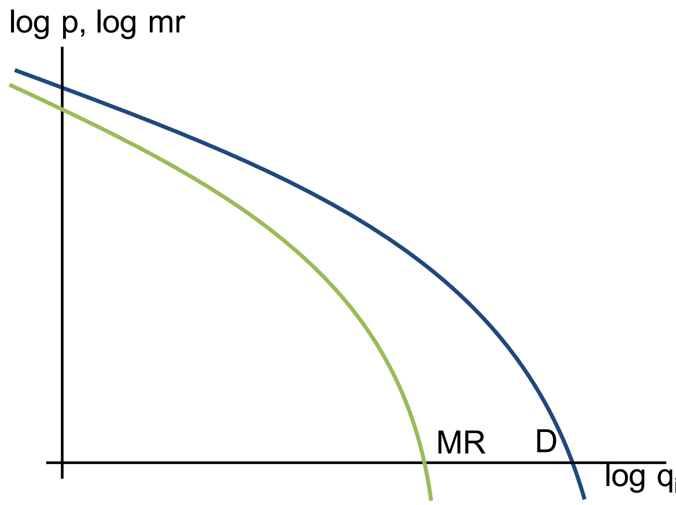


Figure 2: Graphical Representation of Demand Assumptions

Assumption (MSLD') is more restrictive than (MSLD): in the appendix, we show how (MSLD') implies (MSLD). If only (MSLD) holds, then the log demand curve would have the shape shown in Figure 2, but the log marginal revenue curve would need not be globally concave. However, it would still have to be everywhere steeper than log demand: $\varepsilon_\phi(q_i) > \varepsilon_p(q_i)$ for all $q_i \geq 0$ (see appendix). In the following section, we show that (MSLD') is a sufficient condition for the product

for the operating profit to be log-submodular.

[31] Since both higher cost v and higher λ is associated with lower output $q(v,\lambda)$; See (8).

reallocations we previously described for French exporters, in addition to all the evidence from the existing literature on prices, markups, and pass-through.[32]

Lastly we note that conditions (MSLD) and (MSLD') exclude the C.E.S. case, where the derivative of the elasticities $\varepsilon_p'(q_i)$ and $\varepsilon_p'(q_i)$ are zero. In this limiting case, the inverse demand and marginal revenue in Figure 2 are linear. Nevertheless, (MSLD) and (MSLD') are consistent with most of the functional forms that have been used to explore endogenous markups in the theoretical trade literature.[33]

Demand Shocks and Product Reallocations

We have already described how an increase in demand L^c induces an increase in the toughness of competition λ in both the long-run (GE and PE) and the short-run. We now highlight how the demand conditions (MSLD) and (MSLD') generate a link between increases in the toughness of competition and product reallocations towards better performing products.

First, we note that the increase in competition λ induces a downward shift in output sales $q(v, \lambda)$ per-consumer (though not necessarily overall as the number of consumers is increasing). This decrease in output sales $q(v, \lambda)$ in turn generates changes in the price and marginal revenue elasticities ε_p and ε_ϕ, which depend on conditions (MSLD) and (MSLD'). Changes in those two elasticities then determine the changes in the elasticities of output, sales, and profit with respect to marginal cost v (see 8), which govern the reallocation of output, sales, and profit across firms with different costs v. We can now determine exactly how conditions (MSLD) and (MSLD') affect these reallocations:

Proposition 1. *(MSLD) is a necessary and sufficient condition for a positive demand shock to reallocate operating profits to better performing products:* $\pi(v_1, \lambda)/\pi(v_2, \lambda)$ *increases whenever* $v_1 < v_2$.

Proof. $|\varepsilon_{\pi,v}|$ increases for all products v whenever λ increases if and only if $\varepsilon_p(q_i)$ is increasing (see 8) □

Proposition 2. *(MSLD') is a necessary and sufficient condition for a positive demand shock to reallocate output to better performing products:* $q(v_1, \lambda)/q(v_2, \lambda)$ *increases whenever* $v_1 < v_2$.

[32] We will also show how the necessary condition for the French exporters evidence on product reallocations is slightly less restrictive than (MSLD').

[33] Those functional forms include quadratic (linear demand), Bulow-Pfleiderer, CARA, and bipower preferences. In the online appendix, we review those functional forms and describe the parameter restrictions associated with conditions (MSLD) and (MSLD').

Proof. $|\varepsilon_{q,v}|$ increases for all products v whenever λ increases if and only if $\varepsilon_\phi(q_i)$ is increasing (see 8) $\square$

Proposition 3. *(MSLD') is a sufficient condition for a positive demand shock to reallocate revenue to better performing products: $r(v_1,\lambda)/r(v_2,\lambda)$ increases whenever $v_1 < v_2$. The necessary condition is that $[1-\varepsilon_p(q_i)]/\varepsilon_\phi(q_i)$ is decreasing.*

Proof. $|\varepsilon_{r,v}|$ increases for all products v whenever λ increases if and only if $[1-\varepsilon_p(q_i)]/\varepsilon_\phi(q_i)$ is decreasing (see 8). (MSLD') implies that $[1-\varepsilon_p(q_i)]/\varepsilon_\phi(q_i)$ is decreasing.[34] $\square$

We have derived these reallocations using the per-consumer measures of performance, but since they are all evaluated as ratios, multiplying those by the number of consumers L^c would lead to identical outcomes (even though L^c is changing). Thus, we see that (MSLD') is a sufficient condition for all performance measures (profit, output, revenue) to be reallocated toward better performing products. In this case, an increase in competition (higher λ) induces a steeper relationship between a product's cost v and its profit, output, and revenue outcome (higher elasticities $|\varepsilon_{\pi,v}|$,$|\varepsilon_{q,v}|$,$|\varepsilon_{r,v}|$). A given percentage reduction in cost v then translates into a higher percentage increase in those performance outcomes. In the case of C.E.S. preferences, all those performance elasticities would be constant, and hence changes in demand (and corresponding changes in competition λ) would have no effect on the relative performance of products (conditional on selection into production).

The reallocation of output towards better performing products has a direct consequence for firm productivity: the allocation of firm employment to products must respond proportionately to the product-level output changes. Thus, for a given set of products, average productivity (an employment weighted average of product productivity $1/v$) must increase whenever output is reallocated towards better performing products.

Selection

In the short-run, we have already discussed how an increase in demand L^c and the corresponding increase in competition λ induces an increase in the cutoffs $\hat{c} = \hat{v}$. In this scenario, net profit per-product $L^c\pi(v,\lambda) - f$ is increasing for the high cost products with cost v close to the cutoff, even though the operating profit *per-consumer* $\pi(v,\lambda)$ is decreasing for all products (the increase in demand L^c dominates the negative impact of the increase in competition λ). Condition (MSLD)

[34] Bertoletti and Epifani (2014) derive a similar expression for the reallocation of revenue. However, they do not show how that condition is implied by assumption (MSLD') and requires (MSLD) to hold.

then implies that the profits for the better performing products (with lower cost v) increase disproportionately relative to the high cost products. Thus, net operating profit per-product increases for all products.

In the long-run, we mentioned that the change in the cutoffs in response to an increase in demand could not be determined without making additional assumptions on demand. Under (MSLD), such a demand increase induces a disproportionate increase in operating profits for the best performing products; thus, total firm profit $\Pi(c, \lambda)$ becomes steeper (as a function of firm competency c). The free entry condition (10) then requires a single crossing of the new steeper total firm profit $\Pi(c, \lambda)$ curve with the old flatter one (ensuring that average profit in both cases is still equal to the constant entry cost f^e). This crossing defines a new profitability cutoff $\tilde{c}$ whereby better performing firms with $c < \tilde{c}$ enjoy a profit increase whereas worse performing firms with $c > \tilde{c}$ suffer a profit loss. Hence, the zero profit cutoff $\hat{c}$ (and the associated product-level cutoff $\hat{v}$) decreases, leading to the exit of the worse performing firms (and the worse performing products for all firms). The product-level net-profit curve $L^c\pi(v, \lambda) - f$ (as a function of product cost v) rotates in a similar fashion to the firm-level profit curve: profits for the best performing products increase while they decrease for the worse performing products. For those high performing products with low cost v, the increase in demand L^c dominates the effect of tougher competition (higher λ) on per-consumer profits $\pi(v, \lambda)$; whereas the opposite holds for the low performing products.

We further note that (MSLD) is also a necessary condition for this selection effect in the long run: If (MSLD) were violated then the profit curves would rotate in the opposite direction, reducing (increasing) profits for the best (worst) performing firms and products. This would result in an increase in the cutoffs $\hat{c} = \hat{v}$. In the limiting C.E.S. case, the cutoffs would be unaffected by changes in demands: the increase in demand L^c is exactly offset by the increase in competition leaving net-profits $L^c\pi(v, \lambda) - f$ unchanged for all products.

3.2 Open Economy

With our empirical findings in mind, we consider a simplified three-country economy consisting of a Home country (H: France) and a Foreign country (F: Rest of World) both exporting to a Destination country (D). We focus on the equilibrium in this destination D, characterized by a demand level L_D^c. For simplicity, we assume that this destination market is 'small' with respect to economy-wide outcomes in H and F, in the sense that changes in destination D-specific variables do not affect those equilibrium outcomes (apart from those related to exports to D).[35] In particular, this entails that the number of entering firms in H and F, N_H^e and N_F^e, do not respond to changes in demand L_D^c in D. (Naturally, the number of entrants N_D^e into D will respond to demand conditions L_D^c in the long-run.)

Since we are interested in highlighting the impact of demand changes in destination D for competition there, we make one further simplification: We assume that firms in D do not export to either H or F. In this case, trade is necessarily unbalanced so we restrict our analysis to the PE case and assume an exogenous unitary wage. In the appendix, we show how to extend the equilibrium conditions to the GE and PE cases where firms in D export; and highlight how this would not change any of the qualitative results regarding the impact of demand shocks in D.

Exports from $l \in \{H, F\}$ into D incur both a per-unit iceberg cost $\tau_{lD} > 1$ as well as a fixed export cost f_{lD}. In order to streamline the analysis of the production decisions for domestic producers selling in D along with exporters into D, we use the notation $f_{DD} < f_{lD}$ to denote the smaller fixed cost faced by domestic producers and introduce $\tau_{DD} \equiv 1$. Lastly, we can allow for arbitrary technology differences across countries $l \in \{H, F, D\}$ in terms of the product ladder cost $z_l(m)$, the entry cost f_l^e, and the firm distribution of core competencies $\Gamma_l(c)$.

Product-Level Performance and Selection

We now consider the production decisions for sales into D. Since the marginal cost of production is constant and there are no cross-market or cross-product cost synergies, firms will make independent market-level decisions per-product. Any product i sold in D will face the residual inverse demand (4) with a unique endogenous competition level λ_D for that market. Any firm from $l \in \{H, F, D\}$ owning the blueprint for product i with marginal cost v faces a constant delivered marginal cost $\tau_{lD}v$ for market D. All these firms therefore solve the same profit maximization problem with respect to this delivered cost, associated with the same first order condition (6) as in the closed economy. Thus, we can use the same optimal output, operating profit, and revenue functions as in the closed economy to evaluate the performance of a product in destination D: $q(\tau_{lD}v, \lambda_D)$, $\pi(\tau_{lD}v, \lambda_D)$, $r(\tau_{lD}v, \lambda_D)$ capture those performance metrics (per-consumer in D) for a product with delivered cost $\tau_{lD}v$. Producers from $l \in \{H, F, D\}$ will sell a product with cost v in D so long as the associated profits are non-negative. This leads to three (for each origin) new zero-profit cutoff

[35] This small open economy setup with monopolistic competition follows closely the development in Demidova and Rodrigues-Clare (2013) for the case of C.E.S. preferences.

conditions:

$$\pi(\tau_{lD}\hat{v}_{lD}, \lambda_D) = f_{lD},\ l \in \{H, F, D\}\,. \tag{12}$$

All products from l with cost $v \leq \hat{v}_{lD}$ will be sold in D. Since we have assumed that the fixed export cost is higher than the domestic market fixed cost ($f_{lD} > f_{DD}$ for $l \in \{H, F\}$), the marginal exported product will have a lower delivered cost than the marginal domestically produced product: $\tau_{lD}\hat{v}_{lD} < \hat{v}_{DD}$; and it will therefore feature strictly higher performance measures (in terms of operating profit, output, and revenues).

These product-level cutoffs will also be equal to the firm-level cutoffs for the sale of any product in D: Only firms with core competency $c \leq \hat{c}_{lD} = \hat{v}_{lD}$ will operate (sell) in market D. When $l \in \{H, F\}$, those cutoffs represent the firm-level export cutoff into D. When $l = D$, the cutoff represents the production (survival) cutoff for domestic firms in D.

Free Entry in the Long Run

The free entry conditions for markets H and F are irrelevant for destination D, due to our assumption of the latter being "small' relative to the former two. In the long run, free entry into D equalizes the expected profits for prospective entrants with the sunk entry cost. Thus, this new free entry condition is identical to the one for the closed economy; except for the labeling of country-D specific variables:

$$\sum_{m=0}^{\infty}\left[\int_0^{\widehat{c}_{DD}/z_D(m)} \left[\pi\left(cz_D(m), \lambda_D\right) L_D^c - f_{DD}\right] d\Gamma_D(c)\right] = f_D^e. \tag{13}$$

As in the closed economy case, this free entry condition, along with the zero cutoff profit condition (12, for $l = D$) jointly determine the equilibrium cutoffs $\hat{v}_{DD} = \hat{c}_{DD}$ along with the level of competition λ_D. The export cutoffs $\hat{v}_{lD}$ for $l \in \{H, F\}$ are then determined by their matching zero cutoff profit condition in (12) given the competition level λ_D.

In the open economy, consumers in D spread their income over all the domestically produced and imported products. Since the number of entrants into H and F are exogenous with respect to country D, the budget constraint for consumers in D can still be used to directly determine the endogenous number of entrants into D (as was the case for the closed economy):

$$\sum_{l=H,F,D}\left(N_l^e\left\{\sum_{m=0}^{\infty}\left[\int_0^{\widehat{c}_{lD}/z_l(m)} r(\tau_{lD}cz_l(m), \lambda_D) d\Gamma_l(c)\right]\right\}\right) = 1. \tag{14}$$

Short-Run Equilibrium

In the short-run, the number of incumbents in D is fixed at $\bar{N}_D$ (with the same exogenous distribution of core competencies $\Gamma_D(c)$); and the free entry condition for firms in D no longer holds. The budget constraint (14) still holds with the exogenous number of incumbents $\bar{N}_D$ replacing the endogenous number of entrants N_D^e. Together with the three cutoff-profit conditions (12), these four equilibrium conditions determine the competition level λ_D along with the three cutoffs for $l \in \{H, F, D\}$.

Demand Shocks and Product Reallocations

Using the same reasoning as previously developed for the closed economy case, we can show that an increase in demand L_D^c will result in an increase in competition λ_D in D for both the long-run and short-run.[36] Thus, all of our previous results regarding the impact of such a demand shock on the reallocation of profits, output, and revenue towards better performing products still hold (Propositions 1-3). Thus, for exporters to D, we can connect demand conditions (MSLD) and (MSLD') to the reallocation of export sales and profits (in market D) towards better performing products.

Selection

Again using a similar reasoning to our analysis of the closed economy case, demand condition (MSLD) is sufficient for the demand shock to increase the net profit for the sales of the best performing products in D (the profits generated by sales in D) in both the long-run and short-run. Thus, so long as the fixed export cost f_{HD} is high enough, all exported products from H will fall into this category and experience a profit increase following the increase in demand. This, in turn, implies that an increase in demand leads to a fall in the export cutoffs $\hat{v}_{HD}$: Existing exporters from H increase their range of exported products to D, and some firms from H start exporting to D.

In the long-run, condition (MSLD) is also necessary for the demand shock to induce the selection of newly exported products from H to D (so long as the fixed export cost f_{HD} is high enough). Similar to the closed economy case, a violation of condition (MSLD) would imply a reduction in the

[36] Once again, a (weak) decrease in competition λ_D would necessarily lead to a violation of the free entry condition in the long-run, or the budget constraint in the short-run.

profits of the best performing products to D, thus reversing the predicted consequences for export market selection.

3.3 Connecting Back to Empirical Measures of Product Reallocations in Export Markets

We have just shown how our open economy model with demand condition (MSLD') can explain all of the evidence on the response of French exporters to demand shocks that we documented in Section 2. It explains how positive demand shocks induce the entry of new exported products and the reallocation of output and revenues towards the best performing products. The reallocation of output contributes positively to a firm's productivity (by shifting employment shares towards products with higher marginal products).[37] And the reallocation of revenues generates an increase in the skewness of a firm's export sales to that destination.[38] Demand condition (MSLD') and the weaker version (MSLD) are also directly connected to the empirical evidence on firm/product markups and pass-through. In the limiting case of C.E.S. preferences, demand shocks in export market would have no impact on the skewness of export sales; markups are constant across products; and pass-through is complete (equal to 1) for all products.

On its own, the evidence on the positive relationship between demand shocks and export skewness requires that $\left[1-\varepsilon_p(q_i)\right]/\varepsilon_\phi(q_i)$ is decreasing over the range of exported output q_i that we observe. We have pointed out that condition (MSLD') ($\varepsilon_\phi(q_i)$ increasing) is sufficient for this outcome. However, since it is not a necessary condition, our evidence for the skewness of exports does not imply that (MSLD') must hold. On the other hand, we show in the appendix that the weaker condition (MSLD) ($\varepsilon_p(q_i)$ increasing) must nevertheless hold. In particular, we show that even if (MSLD) were violated over a portion of the relevant demand curve ($\varepsilon_p(q_i)$ decreasing over some range), then this would result in a reverse prediction for export skewness over this portion of the demand curve. This result also fits with what we know about the limiting case of C.E.S. preferences, where demand shocks have no impact on the skewness of export sales.

Thus, our empirical evidence on the impact of demand shocks for export skewness provides an independent confirmation for the empirical relevance of this critical property of demand – without relying on the measurement of prices and markups.

[37]We document the strong empirical connection between demand shocks and firm productivity in Section 5.

[38]We showed how the ratio of export sales for any two products (with the better performing product in the numerator) increases in response to a demand shock. This clearly increases the skewness of export sales. In the online appendix, we confirm that such an increase in skewness is reflected in the Theil and Atkinson indices that we use in our empirical work.

4 Trade Competition and Product Reallocations at the Firm-Level

Our theoretical model highlights how our measured demand shocks induce increases in competition for exporters to those destinations; and how the increased competition generates increases in productivity by shifting market shares and employment towards better performing products. We seek to directly measure this connection between demand shocks and productivity. Since we cannot measure the productivity associated with products sold to a particular destination, we need to show that the connection between demand shocks and product reallocations aggregates to the firm-level – before examining the link with firm-level productivity changes (which we can directly measure). Our results in section 2 highlighted how demand shocks lead to reallocations towards better performing products at the destination-industry level. In this section, we show how the destination-industry demand shocks can be aggregated to the firm-level – and this firm-level demand shock strongly predicts product reallocations towards better performing products (higher market shares) at the *firm-level*; that is, changes in skewness to the firm's global product mix (the distribution of product sales across all destinations).

Intuitively, since there is a stable ranking of products at the firm level (better performing products in one market are most likely to be the better performing products in other markets – as we previously discussed), then reallocations towards better performing products within destinations should also be reflected in the reallocations of global sales/production towards better performing products; and the strength of this link between the skewness of sales at the destination and global levels should depend on the importance of the destination in the firm's global sales. Our chosen measure of skewness, the Theil index, makes this intuition precise. It is the only measure of skewness that exhibits a stable decomposition from the skewness of global sales into the skewness of destination-level sales (see Jost 2007).[39] Specifically, let $T_{i,t}$ be firm i's Theil index for the skewness of its global exports by product $x^s_{i,t} \equiv \sum_d x^s_{i,d,t}$ (the sum of exports for that product across all destinations).[40] Then this global Theil can be decomposed into a market-share weighted average of the within-destination Theils $T_{i,d,t}$ and a "between-destination" Theil index $T^B_{i,d,t}$ that measures

[39] This decomposition property is similar – but not identical – to the within/between decomposition of Theil indices across populations. In the latter, the sample is split into subsamples. In our case, the same observation (in this case, product sales) is split into "destinations" and the global measure reflects the sum across "destinations".

[40] The Theil index is defined in the same way as the destination level Theil in (2). We return to our notation $x^s_{i,d,t}$ to denote firm i's exports of product s to destination d in year t, which we use throughout our empirical analysis. In terms of our theoretical model, this corresponds to the export revenues generated for a product m by a firm with core competency c to destination D.

differences in the distribution of product-level market shares across destinations:[41]

$$T_{i,t} = \sum_d \frac{x_{i,d,t}}{x_{i,t}} T_{i,d,t} - \sum_d \frac{x_{i,d,t}}{x_{i,t}} T^B_{i,d,t}, \tag{15}$$

where $x_{i,d,t} \equiv \sum_s x^s_{i,d,t}$ and $x_{i,t} \equiv \sum_d x_{i,d,t}$ represent firm i's total exports to d, and across destinations to the world (global exports). The between-destination Theil $T^B_{i,d,t}$ is defined as

$$T^B_{i,d,t} = \sum_s \frac{x^s_{i,d,t}}{x_{i,d,t}} \log\left(\frac{x^s_{i,d,t}/x_{i,d,t}}{x^s_{i,t}/x_{i,t}}\right).$$

Note that the weights used in this decomposition for both the within- and between-destination Theils are the firm's export shares $x_{i,d,t}/x_{i,t}$ across destinations d. The between-destination Theil $T^B_{i,d,t}$ measures the deviation in a product's market share in a destination d, $x^s_{i,d,t}/x_{i,d,t}$, from that product's global market share $x^s_{i,t}/x_{i,t}$ and then averages these deviations across destinations. It is positive and converges to zero as the distributions of product market shares in different destination become increasingly similar.

To better understand the logic behind (15), note that it implies that the average of the within-destination Theil indices can be decomposed into the sum of two positive elements: the global Theil index, and the between-destination Theil index. This decomposition can be interpreted as a decomposition of variance/dispersion. The dispersion observed in the destination level product exports must be explained either by dispersion in global product exports (global Theil index), or by the fact that the distribution of product sales varies across destinations (between-destination Theil index).

A simple example helps to clarify this point. Take a firm with 2 products and 2 destinations. In each destination, exports of one product are x, and exports of the other product are $2x$. This leads to the same value for the within-destination Theil indices of $(1/3)\ln(1/3) + (2/3)\ln(2/3)$, and hence the same value for the average within-destination Theil index. Hence, if the same product is the better performing product in each market (with $2x$ exports), then the distributions will be synchronized across destinations and the between-destination Theil will be zero: all of the dispersion is explained by the global Theil index, whose value is equal to the common value of the two within-destination Theil indices. On the other hand, if the opposite products perform better in each market, global sales are $3x$ for each product. There is thus no variation in global product sales,

[41] For simplicity, we omit the industry referencing I for the destination Theils. The decomposition across industries follows a similar pattern.

and the global Theil index is zero. Accordingly, all of the variation in the within-destination Theil indices is explained by the between-destination Theil.

The theoretical model of Bernard, Redding and Schott (2011) with C.E.S. demand predicts that the between-destination Theil index would be exactly zero when measured on a common set of exported products across destinations. With linear demand, Mayer, Melitz and Ottaviano (2014) show (theoretically and empirically) that this between-destination index would deviate from zero because skewness varies across destinations. We have shown earlier that this result holds for a larger class of demand systems such that the elasticity and the convexity of inverse demand increase with consumption. Yet, even in these cases, the between-destination Theil is predicted to be small because the ranking of the product sales is very stable across destinations. This leads to a prediction that the market-share weighted average of the destination Theils should be strongly correlated with the firm's global Theil. Empirically, this prediction is strongly confirmed as shown in the firm-level scatter plot (across all years) in Figure 3.

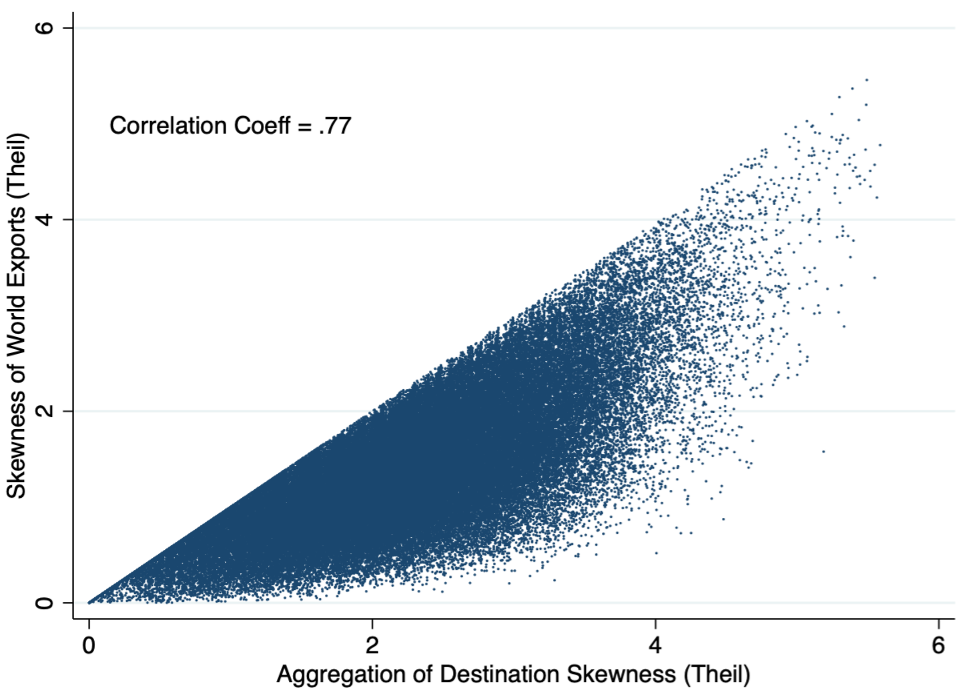


Figure 3: Correlation Between Global Skewness and Average Local Skewness

This high correlation between destination and global skewness of product sales enables us to move from our previous predictions for the effects of the demand shocks on skewness at the destination-level to a new prediction at the firm-level. To do this, we aggregate our destination-industry measures of demand shocks to the firm-level using the same weighing scheme by the firms' export shares across destinations. We thus obtain our firm-level demand shock in (log) levels and first difference:

$$\log \text{shock}_{i,t} \equiv \sum_{d,I} \frac{x^I_{i,d,t_0}}{x_{i,t_0}} \times \log \text{shock}^I_{i,d,t}, \qquad \tilde{\Delta}\text{shock}_{i,t} = \sum_{d,I} \frac{x^I_{i,d,t-1}}{x_{i,t-1}} \times \tilde{\Delta}\text{shock}^I_{i,d,t},$$

where $x_{i,t} \equiv \sum_{d,I} x^I_{i,d,t}$ represents firm i's total exports in year t. As was the case for the construction of our firm-level destination shock (see equation 1), we only use the firm-level information on exported products and market shares in prior years (the year of first export sales t_0 for the demand shock in levels and lagged year $t-1$ for the first difference between t and $t-1$). This ensures the exogeneity of our constructed firm-level demand shocks (exogenous to firm-level actions in year $t > t_0$ for levels, and exogenous to firm-level changes Δ_t for first differences). In particular, changes in the set of exported products or exported market shares are not reflected in the demand shock.[42]

From here on out, we focus exclusively on our trade shock constructed with the product level export flows and drop the version constructed using the ISIC industry-level flows. Once we aggregate the destination trade shocks to the firm-level, we have found that the explanatory power of this ISIC shock is greatly reduced (its explanatory power at the destination level was also always lower than the product level trade shock version). In addition, the trade shock using the product-level trade is the only shock that exhibits variation across firms within a destination; a feature that we will use for some robustness checks later on. The first three columns of Table 5 report the regression of the firms' global skewness (global Theil $T_{i,t}$) on this firm-level trade shock. We see that this trade shock has a very strong and significant (well beyond the 1% significance level) impact on the skewness of global exports.

Table 5: The Impact of Demand Shocks on the Global Product Mix (Firm Level)

Dependent Variable	$T_{i,t}$	$\Delta T_{i,t}$		Exp. Intens$_{i,t}$	Δ Exp. Intens$_{i,t}$	
Specification	FE	FD	FD-FE	FE	FD	FD-FE
log trade shock	0.045^a			0.010^a		
	(0.009)			(0.003)		
$\tilde{\Delta}$ trade shock		0.064^a	0.056^a		0.019^a	0.017^a
		(0.011)	(0.013)		(0.003)	(0.004)
Observations	117987	117987	117987	111863	109052	109052

FE refers to firm-level fixed effects. Standard errors (clustered at the firm level) in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$.

[42] Lileeva and Trefler (2010), Hummels et al (2014), and Bernard et al (2018a) use a similar strategy to construct firm-level trade-related shocks.

Our global Theil measure $T_{i,t}$ measures the skewness of export sales across all destinations, but it does not entirely reflect the skewness of production levels across the firm's product range. That is because we cannot measure the breakdown of product-level sales on the French domestic market. Ultimately, it is the distribution of labor allocation across products (and the induced distribution of production levels) that determines a firm's labor productivity – conditional on its technology (the production functions for each individual product). As highlighted by our theoretical model, the export market demand shocks generate two different types of reallocations that both contribute to an increased skewness of production levels for the firm: reallocations within the set of exported products, which generate the increased skewness of global exports that we just discussed; but also reallocations from non-exported products towards the better performing exported products (including the extensive margin of newly exported products that we documented at the destination-level). Although we cannot measure the domestic product-level sales, we can measure a single statistic that reflects this reallocation from non-exported to exported goods: the firm's export intensity. We can thus test whether the demand shocks also induce an increase in the firm's export intensity. Those regressions are reported in the last three columns of Table 5, and confirm that our firm-level trade shock has a very strong and highly significant positive impact on a firm's export intensity.[43] Thus, our firm-level trade shock predicts the two types of reallocations towards better performing products that we highlighted in our theoretical model (as a response to increased competition in export markets).

5 Trade Competition and Productivity

We just showed that our firm-level trade shock predicts increases in the skewness of global exports, and increases in export intensity. Holding firm technology fixed (the productivity of each individual product), this increase in the skewness of global production will generate productivity increases for the firm as they reallocate their factors of production towards products with higher productivity. Empirically, product skewness is affected by many different types of shocks. In particular, technological changes to individual products will induce both skewness and productivity changes at the firm-level that have nothing to do with the demand-side mechanism that is highlighted by our theoretical model. Thus, we do not test for a direct relationship between skewness and productivity. Instead, we test for a connection between the demand-driven trade shock and productivity at the

[43] Since the export intensity is a ratio, we do not apply a log-transformation to that variable. However, specifications using the log of export intensity yield very similar results.

firm-level. We show that there is a strong and significant response of productivity to this demand shock; and that the dynamics of this response closely mirror the dynamic response of skewness to the demand shock.

We obtain our measure of firm productivity by merging our firm-level trade data with firm-level production data. This latter dataset contains various measures of firm outputs and inputs. As we are interested in picking up productivity fluctuations at a yearly frequency, we focus on labor productivity. We then separately control for the impact of changes in factor intensities and returns to scale (or variable utilization of labor) on labor productivity.

We compute labor productivity at the firm-level as deflated value added per worker assuming a sector-specific price deflator P^I. Note that this measure aggregates to the overall deflated value-added per worker for manufacturing. This aggregate productivity measure accurately tracks a welfare-relevant quantity index – even though we do not have access to firm-level prices: The effect of pure markup changes at the industry level are netted-out of our productivity measure.[44]

More formally, we can write the welfare-relevant aggregate industry labor productivity – the ratio of industry deflated value-added (VA^I/P^I) over industry employment L^I – as the labor share weighted average of firm productivity using that same industry price deflator P^I for firm revenue:

$$\Phi^I \equiv \frac{\mathrm{VA}^I/P^I}{L^I} = \sum_{i\in I} \frac{L_i}{L^I} \frac{\mathrm{VA}_i/P^I}{L_i} \tag{16}$$

In other words, the revenue-based firm productivity measure $\left(\mathrm{VA}_i/P^I\right)/L_i$ aggregates up to a quantity-based industry measure, using the empirically observed firm labor shares L_i/L^I and without any need for a quantity-based output or productivity measure at the level of the firm (which would require measures of firm-product-level prices and qualities). This implicitly assumes the existence of an industry price aggregator P^I, though its functional form is left completely unrestricted. Consequently, we run all of our specifications with sector-time (2 digit NACE) fixed effects, thus eliminating the need for any direct measures of those sector-level deflators.[45] Our productivity results therefore capture within-sector effects of the demand shocks, over-and-above any contribution of the sector deflator to a common productivity change across firms. We will thus report a

[44] At the firm-level, an increase in markups across all products will be picked-up in our firm productivity measure – even though this does not reflect a welfare-relevant increase in output. But if this is the case, then this firm's labor share will decrease, and its productivity will carry a smaller weight in the aggregate index.

[45] We have also experimented with an alternative procedure using deflated value-added per worker (the value added deflator coming from EUKLEMS dataset for France) and year fixed-effects (dropping the industry-year combined fixed effects). The differences in the results are negligible.

welfare-relevant aggregate productivity change by aggregating our firm-level productivity changes using the observed changes in labor shares.

Our firm-level trade shock only aggregates across export destinations. It therefore does not incorporate a firm's exposure to demand shocks in its domestic (French) market. This is not possible for two reasons: most importantly, we do not observe the product-level breakdown of the firms' sales in the French market (we only observe total domestic sales across products); in addition, world exports into France would not be exogenous to firm-level technology changes in France. Therefore, we need to adjust our trade shock using the firm's export intensity to obtain an overall firm-level demand shock relevant for overall production and hence productivity:

$$\log \text{shock\_intens}_{i,t} = \frac{x_{i,t_0}}{x_{i,t_0} + x_{i,F,t_0}} \times \log \text{shock}_{i,t}, \qquad \tilde{\Delta}\text{shock\_intens}_{i,t} = \frac{x_{i,t-1}}{x_{i,t-1} + x_{i,F,t-1}} \times \tilde{\Delta}\text{shock}_{i,t},$$

where $x_{i,F,t}$ denotes firm i's total (across products) sales to the French domestic market in year t (and the ratio thus measures firm i's export intensity).[46] Once again, we only use prior year's information on firm-level sales to construct this overall demand shock. Note that this adjustment using export intensity is equivalent to assuming a demand shock of zero in the French market and including that market in our aggregation by market share relative to total firm sales $x_{i,t} + x_{i,F,t}$.

5.1 Impact of the Trade Shock on Firm Productivity

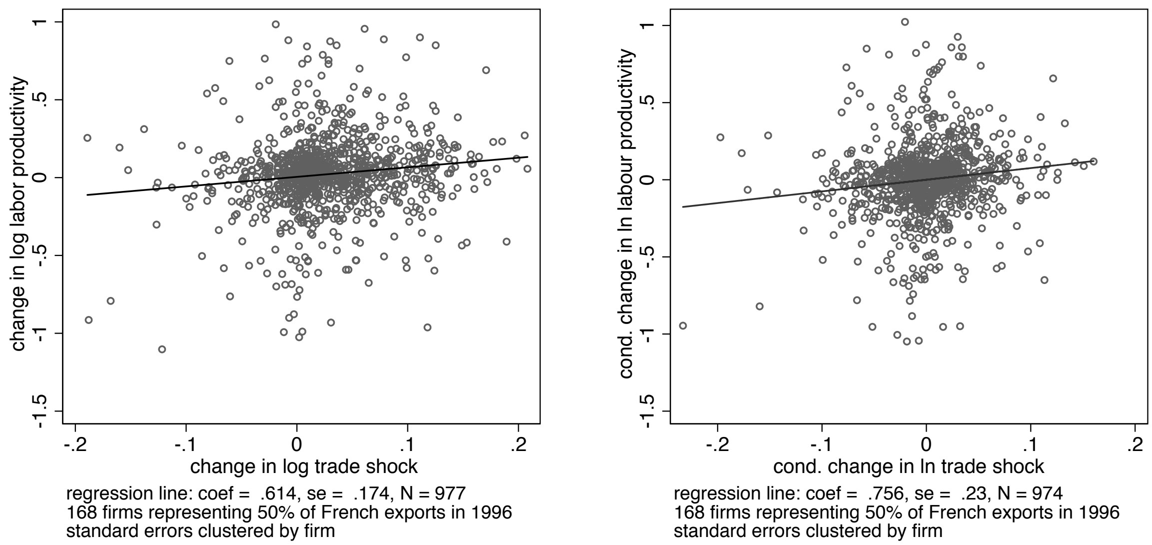
In this section, we investigate the direct link between this firm-level demand shock and firm productivity. Our measure of productivity is the log of value-added per worker. All regressions include industry-year fixed effects, that will capture in particular different evolutions of price indexes across industries. In order to control for changes in capital intensity, we use the log of capital per worker. We also control for unobserved changes in labor utilization and returns to scale by using the log of raw materials (including energy use). Then, increases in worker effort or higher returns to scale will be reflected in the impact of raw materials use on labor productivity. As there is no issue with zeros for all these firm-level variables, we directly measure the growth rate of those variable using simple first differences of the log levels.

We begin with a graphical representation of the strong positive relationship between firm-level productivity and our constructed demand shock. Figure 4 illustrates the correlation between those

[46] Since $x_{i,F,t}$ is only available in the firm balance sheet data (and not in the customs data), we use the reported firm total export figure $x_{i,t}$ from the same balance sheet data to compute this ratio. This ensures a consistent measurement for the firm's export intensity. The correlation between this firm total export figure and the one reported by customs is .95 (very high, though exhibiting some differences between the two data sources).

variables in first differences for the largest French exporters (representing 50% of French exports in 1996). Panel (a) is the unconditional scatter plot for those variables, while panel (b) shows the added-variable plot for the first-difference regression of productivity on the trade shock, with additional controls for capital intensity, raw materials (both in log first-differences) and time dummies. Those figures clearly highlight the very strong positive response of the large exporters' productivity to changes in trade competition in export markets (captured by the demand shock).

Figure 4: Exporters Representing 50% of French Trade in 1996: First Differences 1996-2005



(a) Unconditional (b) Conditional

Table 6 shows how this result generalizes to our full sample of firms and our three different specifications (FE, FD, FD-FE). Our theoretical model emphasizes how a multi-product firm's productivity responds to the demand shock via its effect on competition and product reallocations in the firm's export markets. Thus, we assumed that the firm's technology at the product level (the marginal cost $v(m, c)$ for each product m) was exogenous (in particular, with respect to demand fluctuations in export markets). However, there is a substantial literature examining how this technology responds to export market conditions via various forms of innovation or investment choices made by the firm. We feel that the timing dimension of our first difference specifications – especially our FD-FE specifications which nets out any firm-level growth trends – eliminates this technology response channel: It is highly unlikely that a firm's innovation or investment response to the trade shock in a given year (especially with respect to the trade shock's deviation from trend growth in the FD-FE specification) would be reflected contemporaneously in the firm's productivity.

However, we will also show some additional robustness checks that address this potential technology response.

The first three columns of Table 6 show that, across our three timing specifications, there is a stable and very strong response of firm productivity to the trade shock. Since our measure of productivity as value added per worker incorporates neither the impact of changes in input intensities nor the effects of non-constant returns to scale, we directly control for these effects in the next set of regressions. In the last 3 columns of Table 6, we add controls for capital per worker and raw material use (including energy). Both of these controls are highly significant: not surprisingly, increases in capital intensity are reflected in labor productivity; and we find that increases in raw materials use are also associated with higher labor productivity. This would be the case if there are increasing returns to scale in the value-added production function, or if labor utilization/effort increases with scale (in the short-run). However, even when these controls are added, the very strong effect of the trade shock on firm productivity remains highly significant well beyond the 1% significance level (from here on out, we will keep those controls in all of our firm-level productivity regressions).[47]

Table 6 focuses on the contemporaneous response of productivity to the firm-level demand shock. In Figure 5, we show the dynamic response of productivity by including two years of leads and lags for the demand shock (in a very similar way to our dynamic specification for the response of skewness to the demand shock at the firm-destination level). The contemporaneous coefficients along the vertical dotted line replicate the regressions from the last 3 columns of Table 6 dropping the first and last 2 years of our sample.[48] Figure 5 shows that there are no significant pre-trends associated with the response of productivity to the demand shock. All of the response is contemporaneous, and quickly returns to its baseline level the following year. This dynamic pattern closely mirrors the response of skewness (to the same trade shock), re-enforcing the case for a connection from the latter to the former that we previously argued for.

We now describe several robustness checks that further single out our theoretical mechanism operating through the demand-side product reallocations for multi-product firms. In the next table

[47] A separate concern is a potential selection bias if firms with unobserved characteristics leading to higher productivity growth self-select into destinations with positive aggregate destination shocks – which would then be reflected in our trade shock. In order to eliminate this possibility, we generate a version of our trade shock that is purged (demeaned) of any industry-destination-year effects (trends for the FD-FE specification). Using this purged measure instead of our original one strengthens the impact of the trade shock on firm productivity (but leaves the impact of the other controls virtually un-changed). We have also checked that a potential correlation between export and import destinations is not driving the impact of the trade shock on productivity (which would then capture the impact of lower production costs driven by demand shocks in the import destinations). Both of these robustness checks are reported in the appendix.

[48] As was the case with the response of skewness to the trade shock, the response of productivity to the trade shock at the firm-level is significantly strengthened when those four years are dropped from our sample.

Table 6: Baseline Results: Impact of Trade Shock on Firm Productivity

Dependent Variable	log prod.	Δ log prod.		log prod.	Δ log prod.	
Specification	FE	FD	FD-FE	FE	FD	FD-FE
log trade shock_intens	0.061^a			0.051^a		
	(0.016)			(0.016)		
$\tilde{\Delta}$ trade shock_intens		0.106^a	0.106^a		0.112^a	0.113^a
		(0.019)	(0.023)		(0.020)	(0.024)
log capital stock per worker				0.117^a		
				(0.004)		
log raw materials				0.086^a		
				(0.003)		
Δ log capital stock per worker					0.125^a	0.133^a
					(0.005)	(0.006)
Δ log raw materials					0.092^a	0.090^a
					(0.003)	(0.003)
Observations	213001	185688	185688	203977	175619	175619

FE refers to firm-level fixed effects. All regressions also include industry-year dummies. Standard errors (clustered at the firm level) in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$.

we regress our capital intensity measure on our trade shock; the results in Table 7 show that there is no response of investment to the trade shock. This represents another way to show that the short-run timing for the demand shocks precludes a contemporaneous technology response: if this were the case, we would expect to see some of this response reflected in higher investment (along with other responses along the technology dimension).

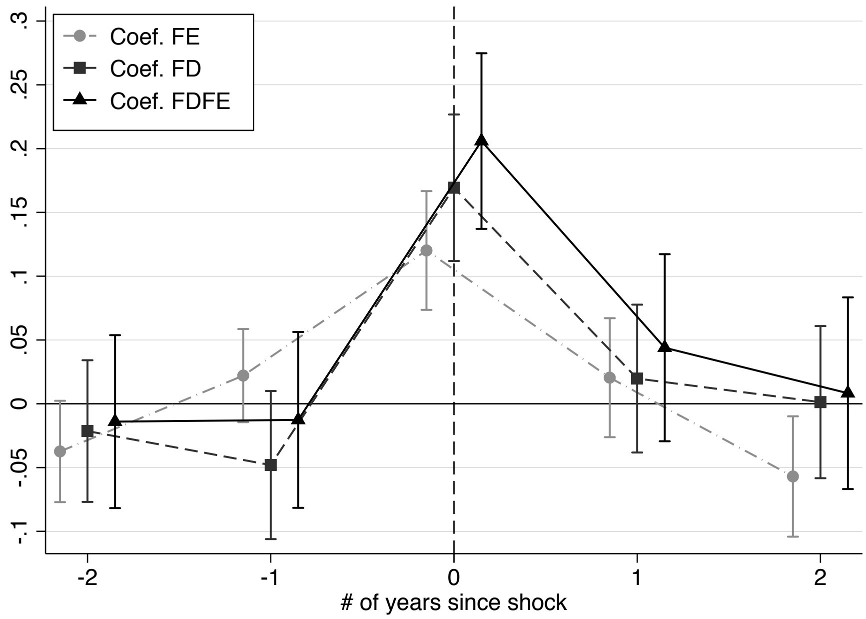
Table 7: Capital Intensity Does Not Respond to Trade Shocks

Dependent Variable	ln K/L	Δ ln K/L	Δ ln K/L
Specification	FE	FD	FD-FE
log trade shock_intens	0.029		
	(0.021)		
$\tilde{\Delta}$ trade shock_intens		0.015	0.002
		(0.022)	(0.027)
Observations	218073	190512	190512

FE refers to firm fixed effects. All regressions also include industry-year dummies. Standard errors (clustered at the firm level) in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$.

Next we use a different strategy to control for the effects of non-constant returns to scale or variable labor utilization: in Table 8, we split our sample between year intervals where firms increase/decrease employment. If the effects of the trade shock on productivity were driven by scale

Figure 5: Impact of Trade Shock on Firm Productivity - leads and lags



effects or higher labor utilization/effort, then we would expect to see the productivity responses concentrated in the split of the sample where firms are expanding employment (and also expanding more generally). Yet, Table 8 shows that this is not the case: the effect of the trade shock on productivity is just as strong (even a bit stronger) in the sub-sample of years where firms are decreasing employment; and in both cases, the coefficients have a similar magnitude to our baseline results in Table 6.[49]

Table 8: Robustness to Scale Effects

Sample	Employment Increase	Employment Decrease
Dependent Variable	Δ log productivity	Δ log productivity
Specification	FD	FD
$\tilde{\Delta}$ trade shock_intens	0.128^a	0.170^a
	(0.034)	(0.033)
Δ log capital stock per worker	0.108^a	0.104^a
	(0.006)	(0.006)
Δ log raw materials	0.100^a	0.096^a
	(0.004)	(0.004)
Observations	69881	65739

All regressions include industry-year dummies. Standard errors (clustered at the firm level) in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$.

[49]Since we are splitting our sample across firms, we no longer rely on the two specifications with firm fixed-effects and only show results for the FD specification.

In order to further single-out our theoretical mechanism operating through the demand-side product reallocations for multi-product firms, we now report two different types of falsification tests. Our first test highlights that the link between productivity and the trade shocks is only operative for multi-product firms. Table 9 reports the same regression (with controls) as our baseline results from Table 6, but only for single-product exporters. This new table clearly shows that there is no evidence of this link among this subset of firms. Next, we show that this productivity-trade link is only operative for firms with a substantial exposure to export markets (measured by export intensity). Similarly to single-product firms, we would not expect to find a significant productivity-trade link among firms with very low export intensity. This is indeed the case. In Table 10, we re-run our baseline specification using the trade shock before it is interacted with export intensity. The first three columns report the results for the quartile of firms with the lowest export intensity, and highlight that there is no evidence of the productivity-trade link for those firms. On the other hand, we clearly see from the last three columns that this effect is very strong and powerful for the quartile of firms with the highest export intensity.[50]

The firms with high export intensity therefore have a response of productivity to trade shocks estimated around 10% (columns 5 and 6 of Table 10). How should we interpret this number in terms of the impact of our mechanism on the productivity of the French economy as a whole? In appendix D, we show how we can use this 10% coefficient to compute a counter-factual contribution of the trade shocks to physical labor productivity at the industry and overall manufacturing levels – aggregating over those firms with the highest export intensity using (16). This aggregation uses the firms' observed labor shares, which magnifies the contribution of firms with growing labor shares and conversely reduces the contribution for those with shrinking labor shares.[51] The contribution of each sector is reported in appendix Table D.1, along with the contribution to aggregate French manufacturing. This contribution is substantial – accounting for a 1.2% average productivity growth rate for the entire French manufacturing sector (working only through the productivity linkages for the firms with the highest export intensities; by construction, the contribution of all firms in the

[50]Since the trade shock has not been interacted with export intensity, the coefficients for this top quartile represent significantly higher magnitudes than the average coefficients across the whole sample reported in Table 6 (since export intensity is always below 1). This is also confirmed by a specification with the interacted trade shock restricted to this same top quartile of firms. We have also experimented with dropping any firm that could potentially impact rest-of-world exports – and hence break the exogeneity of that variable with respect to firm-level decisions. We have used several different threshold market share levels. One of them drops any firm with an average product-destination market share (for any year) exceeding 10%. Those exclusions either leave our key coefficients on the trade shock unaffected or raise them.

[51]Empirically, we find that the firm-level contributions to aggregate productivity are magnified because firms exposed to positive shocks tend to increase their labor shares. This magnification *could* go in the opposite direction – reducing the impact of the firm-level contributions if this condition were reversed.

Table 9: Robustness: Single Product Firms

Dependent Variable	log prod.	Δ log prod.	
Specification	FE	FD	FD-FE
log trade shock_intens	-0.050		
	(0.047)		
log capital stock per worker	0.180^a		
	(0.013)		
log raw materials	0.085^a		
	(0.007)		
$\tilde{\Delta}$ trade shock_intens		0.038	0.012
		(0.044)	(0.066)
Δ log capital stock per worker		0.214^a	0.260^a
		(0.013)	(0.019)
Δ log raw materials		0.103^a	0.100^a
		(0.007)	(0.011)
Observations	33198	25519	25519

FE refers to firm fixed effects. All regressions also include industry-year dummies. Standard errors (clustered at the firm level) in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$.

lowest 3 quartiles of export intensity are set to zero). This amounts to a 12% productivity gain over our ten year sample period from 1995-2005.

6 Conclusion

This paper uses detailed firm-level data to assess the relevance and magnitude of demand shocks in export markets for product reallocations within firms and ultimately for multi-product firm productivity. We find that the impact of those shocks on both reallocations (French firms skew their market shares towards better performing products) and productivity is substantial. We show that this evidence on reallocations provides a new test and validation for endogenous price elasticities that satisfy Marshall's Second Law of Demand (price elasticities decrease with consumption). There is a large literature finding evidence for markup responses consistent with this type of demand. In contrast to this literature, our test only uses data on sales (albeit at a very disaggregated level across products, firms, and destinations) and does not require data on either firm-product prices or quantities (which are typically very noisy), and the recovery/estimation of marginal cost shocks based on functional form assumptions for demand and/or production.

By measuring product reallocations and productivity responses *within* firms, we can control for many alternative explanations that might be correlated with foreign demand shocks – a strategy

Table 10: Robustness: Low/High Export Intensity

Sample	exp. intens. quartile # 1			exp. intens. quartile # 4		
Dependent Variable	log prod.	Δ log prod.		log prod.	Δ log prod.	
Specification	FE	FD	FD-FE	FE	FD	FD-FE
log trade shock	0.003			0.072^a		
	(0.006)			(0.011)		
log capital stock per worker	0.117^a			0.104^a		
	(0.009)			(0.007)		
log raw materials	0.070^a			0.111^a		
	(0.005)			(0.006)		
$\tilde{\Delta}$ trade shock		0.004	0.006		0.092^a	0.101^a
		(0.008)	(0.009)		(0.014)	(0.016)
Δ log capital stock per worker		0.125^a	0.129^a		0.107^a	0.114^a
		(0.011)	(0.013)		(0.008)	(0.010)
Δ log raw materials		0.084^a	0.081^a		0.108^a	0.104^a
		(0.006)	(0.007)		(0.006)	(0.007)
Observations	38806	30909	30909	57267	48716	48716

Standard errors (clustered at the firm level) in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$.

that would not be possible when evaluating the effects *across* firms. Our baseline results shows that the elasticity of labor productivity to trade shocks is between 5 and 11 %. This order of magnitude is very robust to controls for short-run investment by the firm, scale effects, and possibly correlated import shocks. Our measured productivity effect for single product firms is nil, further highlighting the importance of changes in product mix for multi-product firms. We also show that this productivity response is concentrated within the quartile of exporters with the highest export intensities. Taking into account the weight of those firms in the whole economy, we calculate that the average annual increase in French manufacturing productivity – in response to growth in world trade – over our 10 year sample (from 1995-2005) is slightly over 1 percent per year.

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Appendix

A Demand Conditions (MSLD) and (MSLD')

We restrict our attention to the range of quantities with positive marginal revenue (elastic demand) consistent with profit maximizing output choices on the firm side. Given our assumption of decreasing marginal revenue (A2), this quantity range will consist of all non-negative quantities up to a threshold value (potentially infinite if marginal revenue remains positive). Within this quantity range, $0 \leq \varepsilon_p(q_i) < 1$ and $\varepsilon_\phi(q_i) > 0$. The definitions of inverse demand (4) and marginal revenue (5) further imply that these elasticities must satisfy:

$$\frac{\varepsilon_p'(q_i)q_i}{1-\varepsilon_p(q_i)} = \varepsilon_\phi(q_i) - \varepsilon_p(q_i). \tag{17}$$

Thus, we see that $\varepsilon_p(q_i)$ is increasing (decreasing) if and only if $\varepsilon_\phi(q_i)$ is above (below) $\varepsilon_p(q_i)$. Thus, demand condition (MSLD) ($\varepsilon_p(q_i)$ increasing) holds if and only if the pass-though elasticity $\theta \equiv \partial \ln p(q(v,\lambda)/\partial \ln v = \varepsilon_p/\varepsilon_\phi$ is less than 1 (pass-through is incomplete).

We now show that demand condition (MSLD') implies (MSLD) and that $\left[1-\varepsilon_p(q_i)\right]/\varepsilon_\phi(q_i)$ decreasing also implies (MSLD). To show this, we impose one further – but very mild – condition on the convexity of demand at $q_i = 0$: $\lim_{q_i \to 0} \varepsilon_p'(q_i)q_i \geq 0$. This just rules out an extreme form of demand convexity at zero consumption (though, implicitly, this assumption also relies on the continuity of demand for $q_i \geq 0$). It can only be violated if $\lim_{q_i \to 0} \varepsilon_p'(q_i) = -\infty$ and in addition requires $\varepsilon_p'(q_i)$ to decrease to $-\infty$ faster than $-1/q_i$ as $q_i \to 0$. So long as this condition holds, then $\varepsilon_\phi(0) \geq \varepsilon_p(0)$ with equality if $\varepsilon_p'(0) \leq 0$.

A.I (MSLD') Implies (MSLD)

Assume (MSLD') holds: $\varepsilon_\phi'(q_i) > 0$. Given (17), $\varepsilon_p'(q_i) \leq 0$ implies $\varepsilon_p(q_i) \geq \varepsilon_\phi(q_i)$ over that range for q_i. Given our assumption that $\varepsilon_p(0) \leq \varepsilon_\phi(0)$, this can only happen after $\varepsilon_p(q_i)$ cuts $\varepsilon_\phi(q_i)$ from below (or at $q_i = 0$). This in turn would imply that $\varepsilon_p(q_i)$ is strictly increasing at the intersection point $q_i = \bar{q}$: $\varepsilon_p(\bar{q}) \geq \varepsilon_\phi(\bar{q}) > 0$. This contradicts (17) which requires $\varepsilon_p'(\bar{q}) = 0$. Thus, $\varepsilon_p(q_i)$ must be strictly below $\varepsilon_\phi(q_i)$ for all $q_i > 0$. Given (17), this entails $\varepsilon_p'(q_i) \geq 0$ with the inequality strict for $q_i > 0$. Thus, $\varepsilon_p(q_i)$ must be strictly increasing.

A.II $[1-\varepsilon_p(q_i)]/\varepsilon_\phi(q_i)$ Decreasing Implies (MSLD)

If $[1-\varepsilon_p(q_i)]/\varepsilon_\phi(q_i)$ is decreasing, then $\varepsilon_p(q_i)$ and $\varepsilon_\phi(q_i)$ cannot both be decreasing. However $\varepsilon_p'(q_i)<0$ would imply that $\varepsilon_\phi(q_i)$ is also decreasing and thus represents a violation. More formally, the average $\varepsilon_\phi'(q_i)$ over any interval $[0,\bar{q}]$ must then be negative (given (17) and $\varepsilon_p'(q_i)<0$):

$$\overline{\varepsilon_\phi'}=\frac{1}{\bar{q}}\int_0^{\bar{q}}\varepsilon'(q_i)dq_i=\varepsilon_\phi(\bar{q})-\varepsilon_\phi(0)\leq\varepsilon_p(\bar{q})-\varepsilon_p(0)<0.$$

This highlights that $\varepsilon_\phi'(q_i)\geq 0$ cannot hold over the entire interval $[0,\bar{q}]$. So $\varepsilon_\phi(q_i)$ is decreasing on average, and must be decreasing over a subset of $[0,\bar{q}]$ for any $\bar{q}>0$. This reasoning also applies to cases where $\varepsilon_p(q_i)$ is initially increasing then decreasing. Say that $\varepsilon_p(q_i)$ is decreasing starting at $q_1>0$. Then, the average $\overline{\varepsilon_\phi'}<0$ over any interval $[q_1,q_2]$. (Since the ε_ϕ and ε_p curves must cross at q_1 where $\varepsilon_p(q_1)=0$.)

B Allowing for the Destination Country to Export

In the main text we simplified our analysis by assuming that firms in D do not export. In the short-run, allowing for such exporting opportunities would have no impact on the equilibrium outcome for D. In the long-run, the free entry condition for D would change, reflecting the average exporting profits for a prospective entrant:

$$\sum_{l=F,H,D}\left(\sum_{m=0}^{\infty}\left\{\int_0^{\hat{c}_{Dl}/z_D(m)}\left[\pi\left(\tau_{Dl}cz(m),\lambda_l\right)L_l^c-f_{Dl}\right]d\Gamma_D(c)\right\}\right)=f_D^e,$$

where τ_{Dl} and f_{Dl} represent the export costs from D to $l=H,F$; L_l^c and λ_l represent market size and competition in export market l (exogenous due to the 'small' country assumption); and $\hat{c}_{Dl}$ represent the export cutoffs. Although those cutoffs are endogenous, they only depend on the exogenous demand conditions in l (along with the exogenous export costs). Thus, those cutoffs do not depend on demand conditions in D (either L_D^c or λ_D). Thus, the average export profits in the condition above can be written in terms of variables that are exogenous to those demand conditions;

moving those average profits to the right-hand side, we obtain:

$$\sum_{m=0}^{\infty}\left[\int_{0}^{\widehat{c}_{DD}/z_D(m)}\left[\pi\left(cz_D(m),\lambda_D\right)L_D^c - f_{DD}\right]d\Gamma_D(c)\right] =$$

$$f_D^e - \sum_{l=F,H}\left(\sum_{m=0}^{\infty}\left\{\int_{0}^{\hat{c}_{Dl}/z_D(m)}\left[\pi\left(\tau_{Dl}cz(m),\lambda_l\right)L_l^c - f_{Dl}\right]d\Gamma_D(c)\right\}\right).$$

The left-hand side of this free entry condition is identical to the one we derived in (13) for the case where there are no exports from D. Since the right-hand side does not depend on market conditions in D, all of our comparative statics with respect to those conditions will remain unchanged (it is as-if we changed the level of the entry cost for D to this new right-hand side level).

C Robustness Tables

Table C.1 replicates Table 6 using a trade shock that is purged (demeaned) of any industry-destination-year effects (trends for the FD-FE specification).

Table C.1: Impact of Purged Trade Shock on Firm Productivity

Dependent Variable	log prod.	Δ log prod.		log prod.	Δ log prod.	
Specification	FE	FD	FD-FE	FE	FD	FD-FE
log trade shock_intens–purged	0.118^a			0.101^a		
	(0.021)			(0.021)		
$\tilde{\Delta}$ trade shock_intens–purged		0.128^a	0.134^a		0.136^a	0.141^a
		(0.023)	(0.027)		(0.024)	(0.028)
log capital stock per worker				0.117^a		
				(0.004)		
log raw materials				0.086^a		
				(0.003)		
Δ log capital stock per worker					0.125^a	0.133^a
					(0.005)	(0.006)
Δ log raw materials					0.092^a	0.090^a
					(0.003)	(0.003)
Observations	213001	185688	185688	203977	175619	175619

FE refers to firm-level fixed effects. All regressions also include industry-year dummies. Standard errors (clustered at the firm level) in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$.

Table C.2 adds control for demand shocks in a firm's import destinations. We construct a symmetric set of variables that weight changes in exports (to the world except France) from a given product/country by the firm-level import shares from that product/country. Those new variables are introduced into our baseline specification from Table 6. Although import shocks have a separate large and very significant effect, they do not affect our main effect of interest in any major way.

Table C.2: Robustness to Import Shocks

Dependent Variable	log prod.	Δ log prod.		log prod.	Δ log prod.	
Specification	FE	FD	FD-FE	FE	FD	FD-FE
log trade shock_intens	0.068^{a}			0.056^{a}		
	(0.020)			(0.019)		
log import trade shock_intens	0.078^{a}			0.065^{b}		
	(0.029)			(0.028)		
$\tilde{\Delta}$ trade shock_intens		0.110^{a}	0.111^{a}		0.129^{a}	0.133^{a}
		(0.022)	(0.026)		(0.022)	(0.027)
$\tilde{\Delta}$ import trade shock_intens		0.225^{a}	0.245^{a}		0.197^{a}	0.218^{a}
		(0.034)	(0.041)		(0.033)	(0.041)
log capital stock per worker				0.095^{a}		
				(0.004)		
log raw materials				0.090^{a}		
				(0.004)		
Δ log capital stock per worker					0.107^{a}	0.115^{a}
					(0.005)	(0.006)
Δ log raw materials					0.091^{a}	0.090^{a}
					(0.003)	(0.003)
Observations	133382	152171	152171	129517	144938	144938

FE refers to firm-level fixed effects. All regressions also include industry-year dummies. Standard errors (clustered at the firm level) in parentheses: $^{c} < 0.1$, $^{b} < 0.05$, $^{a} < 0.01$.

D Aggregate Productivity Impact

We start with the coefficient on the trade shock for the high export-intensity quartile β_{q4} for the specifications in first differences (reported in Table 10, column 5). This gives us the percentage productivity response to a 1% trade shock for the firms in the fourth quartile. We assume that there is no response of productivity for the firms in the remaining 3 quartiles. We can then use each firm's measured trade shock to calculate an induced percentage productivity change for each firm in the fourth quartile. Aggregating those using the observed changes in the firms' labor shares yields the overall contribution to aggregate physical productivity changes from the observed trade shocks (at the sector or total manufacturing level). Since equation (16) aggregates productivity in levels, we calculate the counterfactual productivity level for each firm in period $t + 1$ by applying this productivity change to the firm's observed productivity in period t. We then compute the ratios of the counterfactual aggregate productivity level for $t + 1$ and the observed aggregate productivity level in period t.

The percentage changes reported in column 1 of Table D.1 are the yearly averages of those ratios. This table uses the $\beta_{q4} = .092$ coefficient from the FD specification (the results for $\beta_{q4} = .101$ for the FD-FE specification would be roughly 10% higher). We use the same aggregation method to obtain sector and total manufacturing level changes in the trade shock – only for the firms in the fourth quartile (the trade shock for all remaining firms is set to 0). Those aggregate changes in the trade shock are reported in column 2. The labor shares used to compute those aggregate changes in columns 1 and 2 are based on total employment across all export intensity quartiles (not just as a fraction of employment in the fourth quartile). Those reported changes are therefore diluted by the zero contributions for all firms in the bottom three quartiles. Column 3 reports the employment share for those firms in the fourth quartile, while column 4 reports the overall employment share (all quartiles) for the sector (as with the first two columns those numbers are yearly averages). Taking the ratio of the annual 1.2% productivity gain to the 6.2% trade shock change, we see that the .092 firm-level elasticity obtained in Table 10 is doubled to .193 for aggregate productivity. This reflects the contribution of labor share reallocations towards firms with relatively higher trade shocks.

Table D.1: Quantification of Trade Shock Effect on Productivity

Industry	prod.	trade shock	% high exp.intens.	% mfg. emp.
Wearing Apparel	3.38	5.21	27.36	2.26
Wood	3.37	6.34	20.36	1.70
Tobacco	3.22	43.60	0.48	0.16
Printing and publishing	2.81	8.48	5.36	3.31
Radio, television and communication	1.80	4.94	59.77	4.31
Leather and footwear	1.79	3.59	26.86	1.21
Textiles	1.69	1.99	33.04	3.29
Motor vehicles, trailers and semi-trailers	1.62	9.80	52.39	7.82
Machinery	1.32	5.54	45.40	9.12
Manufacturing nec	1.19	5.94	22.72	3.56
Pulp and paper	1.18	3.67	30.62	2.82
Chemicals	1.15	6.58	40.55	9.63
Fabricated metal	0.94	7.04	17.41	8.81
Medical, precision and optical instruments	0.85	5.84	46.82	3.53
Rubber and plastics	0.80	5.75	36.97	7.18
Electrical machinery	0.73	5.83	53.12	5.17
Basic metals	0.70	6.27	58.91	4.06
Food and beverages	0.66	6.20	14.12	11.88
Other transport equipment	0.65	7.25	69.14	4.30
Office machinery	0.64	3.70	42.55	1.09
Other Non-Metallic Mineral	0.46	3.89	35.52	3.86
Coke, ref. petr. and nuclear fuel	-0.18	5.12	25.54	0.93
Total mfg	1.17	6.20	36.66	100.00

Columns (1) and (2) provide average percentage changes over the 1996-2005 period.

Online Appendix

I Properties of different skewness measures

In this appendix, we characterize the conditions under which tougher competition (a larger λ) increases the "skewness" of a firm's product mix (for a given product range) when "skewness" is measured in terms of the Ratio, the Atkinson or the Theil indexes.

I.i Preliminary Results

Consider a firm supplying M products indexed $m = 0, ..., M-1$ in increasing order of distance from its core product (i.e. in increasing order of marginal cost v_m). For product m, the elasticity of output per consumer q_m with respect to competition λ can be expressed as

$$\frac{dq_m}{d\lambda}\frac{\lambda}{q_m} = -\frac{1}{\varepsilon_\phi\left(q_m\right)},$$

while the elasticity of its markup μ_m can be written as

$$\frac{d\mu_m}{d\lambda}\frac{\lambda}{\mu_m} = \left(\varepsilon_\phi(q_m) - \varepsilon_p(q_m)\right)\frac{dq_m}{d\lambda}\frac{\lambda}{q_m} = -\frac{\varepsilon_\phi(q_m) - \varepsilon_p(q_m)}{\varepsilon_\phi\left(q_m\right)}.$$

As marginal cost v_m is constant, the sum of these two elasticities determines the elasticity of revenue per consumer $r_m = p_m q_m = \mu_m v_m q_m$ as

$$\frac{dr_m}{d\lambda}\frac{\lambda}{r_m} = \frac{d\mu_m}{d\lambda}\frac{\lambda}{\mu_m} + \frac{dq_m}{d\lambda}\frac{\lambda}{q_m} = -\left(1 + \frac{1-\varepsilon_p(q_m)}{\varepsilon_\phi\left(q_m\right)}\right). \tag{OA.1}$$

I.ii Ratio Index

Consider two products, m and m' with $0 \leq m < m' \leq M-1$. The Ratio Index is defined as the ratio of their revenues

$$\frac{r_m}{r_{m'}} = \frac{p_m q_m}{p_{m'} q_{m'}} = \frac{\mu_m v_m q_m}{\mu_{m'} v_{m'} q_{m'}},$$

which is larger than 1 under **(A1)**-**(A2)**. All bilateral ratios between any two products m and m' with $m < m'$ increase when λ increases if and only if $\left(dr_m/d\lambda\right)\left(\lambda/r_m\right)$is increasing in q_m, or equivalently if and only if $\left[1-\varepsilon_p(q_m)\right]/\varepsilon_\phi(q_m)$ is decreasing in q_m.

I.iii Atkinson Index

Define the Atkinson Index of the firm's revenues across products as

$$A = 1 - \left(\frac{1}{M}\right)^{\frac{\eta}{1-\eta}} \frac{\left[\sum_m (p_m q_m)^{1-\eta}\right]^{\frac{1}{1-\eta}}}{\sum_m p_m q_m} = 1 - \left(\frac{1}{M}\right)^{\frac{\eta}{1-\eta}} \left[\sum_m \left(s_m^R\right)^{1-\eta}\right]^{\frac{1}{1-\eta}},$$

where s_m^R is the revenue share of product m:

$$s_m^r = \frac{p_m x_m}{\sum_{m=0}^{M-1} p_m x_m} = \frac{\mu_m v_m x_m}{\sum_{m=0}^{M-1} \mu_m v_m x_m}.$$

To streamline the subsequent derivations, apply the monotonic transformation $A_M = -(A-1)\, M^{\frac{\eta}{1-\eta}}$ so that A_M *decreases* (A increases) as the revenue distribution becomes more concentrated ('skewed'). We can rearrange $A_M = -(A-1)\, M^{\frac{\eta}{1-\eta}}$ to obtain

$$A_M \sum_m \mu_m v_m x_m = \left[\sum_m (\mu_m v_m x_m)^{1-\eta}\right]^{\frac{1}{1-\eta}},$$

which in turn can be differentiated to yield

$$\begin{aligned} & \frac{dA_M}{d\lambda}\frac{\lambda}{A_M} + \sum_m \frac{\mu_m v_m x_m}{\sum_m \mu_m v_m x_m}\left(\frac{d\mu_m}{d\lambda}\frac{\lambda}{\mu_m} + \frac{dx_m}{d\lambda}\frac{\lambda}{x_m}\right) \\ = \;& \sum_m \frac{\left(\frac{\mu_m v_m x_m}{\sum_m \mu_m v_m x_m}\right)^{1-\eta}}{\sum_m \left(\frac{\mu_m v_m x_m}{\sum_m \mu_m v_m x_m}\right)^{1-\eta}}\left(\frac{d\mu_m}{d\lambda}\frac{\lambda}{\mu_m} + \frac{dx_m}{d\lambda}\frac{\lambda}{x_m}\right) \end{aligned}$$

Given the definition of s_m^r and (OA.1), we can then rewrite

$$\frac{dA_M}{d\lambda}\frac{\lambda}{A_M} = \sum_m \left[s_m^r - \frac{\left(s_m^r\right)^{1-\eta}}{\sum_m \left(s_m^r\right)^{1-\eta}}\right]\frac{1-\varepsilon_p(x_m)}{\varepsilon_\phi(x_m)}$$

with

$$\begin{aligned} \left(s_m^r - \frac{\left(s_m^r\right)^{1-\eta}}{\sum_m \left(s_m^R\right)^{1-\eta}}\right) &< 0 \text{ for small } s_m^r \\ \left(s_m^r - \frac{\left(s_m^r\right)^{1-\eta}}{\sum_m \left(s_m^r\right)^{1-\eta}}\right) &> 0 \text{ for large } s_m^r \end{aligned}$$

so that $d\ln A_M/d\ln\lambda < 0$ ($d\ln A/d\ln\lambda > 0$) requires that $\left[1-\varepsilon_p(q_m)\right]/\varepsilon_\phi(q_m)$ is decreasing in q_m.

I.iv Theil Index

Define the Theil Index of the firm's revenues across products as

$$T \equiv \sum_m \frac{p_m x_m}{\sum_m p_m x_m} \log \frac{p_m x_m}{\sum_m p_m x_m} = \sum_m s_m^r \log s_m^r$$

To streamline the subsequent derivations, define $T^M = -T$ so that T^M *decreases* (T increases) as the sales distribution becomes more concentrated ('skewed'). Given $p_m x_m = \mu_m v_m x_m$, we can rearrange $T^M = -T$ to obtain

$$T^M \sum_m \mu_m v_m x_m = -\sum_m \mu_m v_m x_m \log \mu_m v_m x_m + \sum_m \mu_m v_m x_m \log \sum_m \mu_m v_m x_m,$$

which can be differentiated to yield

$$\begin{aligned} & \frac{dT^M}{d\lambda}\frac{\lambda}{T^M} + \sum_m \frac{\mu_m v_m x_m}{\sum_m \mu_m v_m x_m}\left(\frac{d\mu_m}{d\lambda}\frac{\lambda}{\mu_m} + \frac{dx_m}{d\lambda}\frac{\lambda}{x_m}\right) \\ = \quad & -\frac{1}{T^M}\sum_m \frac{v_m x_m \mu_m}{\sum_m \mu_m v_m x_m}\left(\frac{d\mu_m}{d\lambda}\frac{\lambda}{\mu_m} + \frac{dx_m}{d\lambda}\frac{\lambda}{x_m}\right)\log\frac{\mu_m v_m x_m}{\sum_m \mu_m v_m x_m} \end{aligned}$$

Using the definitions of s_m^r and T^M then gives

$$\frac{dT^M}{d\lambda}\frac{\lambda}{T^M} = \sum_m \left[s_m^r - \frac{s_m^r \log s_m^r}{\sum_m s_m^r \log s_m^r}\right]\frac{1-\varepsilon_p(x_m)}{\varepsilon_\phi(x_m)}$$

with

$$\begin{aligned} \left(s_m^r - \frac{s_m^r \log s_m^r}{\sum_m s_m^R \log s_m^R}\right) &< 0 \text{ for small } s_m^r, \\ \left(s_m^r - \frac{s_m^r \log s_m^r}{\sum_m s_m^r \log s_m^r}\right) &> 0 \text{ for large } s_m^r, \end{aligned}$$

so that $d\ln T^r/d\ln\lambda < 0$ (more concentration) requires $\left[1-\varepsilon_p(q_m)\right]/\varepsilon_\phi(q_m)$ to be decreasing in q_m.

II Specific demand system functional forms

II.i Bulow-Pfleiderer, Linear and CES (Fabinger and Weyl, 2014)

In our setup, this family of functional forms is associated with the sub-utility

$$u(q_i) = \alpha q_i + \frac{\beta}{1-\gamma}(q_i)^{1-\gamma}$$

which has the appealing feature of *nesting both CES demand and linear demand as special cases.* The first order condition for the corresponding utility maximization problem

$$\max_{q_i \geq 0} \int_0^M \left[\alpha q_i + \frac{\beta}{1-\gamma}(q_i)^{1-\gamma}\right] di \text{ s.t. } \int_0^M p_i q_i di = 1,$$

is

$$p_i = \frac{\alpha + \beta (q_i)^{-\gamma}}{\lambda}, \text{ with } \lambda = \int_0^M \left[\alpha q_i + \beta (q_i)^{1-\gamma}\right] di,$$

where $\lambda > 0$ is the marginal utility of income. This demand paramatrization includes CES demand as a special case for $\alpha = 0$, $\beta = 1-\gamma$ and $\gamma = 1/\sigma \in (0,1)$ (where $\sigma > 1$ is the price elasticity of demand). It also includes linear demand as another special case for $\alpha > 0$, $\beta < 0$ and $\gamma = -1$. More generally, $u(q_i)$ is increasing and concave if and only if $\beta < 0$ and $\gamma < 0$. Moreover, conditional on $u(q_i)$ being increasing and concave, our assumption **(MSLD)**, i.e. $\varepsilon_p'(q_i) > 0$, holds if and only if $\alpha > 0$. The same applies to assumption **(MSLD')**: conditional on $u(q_i)$ being increasing and concave, $\varepsilon_\phi'(q_i) > 0$ holds if and only if $\alpha > 0$. Accordingly, functional forms of the Bulow-Pfleiderer family with $\alpha > 0$, $\beta < 0$ and $\gamma < 0$ (and thus the special case of linear demand) are consistent with our observed reallocation and productivity effects while CES is not.

II.ii Constant Absolute Risk Aversion (CARA, Behrens and Murata 2007)

In our setup, this family of functional forms is associated with the sub-utility

$$u(q_i) = 1 - e^{-\alpha q_i} \text{ with } \alpha > 0.$$

For $\alpha > 0$ this sub-utility is increasing, concave with $\varepsilon_p'(q_i) > 0$ and $\varepsilon_\phi'(q_i) > 0$. Accordingly, functional forms of the CARA family are consistent with our observed reallocation and productvity effects.

II.iii Bipower Preferences, Bulow-Pfleiderer, IES and CES (Mrazova and Neary, 2016)

In our setup, bipower preferences (Mrazova and Neary, 2016) are associated with the sub-utility

$$u(q_i) = \frac{\alpha\,(q_i)^{1-\eta}}{1-\eta} + \frac{\beta\,(q_i)^{1-\theta}}{1-\theta} \text{ with } 0 < 1-\eta < 1-\theta \leq 1,$$

which encompasses:

- IES ('increasing elasticity of substitution', Bertoletti et al, 2008)

$$u(q_i) = \frac{(q_i)^{\rho}}{\rho} + \frac{(q_i)^{\gamma}}{\gamma} \text{ with } 0 < \rho < \gamma \leq 1$$

  for $\alpha = \beta = 1$, $\rho = 1-\eta$ and $\gamma = 1-\theta$;

- Bulow-Pfleiderer for $\alpha < 0$ and $\eta = 0$ or $\beta < 0$ and $\theta = 0$;

- CES for $\alpha = 0$ or $\beta = 0$.

For $0 < \rho < \gamma \leq 1$ this sub-utility is increasing and concave. It also features $\varepsilon_p'(q_i) > 0$ if and only if $\alpha\beta < 0$ we never have. The same condition is necessary and sufficient for $\varepsilon_\phi'(q_i) > 0$. Accordingly, functional forms of the bipower family with $\alpha\beta < 0$ (and thus the special case of Bulow-Pfleiderer and linear demand discussed above) are consistent with our observed reallocation and productvity effects while CES and IES are not.

III Results for wholesale and retail trade firms

This appendix replicates our baseline results for the sample of firms in the wholesale and retail trade sectors. The reason why there are excluded from the main analysis is that measuring productivity for this set of firms is much more complex than for manufacturers. We therefore restrict analysis to how trade shocks affect export values and counts of products (Table OA.1) and skewness (Tables OA.2 and OA.3).

Table OA.1: Demand shocks and local exports, wholesale and retail trade firms

Dependent Variable	Δ log Exports per Product			Δ log # Products Exported		
$\tilde{\Delta}$ GDP Shock	0.399^a			0.141^a		
	(0.065)			(0.027)		
$\tilde{\Delta}$ trade shock		0.219^a			0.071^a	
		(0.010)			(0.005)	
$\tilde{\Delta}$ trade shock - ISIC			0.012^b			0.018^a
			(0.005)			(0.003)
Observations	236828	242772	242772	236828	242772	242772

Standard errors in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$. All regressions include year dummies, and standard errors clustered at the level relevant for the variable of interest: destination country for columns (1) and (4), firm-destination for columns (2) and (5) and ISIC-destination for columns (3) and (6).

Table OA.2: Demand shocks and local skewness, wholesale and retail trade firms

Dependent Variable	$T^I_{i,d,t}$	$T^I_{i,d,t}$	$\Delta T^I_{i,d,t}$			
Specification	FE	FE	FD	FD	FD-FE	FD-FE
log trade shock	0.030^a					
	(0.007)					
log trade shock - ISIC		0.003^a				
		(0.000)				
$\tilde{\Delta}$ trade shock			0.034^a		0.032^a	
			(0.007)		(0.008)	
$\tilde{\Delta}$ trade shock - ISIC				0.005^b		-0.001
				(0.002)		(0.003)
Observations	246796	246796	236800	236800	215974	215974

Standard errors in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$. FE refers to firm-destination-ISIC fixed effects. All regressions include year dummies, with standard errors clustered at the level of the destination country. All regressions include a control for income per capita shocks in the destination country.

Table OA.3: The Impact of Demand Shocks on the Global Product Mix (Firm Level), non mfg firms

Dependent Variable	$T_{i,t}$	$\Delta T_{i,t}$		Exp. Intens$_{i,t}$	Δ Exp. Intens$_{i,t}$	
Specification	FE	FD	FD-FE	FE	FD	FD-FE
log trade shock	0.031^a			0.006^a		
	(0.007)			(0.002)		
$\tilde{\Delta}$ trade shock		0.043^a	0.050^a		0.012^a	0.012^a
		(0.009)	(0.011)		(0.003)	(0.003)
Observations	107075	107075	107075	93279	88209	88209

FE refers to firm-level fixed effects. Standard errors (clustered at the firm level) in parentheses: $^c < 0.1$, $^b < 0.05$, $^a < 0.01$.

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