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Export Big Hits

Self-Discovery,
Demand Shocks, or
Idiosyncratic?



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Big hits in exports: Growing by leaps and bounds¹

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Abstract

This paper identifies sudden export surges at the origin-destination-product level, combining international trade statistics with firm-level customs data for eight developing and emerging countries. These “big hits” are rare events (fewer than one percent of all export spells), yet account for over half of aggregate export growth in all countries in the sample except one. Big hits have a ratchet effect on export value: post take-off growth reverts roughly to its baseline rate, while export values remain permanently higher. They seem to be neither purely demand-driven nor purely supply-driven; however, a big hit in one product-destination cell makes it eight times likelier that the same product will be a big hit in any other destination. Big hits typically generate strong bandwagon effects across firms, but the crowding-in does not systematically lead to price collapses, as big hits seem to associate with less negative pecuniary externalities between exporters. A firm involved in a big hit is 25 times more likely to be associated with a big hit of the same product in a different destination, and 22 times more likely to be with a different product. Together, our results suggest that a “big-hit watch” enabling export-promotion agencies to spot them rapidly and disseminate information among potential participating exporters could have positive returns.

JEL codes: F13, F14, F15

Keywords: Export, big hits, firms, externalities, learning.

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1. Introduction

What do we know about export success in developing countries? A recent case study of Uganda's Roofings Group (Eberhard, 2014) illustrates the difficulty of making any general statement that could inform policymakers and serves as a warning for the rest of this paper. Founded in 1994 by a British national of Indian roots, the Roofings group recently evolved from a trading company specialized in steel products for the construction sector into a full-fledged steelmaker. Over the last decade, Roofings' exports—mostly to neighboring DRC and South Sudan—jumped from \$7 million to over \$40 million per year, accounting for half of the group's sales; based on current investment plans, it expects to export over \$100 million in coming years. Roofings currently employs more than two thousand skilled workers and is one of Uganda's largest taxpayers. Yet, steel, a highly capital- and energy-intensive industry, is hardly Uganda's comparative advantage; nor does Uganda produce much of the manufactured products that could provide downward linkages or “related” products in the sense of the product space. It is difficult to think of any policy-relevant generalization to make of this case. Is it representative of the utter unpredictability of export success, and does it mean that the quest for policies to facilitate it is doomed?

Recent work on the determinants of export-led growth has broadly fallen in two categories. One strand of papers, starting with Hausmann and Rodrik (2003) argues that the main driver of export growth and diversification is “self discovery”, i.e. “learning what one is good at producing”. The argument is that broad determinants of comparative advantage based on country endowments can explain only a small part of why some export products succeed while others fail (with more goods than factors, trade patterns are anyway indeterminate in a Heckscher-Ohlin model). In this view, export entrepreneurs explore by trial and error how efficiently they can produce particular products for export. While this search takes place at the firm level, it generates information that has value beyond the boundaries of the firm, as export success at the product-destination level is easily imitable. Thus, export entrepreneurship has the characteristics of a public good and is under-supplied in equilibrium, justifying government support. Subsequent papers in this strand reinforced the case for some sort of targeted industrial policy with the argument that export structures in themselves affect subsequent growth (Hausmann, Hwang and Rodrik 2007, Hidalgo and Hausmann 2009), and that diversification patterns follow semi-deterministic paths in the “product space” (Hausmann and Klinger 2006, Hidalgo, Klinger, Barabasi, and Hausmann 2007). In all this work, the determinants of export success are viewed essentially as supply-side “capabilities” at the product level, and their existence makes it possible to think of predicting future patterns of export growth at the country-product level, and hence to advise governments on that basis (see e.g. Hidalgo 2012).

Another strand of work has developed in recent years, largely as a counterpoint to this activist view, arguing that export “big hits” are essentially rare, random events that cannot be explained or predicted. Easterly, Reshef and Schwenkenberg (2009) highlighted the hyper-concentration of manufacturing exports over a small number of product-destination cells that account for the bulk of a country's export value (the top one percent of product-destination pairs accounted on average for over half of manufacturing export value in their sample of 151 countries). They further showed that

the distribution of export values by product-destination cell invariably followed a power law, implying that the unconditional probability of finding a big hit would decrease exponentially with its size. This, they conjectured, might reflect the need to satisfy a large number of necessary conditions for success, each of which has a given probability of being met in any particular entrepreneurial situation. The implication was that it would be very difficult to know *ex ante* where to target support. Easterly and Resheff (2009) further documented that many big-hit products were exported to only a few destinations, with a mode of one. In Easterly and Resheff (2010), where the authors explore African export successes on the basis of both trade statistics and case studies, the furthest they are willing to go in terms of deterministic explanations of big hits is to “document the following conventional determinants: moving up the quality ladder, utilizing strong cases of comparative advantage, responding to trade liberalization, investing in technological upgrades, foreign ownership, exploiting ethnic networks, and relying on personal foreign experience of the entrepreneur” (p. 4). The take-away from this strand of the literature is that we don’t know much more about what drives export success than we did twenty years ago, so governments may as well stick to the traditional hands-off approach of the Washington consensus rather than return to picking-winners industrial policy.

Lending indirect support to Easterly and Resheff’s skepticism, product-space approaches have had limited success in predicting future patterns of specialization (see e.g. Kniahin 2014), although they have been widely used as a descriptive tool to characterize the structure of country export portfolios. Does this mean that the debate is over? For all the unpredictability of export success, a growing empirical literature shows that government intervention in the form of export promotion has strong effects, whether estimated on cross sections of countries (Lederman, Olarreaga and Payton 2010) or in individual impact evaluations (Alvarez and Crespi, 2000; Bernard and Jensen, 2004; Görg, Henry and Strobl, 2008; Volpe and Carballo, 2008, 2010; Girma, Gong, Görg and Yu, 2009; van Biesebroeck, Yu and Chen; 2010). This is a paradox: If export successes were purely random events, it is hard to imagine how simple actions like reducing the cost of accessing trade fairs could have a statistically traceable effect on their occurrence. The success of export promotion is all the more surprising given that it does not seem to lie so much in fostering entry (which would mechanically raise the probability of export successes by widening their base) but rather in helping firms expand at the intensive margin.

In order to bridge these seemingly conflicting observations, the first task is to identify events that are sufficiently rare to qualify as (non-trivial) successes, while accounting for a large enough fraction of aggregate export growth to be policy-relevant. This is what we set out to do in this paper, using disaggregated (HS6) bilateral trade data from BACI. Building on the criteria used by Freund and Pierola (2012b) to define export surges at the aggregate level, we define origin-destination-product surges, which we call “big hits”, that represent fewer than 10 per cent of long (seven-year or more) origin-destination-product spells and one percent of all spells, but over half of aggregate export growth for most countries in the sample. We show that our big hits, like Easterly and Resheff’s, are essentially driven by quantity increases rather than price effects. An important difference between our approaches, though, is that we identify big hits on the basis of export growth whereas theirs are identified by export levels. Most importantly, our big hits have a ratchet effect on

export values: the sharp increase during take-off is typically followed by a plateau rather than by a collapse (although individual experiences vary of course).

Then, we provide a preliminary exploration of the broad nature of the determinants of these rare but highly significant events. The originality of our approach is that instead of running a kitchen-sink regression on conventional determinants, we use different combinations of fixed effects to explore to what extent unobservable demand-side or supply-side effects might “explain” them in a statistical sense. Surprisingly, we find that powerful arrays of fixed effects at either the origin-product-year level (for supply shocks) or the destination-product-year level (for demand shocks), after controlling for time-invariant dyadic effects (origin-destination-product) fail to explain big hits. At this stage, big hits seem to have an idiosyncratic aspect reflecting neither cost discovery (which would presumably generate shocks across destinations) nor demand shocks (which would generate shocks across origins), consistent with the approach in Alvarez, Buera and Lucas (2008, 2013) where interaction takes place between business partners in the origin and destination countries.

Next, in order to explore whether favorable cost shocks could generate a big hit on a destination followed by progressive diffusion in other destinations (something that would not be picked up by origin-product-year fixed effects which crush the time dimension), we test for the existence of “cascades” of big hits within a product but across destinations. Similarly, in order to explore whether favorable demand shocks could be identified first by exporters in one country and then diffuse to other exporters, we test for cascades across origins. Whereas the power of the demand-side test is limited by the small number of origin countries in the sample, the supply-side test does not reject cascading big hits across destinations for a given origin-product pair, suggesting progressive diffusion of product-level success across destinations.

Finally, we combine BACI data with customs data from a number of developing and emerging countries to explore the firm-level dynamics of big hits. We find evidence of diffusion of big hits across firms in the first years of the big hit’s take-off, after which the entry process stops (although we find no clear evidence of exit). The externality (or imitation) function also has a concave form, with not much bandwagon left beyond about a dozen firms involved in the big hit (on average over the entire sample).

All in all, although our approach managed to identify through big hits a potentially relevant policy object, so far our results suggest that the quest for policy levers to make those big hits more likely to happen or more sustained is still elusive, although the balance of the evidence seems to weigh in the direction of supply-side shocks that could, potentially, be amenable to some nurturing.

The paper is organized as follows. The next section describes the data and the criteria used to construct big hits and offer some descriptive statistics. Section 3 explores the drivers of big hits take-off. Section 4 explores the firm-level dynamics of big hits and finally section 5 concludes.

2. Data and definitions

2.1 Data

We use two distinct types of data. First, the identification of big hits uses BACI, a bilateral trade database maintained by the CEPII that reconciles mirrored and direct export data in COMTRADE. The format and nature of the data is thus very similar to COMTRADE (bilateral trade flows in U.S. dollars at the HS6 disaggregation level), but differs from both direct and mirrored data because the CEPII team reconciles the two sources using a number of consistency checks (see Gaulier and Zignano 2010).² We exclude mineral products (chapters HS 25 to 27) and focus our analysis on eight developing countries for which we also have firm-level data; namely Bangladesh, Chile, Kenya, Mexico, Morocco, Rwanda and Uganda, over the period 1995-2012.³

Second, the analysis of firm participation patterns in big hits is performed on customs data obtained by the World Bank from the customs administrations of a number of developing countries as part of the Exporters Dynamics Database (EDD) project described in Cebeci et al. (2012). The EDD customs data is “raw” and has not undergone any cleaning; therefore it differs from both BACI and COMTRADE’s direct export data.⁴ The sample size and sample period for the customs data are shown in Table 1.

Table 1: Sample characteristics: Customs data

Country	Period	# obs.	# obs./year	# dest.	# products	# firms/dest- product
Bangladesh	2005-11	31,242	4,720	166	1,431	9.9
Chile	2003-09	103,716	14,845	169	3,598	2.5
Kenya	2005-11	36,360	6,189	164	3,138	2.2
Mexico	2000-09	246,009	31,068	183	4,222	4.3
Morocco	2002-12	104,716	9,738	167	3,537	3.3
Rwanda	2005-11	1,553	278	102	600	1.4
South Africa	2001-09	338,453	37,647	187	4,515	2.5
Uganda	2004-11	8,112	1,220	137	1,527	1.8

Note: mineral products are excluded from the analysis.

2.2 Identifying big hits

In order to capture the dynamics of “big hits”, we retain only long export spells (seven consecutive years or more) at the origin-destination-product level. Our sample has 141’711 such spells, accounting for 44 per cent of total trade flows in the sample. On this subset of long spells, we define big hits as three-year accelerations at the origin-destination-product level using five independent criteria. This strong array of criteria allows us to filter out many pathological situations.

² Note that because of the detailed consistency checks, BACI trails COMTRADE by one to two years.

³ Mineral and primary products are commonly disregarded due to large and sudden fluctuations in international prices and associated terms-of-trade shocks, arbitrarily driving the export performance.

⁴ Customs data is sometimes reviewed by Trade or Finance Ministry committees in reporting countries before being forwarded to the UN Statistical Division for publication in COMTRADE, generating discrepancies with raw customs data.

Let o and d index respectively origin and destination countries, p products at the HS6 level of disaggregation, t time, and let v_{odpt} be the dollar value of origin country o 's exports to destination d in year t . Let $g_{odpt} = \ln(v_{odpt}) - \ln(v_{odp,t-1})$ be the growth rate of exports of product p exported from origin o to destination d in year t , defined from the second year of an export spell onward.⁵ Let \bar{v}_{odpt}^0 and \bar{g}_{odpt}^0 be respectively average export value and growth during any arbitrary three-year period. Let \bar{v}_{odpt}^1 and \bar{g}_{odpt}^1 be average value and growth during the next three years. We will define big hits by imposing a number of criteria on \bar{v}_{odpt}^1 and \bar{g}_{odpt}^1 relative to \bar{v}_{odpt}^0 and \bar{g}_{odpt}^0 defining the former as a take-off and the latter as a baseline. Finally, for future purposes, define $\tilde{v}_{odpt}^1 = \min(v_{odp,t}, v_{odp,t+1}, v_{odp,t+2})$ and $\tilde{v}_{odpt}^0 = \max(v_{odp,t-1}, v_{odp,t-2}, v_{odp,t-3})$. The four criteria that define three-year origin-destination-product (odp) spells as “big hits” are as follows:

- | | |
|--|--|
| C1 (growth over 6 per cent during take-off) | $\bar{g}_{odpt}^1 \geq 0.06$ |
| C2 (growth acceleration) | $\bar{g}_{odpt}^1 \geq 1.3 \bar{g}_{odpt}^0$ |
| C3 (significant size) | $\bar{v}_{odpt}^1 \geq \text{US } \$500'000$ |
| C4 (stability) | $\tilde{v}_{odpt}^1 \geq \tilde{v}_{odpt}^0$ |

Criterion C1 requires average growth during a three-year take-off to be at least six per cent (see Freund and Pierola, 2012, for a discussion in the context of aggregate export surges). C2 requires average growth during take-off to be at least 30 per cent higher than during the baseline period.⁶ C3 requires that average export value during take-off be over a “significant size” cutoff set at U.S. \$500'000, ruling out very small surges.⁷ Finally, C4 requires the minimum value during take-off to be at least as large as the maximum value during baseline. This rules out surge episodes reflecting only large swings.

Let τ_{odp} be the first year in the sample that meets C1-C4 for cell odp , and suppose that at least two years after τ_{odp} also meet C1-C4. Then cell odp is undergoing a big hit whose take-off starts in τ_{odp} , the “initiation year”, and continues over the following two years. The years from $\tau + 3$ until the spell's end are called the post-take off period. If criteria C1-C4 hold without interruption over years $\tau + 3, \tau + 4, \dots, \tau + k$, we say that the big hit is sustained, and its total duration is $k + 1$. If there is an

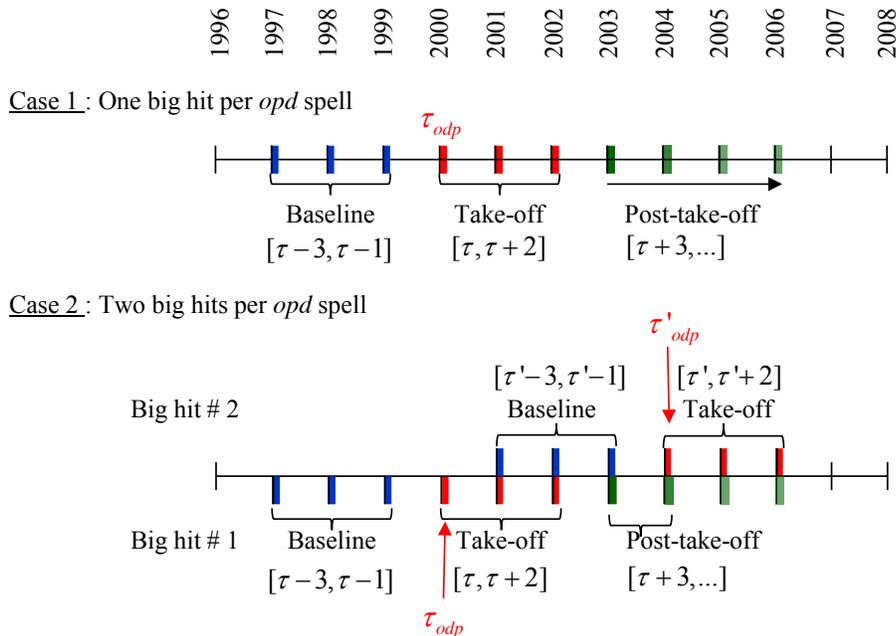
⁵ By imposing that spells be at least seven years and that big hits be initiated in the fifth year onward, we de facto exclude instances of export success that occur within less than five years, the so called “born big”. In practice there are only few such cases in our dataset, possibly reflecting foreign firm entry in the domestic market.

⁶ We experimented with an additional criterion requiring average growth during take-off *excluding the strongest year* to be at least as high as average growth before in order to filter out single-year spurts, with no substantial difference in the results. We also imposed that growth during the first year of take-off be non-negative, again with little difference.

⁷ For robustness, we also tried a cutoff at a million dollars with little major change in the results except a smaller number of big hits.

interruption during which C1-C4 do not apply, followed by three years of renewed take-off, the spell undergoes multiple big hits (Figure 2).⁸

Figure 2: Big hit: initiation year, baseline and take-off periods



2.3 Descriptive statistics

Table 3 reports descriptive statistics for BACI (product-level) data and for big hits. Criteria 1-4 generate 15,481 big hits out of a grand total of 1,542,974 spells and 141,711 spells of seven years or more. Thus, big hits account for less than one percent of all spells and for 10.9 percent of the long ones (themselves rare events). Their incidence varies substantially across countries. Naturally, those having the largest export base (e.g. South Africa or Mexico) have the largest absolute number of big hits. Mexico, Bangladesh and Chile also have a high incidence of big hits relative to their number of spells (1.75%, 1.42% and 0.99% respectively) and long spells (14.70%, 20.89%, and 11.66% respectively). For big-hit spells, Table 3 also reports, by origin country, the absolute difference in export value and growth rate between baseline and take-off, and between take-off and post-take-off.⁹ Our identification criteria imply that differences in levels and growth between baseline and take-off should be positive. Indeed, they range, across countries, between two and ten million dollars in value per big hit, and between 76 and 102 percentage points in growth rates. Most interestingly, differences in value grow even larger when comparing take-off and post-take-off

⁸ Thus, part or all of a big hit's take-off can be the baseline of another. This is however a rare occurrence.

⁹ Specifically, let $n_o = 1, \dots, N_o$ index big-hits spells in country o . When comparing take-off and baseline, we report

$\sum_{n_o} (\bar{v}_{odpt}^1 - \bar{v}_{odpt}^0) / N_o$ for values and $\sum_{n_o} (\bar{g}_{odpt}^1 - \bar{g}_{odpt}^0) / N_o$ for growth rates, where N_o is the number of big hits in country o ; the expressions are similar for differences between post-take-off and take-off.

(defined as $\tau + 3$ until the spell's end), ranging between four and 17 million US dollars; while growth rates are roughly back to baseline levels. This suggests that big hits have a ratchet effect, with export values remaining permanently higher after takeoff. We will return to this crucial aspect of big hits later on.

Table 3: Descriptive statistics by origin country

Country	# obs.	# export spells	# export spells ≥ 7	# big hits	Avg. # big hit/year	Avg. big hit length	Avg. Δ value btw baseline and:		Avg. Δ growth btw baseline and:	
							takeoff	post-takeoff	takeoff	post-takeoff
Bangladesh	200'571	86'796	5'889	1'230	76	3.32	4'253	10'649	0.76	0.14
Chile	461'366	181'608	15'409	1'796	105	3.18	6'455	12'868	0.88	-0.03
Kenya	218'934	111'325	5'265	293	19	3.20	2'206	4'045	0.97	0.01
Morocco	355'761	154'365	10'795	1'097	67	3.18	3'834	6'715	0.86	-0.04
Mexico	1'214'960	393'173	46'905	6'893	403	3.21	10'222	17'187	1.00	0.05
Rwanda	11'707	8'717	90	9	1	3.00	4'558	6'512	0.79	0.03
Uganda	64'309	39'926	889	102	6	3.15	4'068	6'268	1.00	0.05
South africa	1'585'762	567'064	56'469	4'061	244	3.13	5'220	9'305	1.02	-0.05
Total	4'113'370	1'542'974	141'711	15'481	115		5'102	9'193	0.91	0.02

Note: BACI trade data between 1995 and 2012. Mineral products are excluded from the analysis. Values are reported in thousand US dollars and growth rate are reported in 1/100th percentage points.

In terms of duration, by construction a big hit cannot be shorter than the three years of its take-off period, but it can be longer if part or all of its post-take off period (extending from $\tau + 3$ onward to the spell's end) meets the criteria of a take-off (relative to the same baseline). Table 3 shows that average duration is barely over three years, implying that in most cases the post-take off period is a cooling-off period. This is confirmed by Table 4, which reports the full distribution in terms of duration. While the rapid fall in the number of big hits as duration increases is in part due to censoring in our dataset, it also reflects the fact that only very few export spells maintain growth at the exceptional pace of the take-off period beyond three years. Table 4 also shows the incidence of multiple-big hit spells, with the first column reporting data for the first big hit, the second for the second big hit, and so on. Most export spells have a single big hit.

Table 4: Distribution of big hits, by length

Big hit takeoff period length (in years)	Multiple big hit spells			All big hits
	First in spell	Second in spell	Third in spell	
3	12,072	1084	22	13,178
4	1635	143	5	1,783
5	386	36	0	422
6	64	1	0	65
7	27	1	0	28
8	2	0	0	2
9	2	0	0	2
10	1	0	0	1
Total	14,189	1265	27	15,481

Note: BACI trade data between 1995 and 2012. Mineral products are excluded from the analysis.

Table 5 further tabulates sectors with the highest incidence of big hits, in numbers, by exporting country. The results are plausible, with textiles coming first in Bangladesh, Morocco, and Chile, and machinery in Mexico and South Africa. Big hits are most common in the vegetable sector for Kenya and Rwanda. Note that Rwanda, the smallest economy in our sample, only experienced nine big hits throughout the period, all of which were in the unroasted coffee sector. Chile has the most diversified pattern of big hits (in contrast e.g. to Bangladesh, heavily concentrated on textiles).

Table 5: Top five big-hit sectors, by country

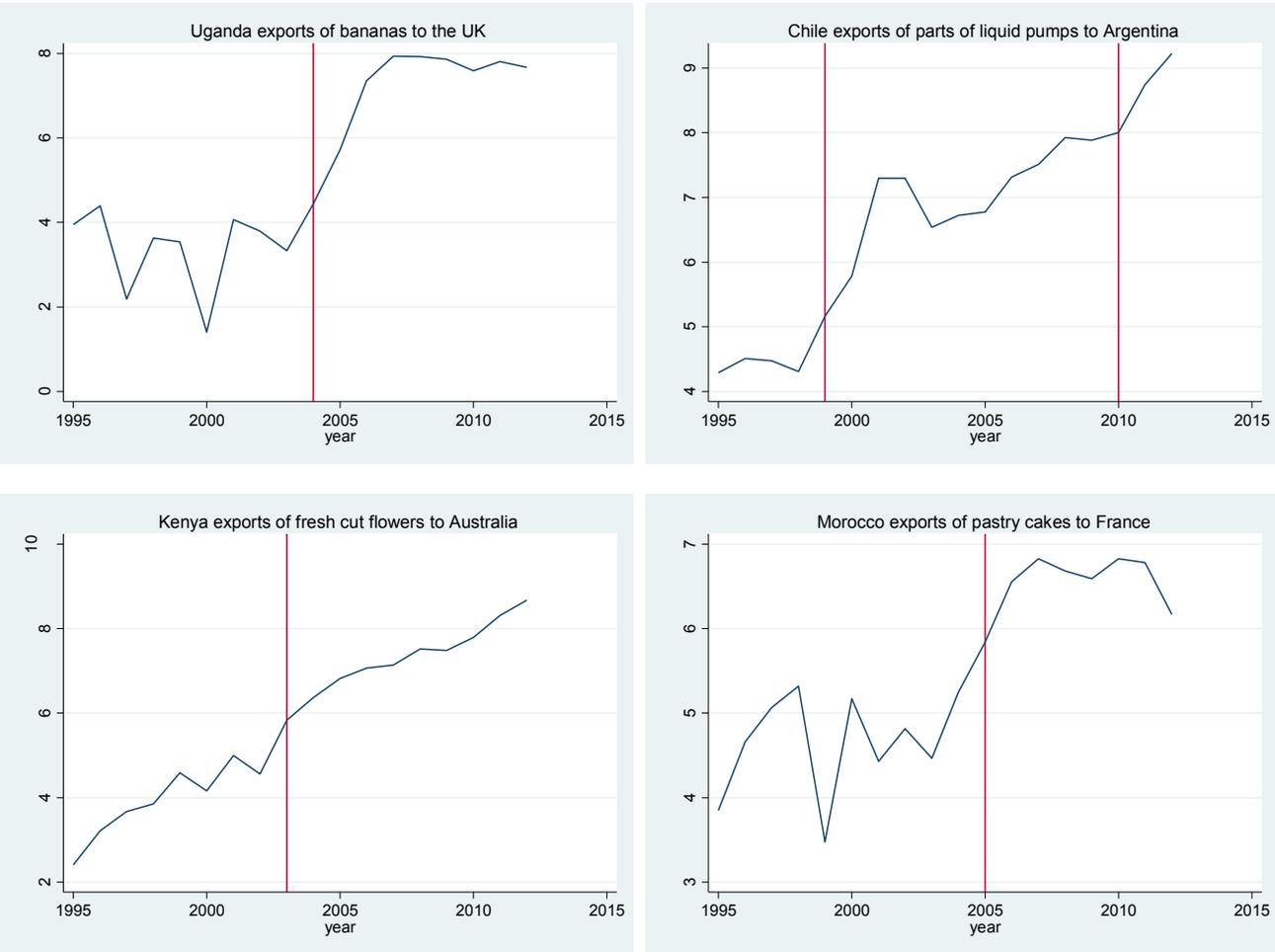
	Bangladesh	Chile	Kenya	Morocco	Mexico	Rwanda	Uganda	South africa							
Textiles	1,051	Vegetable Products	355	Vegetable Products	95	Textiles	441	Machinery / Electrical	2,342	Vegetable Products	9	Vegetable Products	40	Machinery / Electrical	795
Footwear, Headgear	48	Prepared Foodstuffs	239	Products of Chemicals	37	Vegetable Products	146	Products of Chemicals	933			Animal & Animal Product	21	Metals	739
Raw Hides, Leather	39	Products of Chemicals	184	Prepared Foodstuffs	31	Machinery / Electrical	137	Metals	588			Prepared Foodstuffs	16	Products of Chemicals	525
Animal & Animal Product	28	Animal Products	182	Textiles	22	Prepared Foodstuffs	68	Plastics / Rubbers	529			Metals	9	Prepared Foodstuffs	319
Prepared Foodstuffs	18	Metals	156	Metals	20	Animal & Animal Product	56	Optical & Medical Instruments	432			Products of Chemicals	5	Transportation	318
Total # big hits	1,230		1,796		293		1,097		6,893		9		102		4,061
# opd spells ≥ 7 y	5,889		15,409		5,265		10,795		46,905		90		889		56,469

Note: BACI trade data between 1995 and 2012. Mineral products are excluded from the analysis. In the table “odp” stands for origin-product-destination.

In order to illustrate the variety of export trajectories during baseline and take-off periods, Figure 1 shows examples of big hit at the product-destination level for the exporting countries in our dataset.

The vertical line marks the “initiation year”, i.e. the first year of the take-off period. The different cases illustrate the varied patterns that fall into our categorization. In some cases (Kenyan cut flowers to Australia), the growth acceleration is hardly visible to the naked eye as the baseline itself is characterized by substantial growth and the scale is in logs. In some others, the contrast between baseline and take-off is very sharp (e.g. Chilean pump parts to Argentina). In some cases fast growth is sustained beyond the take-off period (South African oranges to Russia), while in others it tapers off (Moroccan pastries to France) or collapses (Kenyan sodium carbonate to South Africa).

Figure 1: Examples of big hits





Note : BACI trade data between 1995 and 2012. Mineral products are excluded from the analysis. Export values are computed at the origin-destination-hs6 product level and taken in log terms.

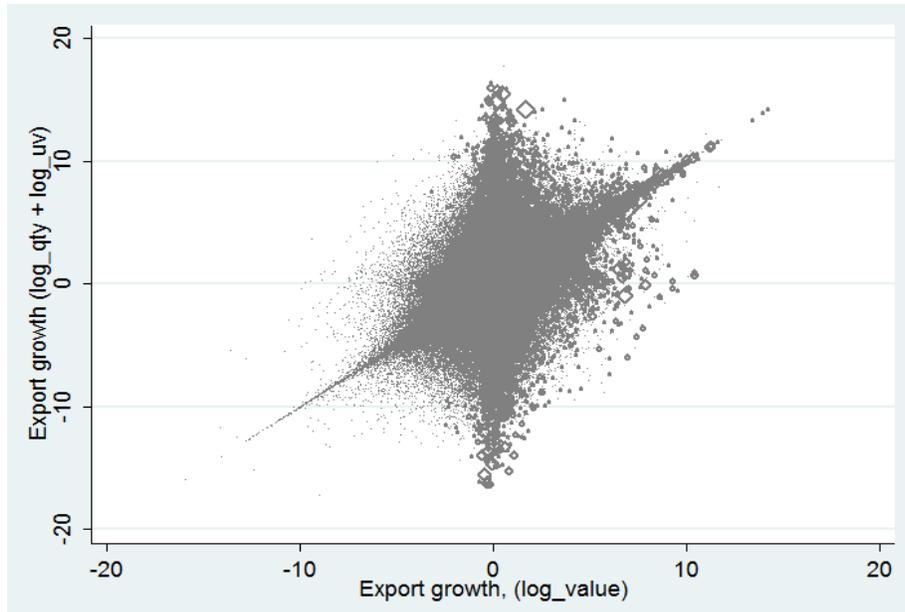
How much of the growth acceleration during big hits is accounted for by pure price variation vs. quantity variation? If big-hit export growth was mostly driven by large price swings, there would be little policy message that could be drawn from their analysis. In order to explore this, we use a simple decomposition of big-hit growth between price and quantity changes using BACI’s trade unit values and volumes. Let p_{odpt} and q_{odpt} stand for unit value and volume. In an ideal world where quantities, unit values and trade values where perfectly reconciled, value growth could be decomposed simply as

$$g_{odpt} \equiv \Delta \ln v_{odpt} = \Delta \ln p_{odpt} + \Delta \ln q_{odpt} \cdot \quad (1)$$

In reality, the right-hand side rarely adds up exactly to the left-hand side because large measurement errors affect quantities and unit values in international trade data.¹⁰ Figure 2 shows a scatterplot of the right-hand side (RHS) of equation (1) against its left-hand side (LHS). The fit is apparently very poor, but most of the noise is in relatively small items, so that cross-product averages of the two sides of equation (1) are ultimately not so far away from each other.

Figure 2: Quantity plus unit-value growth vs. total value growth

¹⁰ However, BACI’s unit value data is cleaned of some of major problems in COMTRADE. For instance, COMTRADE contains “imputed” unit values calculated by application of unit value/total value ratios from one product to the other.



Note : BACI trade data between 1995 and 2012. Mineral products are excluded from the analysis.

Table 6 shows the decomposition averaged over all products (first line) and over only big hits in the take-off phase (second line). For all products, the RHS of (1) (the sum of the log-change in quantities and prices), i.e. $0.05 + 0.03$, adds up to just the LHS (0.08), and quantity variation accounts for 56 per cent of total export variation. For big hits, the RHS adds up to 0.73, slightly less than the LHS (0.78). With this caveat, quantity variation now accounts for 81 per cent of total export variation. Thus, like Easterly and Resheff (2010), we find that volume growth accounts for the bulk of value growth for our big hits—substantially more than for non-big hit exports. This partly reflects the fact that we excluded commodities from our sample.

Table 6: Decomposition of spell growth, big hits vs total

Sample	# obs.	average $\Delta \ln$		
		value	price	quantity
All	2'570'396	0.08	0.03	0.05
big hit	49'406	0.78	0.09	0.63

Note: BACI trade data between 1995 and 2012. Mineral products are excluded from the analysis.

2.4 Big hits and aggregate export growth

In this section we examine the contribution of big hits to aggregate export performance at the country level. Table 7 shows a decomposition of aggregate export growth at the origin-country

level, by year, between big hits and non big hits for years without censoring effects.¹¹ To clarify what Table 7 does, let $V_{ot} = \sum_p \sum_d v_{odpt}$ be aggregate exports (excluding commodities).¹² By construction, the net change in aggregate exports from $t-1$ to t is the sum of net changes at the destination-product level:

$$G_{ot} \equiv V_{ot} - V_{o,t-1} = \sum_p \sum_d \Delta v_{odpt} . \quad (2)$$

Note that, in equation (2), we take first differences of dollar values without taking logs. We do not treat product entries ($v_{odp,t-1} = 0$ so $\Delta v_{odpt} = v_{odpt}$) or exits ($v_{odpt} = 0$ so $\Delta v_{odpt} = -v_{odp,t-1}$) any differently from intensive-margin variations. In doing so, we understate the importance of big hits since they are, by construction, only intensive-margin events. A “fair” comparison would be of big hits relative to aggregate intensive-margin export growth. We use total growth purposefully as aggregate export growth, rather than any of its analytical components, is typically the magnitude of interest to policymakers. Let

$$I_{odpt}^{\text{big hit}} = \begin{cases} 1 & \text{if cell } odpt \text{ is a big hit in take-off phase} \\ 0 & \text{otherwise} \end{cases}$$

and

$$H_{ot} = \sum_p \sum_d I_{odpt}^{\text{big hit}} \Delta v_{odpt}$$

be the increase in the dollar value of exports of big-hit products during their take-off phase. The ratio reported in Table 7 is

$$h_{ot} = \frac{H_{ot}}{G_{ot}} \text{ if } G_{ot} \geq 0 .$$

The ratio can be higher than one if aggregate growth outside of big-hit episodes is negative (the export growth of big-hit products during their take-off phase is positive by construction). However, in order to avoid negative ratios, we do not report it when total aggregate export growth G_{ot} (big hits and non-big hits together) is negative. The omission of negative-export growth years at the country level again under-estimates the contribution of big hits to long-run, aggregate export growth (although take-off periods can occasionally encompass a negative Δv_{odpt} , there is no instance in which H_{ot} is negative).

Table 7 shows that, on average, big hits contributed three quarters of Bangladesh’s overall net export growth in positive-growth years; they over-explain export growth in Mexico, as growth in non-big hit products was negative in 2003 and 2008, generating higher-than-unity ratios; they

¹¹ By construction, big hits require seven years (three years for the baseline period, three years for take-off and one year needed to calculate log-differences) so censoring affects their share four years after the start of the sample period and three years before its end. Only years in the middle are uncensored.

¹² We define commodities as HS chapters 25, 26 and 27. For Morocco, this does not exclude phosphates which fall under chemicals. We refrained from ad-hoc exclusion of particular products falling out of chapters 25-27.

contributed close to two thirds of overall export growth in Morocco and Uganda, one third in Chile and South Africa, one quarter in Kenya and Rwanda. Thus, all in all, big hits as we define them are rare but highly significant drivers of export growth.

Table 7: Contribution of big hits to export value and growth, by origin country

year	Bangladesh	Chile	Kenya	Morocco	Mexico	Rwanda	Uganda	South Africa
1999	neg. growth	0.60	neg. growth	0.52	0.25	neg. growth	0.05	0.32
2000	0.21	0.22	neg. growth	neg. growth	0.34	neg. growth	neg. growth	0.75
2001	3.60	1.07	0.68	3.32	neg. growth	neg. growth	3.90	neg. growth
2002	neg. growth	neg. growth	neg. growth	0.40	2.00	-	0.18	0.40
2003	0.38	0.54	0.19	0.38	10.53	-	neg. growth	0.61
2004	0.43	0.38	0.62	0.59	0.42	neg. growth	0.30	0.37
2005	neg. growth	0.58	neg. growth	0.61	0.60	0.49	0.56	0.41
2006	0.28	0.40	0.08	0.35	0.50	0.10	0.64	0.52
2007	0.67	0.10	0.22	0.36	0.57	0.52	0.20	0.20
2008	0.64	0.26	0.09	0.21	1.32	0.02	0.28	0.36
2009	neg. growth							
2010	0.22	0.14	0.03	0.24	0.24	neg. growth	0.07	0.20
2011	0.24	0.19	neg. growth	0.82	0.23	0.09	0.04	0.12
2012	neg. growth	neg. growth	neg. growth	0.02	neg. growth	-	neg. growth	neg. growth
<i>Average</i>	<i>0.74</i>	<i>0.41</i>	<i>0.27</i>	<i>0.65</i>	<i>1.54</i>	<i>0.25</i>	<i>0.62</i>	<i>0.39</i>

Note: BACI trade data between 1995 and 2012. Mineral products are excluded from the analysis. We exclude years 1995 to 1998 where by our criteria no big hits can be identified.

In the contributions to growth shown in Table 7, the contributions of big hits are counted only during their take-off phase, during which, by construction, they contribute (mostly) positively. Could it be that the profile of big hits is like a factory roof, with most take-offs followed by collapses? In that case, the *net* contribution of big hits to growth would be much less than suggested by Table 7, and possibly zero. In order to test for this, let τ_{odp} be the initiation year of big hit odp 's take-off. If odp is not a big hit, τ_{odp} is undefined. Let also

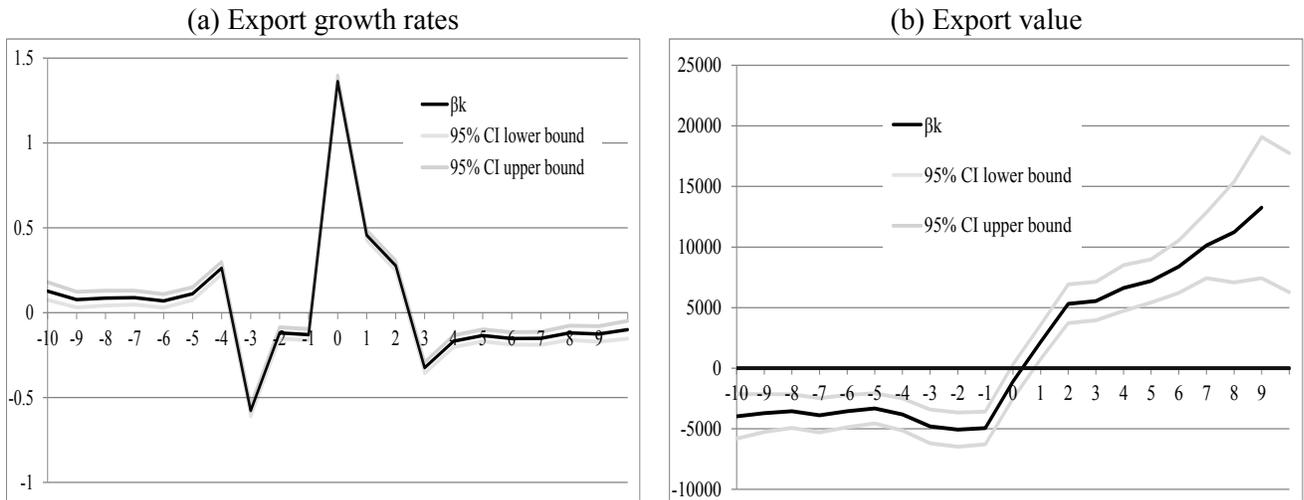
$$I_{odpt}^k = \begin{cases} 1 & \text{if } t = \tau_{odp} + k \\ 0 & \text{otherwise, including when } \tau \text{ is undefined} \end{cases}$$

with $k = -10, \dots, +10$ be a set of dummy variables marking, for each big-hit spell odp , the twenty years around the initiation year, which include the three years of baseline ($k = -3, -2, -1$), the three years of “mandatory” take-off (which define big hits) and, depending on the case, any number of post take-off years. For non-big-hit spells, the I_{odpt}^k are all zero. Let δ_t be time effects for real calendar years, and δ_{odp} be origin-destination product fixed effects. We run the following regression:

$$g_{odpt} = \sum_{k=-10}^{+10} \beta_k I_{odpt}^k + \delta_t + \delta_{odp} + u_{odpt} \quad (3)$$

where g_{odpt} is the growth rate of exports in cell odp . We also examine the time path of export values and run a regression similar to equation (3) but using v_{odpt} (values) instead of growth as the dependent variable. Again, the counterfactual is the value of big hits in all years other than $\tau + k$ plus that of non-big hits. We retrieve the β_k coefficients from both equations and plot them against “analytical time” reset, for each spell odp , to be equal to zero at τ . The results are shown in Figure 3. Panel (a) reports results for growth rates and panel (b) for export values.

Figure 3: Export growth and value around take-off

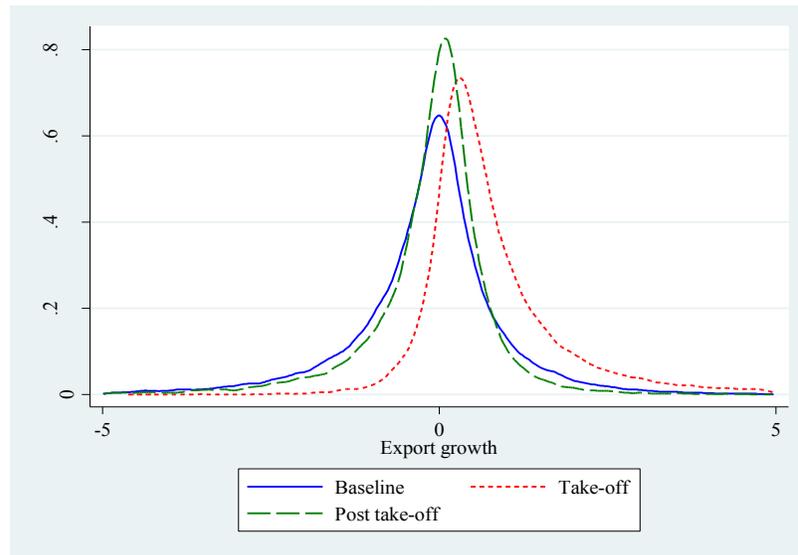


Note: Export values are in thousand US dollars.

The height of the curve in panel (a) can be interpreted as the average differential between, on one hand, the growth of big-hit spells evaluated k years before or after the start of take-off, and, on the other hand, that of a control group made of (i) big-hit spells in any other year and (ii) all other spells. The interpretation of panel (b) is similar. As expected, growth and values spike sharply during take-off. What is interesting is that growth reverts quickly to a level slightly lower than its pre-take-off level without a large negative jump, while export values remain permanently higher post take-off. Thus, there is mean reversion in growth rates but not in levels: The ratchet effect of big hits on export values observed in descriptive statistics is confirmed.

While all big hits experience tremendous growth during the take-off period, growth post take-off seems to return to baseline levels on average. Does this average hide large heterogeneity, with some big hit spells continuing to grow, some stabilizing and some collapsing? Figure 4 shows the distribution of growth rates during baseline, take-off and post take-off. While there is a clear shift to the right from baseline to take-off, there is no additional heterogeneity in growth rates in the post-take off period compared to the baseline; in fact, there is slightly *less*.

Figure 4: Distribution of growth rates during baseline, take-off and post-take off periods, big hits only



To sum up, big hits identified using our set of criteria (i) are rare events accounting for fewer than 10 per cent of long spells (7 years or more) and a negligible fraction of all spells in our dataset; (ii) matter for overall export growth, accounting for more than half of aggregate export growth in all countries in the sample except Kenya and Rwanda; (iii) are driven overwhelmingly by volume rather than price increases, and (iv) are not systematically followed by offsetting collapses. Thus, they constitute a natural object of policy attention.

3 What drives big hits?

3.1 What drives take-off? Supply vs demand shocks

We now turn to a first-pass exploration of where the drivers of big hits might be. One key aspect of our approach is that, rather than running a kitchen-sink regression of the probability of a big hit on possible determinants at the country and product level (comparative advantage, financial dependence and development, etc.), we selectively introduce fixed effects to pick up unobservable determinants that would be more likely, depending on their form, to be demand-side or supply-side ones. Fixed effects at the *dpt* level capture shocks within a destination-product-time cell, but shifting exports from all origins. We interpret them as demand shocks. Conversely, fixed effects at the *opt* level capture shocks within an origin-product-time cell, but shifting exports to all destinations. We interpret them as supply shocks. Our approach has two advantages. First, it takes full advantage of the large size and dimensionality of our dataset. Second, it goes around a traditional problem with most of the indicators used in the literature, which typically have substantial variation across either products or countries, but rarely have much variation over time. Our fixed effects are agnostic about what unobservables they pick up within broad categories, but they vary across both time and products/countries. Consider first the following regression:

$$g_{odpt} = \delta_{odp} + \delta_{ot} + \delta_{dt} + \beta_1 e_{odt} + \beta_2 I_{odpt}^{\text{big hit}} + u_{odpt}. \quad (4)$$

where δ_{odp} , δ_{ot} and δ_{dt} are fixed effects and e_{odt} is the bilateral exchange rate. The dependent variable is export growth at the $odpt$ level, and the key regressor is the big-hit dummy $I_{odpt}^{\text{big hit}}$. As big hits have, by construction, higher growth than normal, $\hat{\beta}_2$ must be positive and significant, and the regression is tautological. Note, however, that it is not a simple comparison of means since it includes dyadic controls, in the form of odp fixed effects, to control for time-invariant unobservables at the origin-destination-product level (distance, etc.), as well as fixed effects at the origin-year and destination-year levels to control respectively for aggregate supply and demand shocks in the exporting and destination country. It also includes the bilateral exchange rate e_{odt} , an obvious determinant of export variations. Basic descriptive statistics for the main variable in our dataset are reported in Table 8.

Table 8: Descriptive statistics, BACI export data

Variable	# observations	Mean	Std. Dev.	Median	min	max
growth	639,206	0.2	1.4	0.1	-12.3	14.2
ln value	748,771	4.0	2.3	3.8	-6.9	16.2
ln quantity	651,092	2.0	3.1	2.0	-12.9	18.0
ln unit value	651,092	2.0	1.8	1.9	-13.6	19.9
big hit dummy	748,771	0.0	0.2	0.0	0.0	1.0
sustained bh dummy	748,771	0.0	0.1	0.0	0.0	1.0
ln number firm	748,771	0.6	0.9	0.0	0.0	7.8
ln destination GDPpc	710,931	9.2	1.3	9.3	5.8	11.2
ln origin GDPpc	748,771	9.0	0.6	9.1	6.8	9.6
ln real exchange rate	582,172	0.3	3.0	0.5	-8.3	8.8

Notes: BACI trade data is used but the sample countries and years are restricted to those available in the customs data. Mineral products are excluded from the analysis. Growth computed as the log difference in export value, ln unit value, ln quantity, ln unit value and ln number of firms are at the origin-destination-product-year level; unit values are in current U.S. dollars and taken from BACI. GDP per capita are in current U.S. dollars, from the World Bank's World Development indicators. Real exchange rates are from the IMF's International Financial Statistics database.

Table 9 shows the results for the whole sample (columns 1 to 3) and by origin country. The regression for Rwanda cannot be estimated because of the small number of observations and small number of big hits. Results from our preferred regression in column (3) suggest that on average, export growth is 125 percentage points (pp) higher for big hits than normal.¹³ The coefficient is positive and significant for all countries taken individually and the magnitude of the effect varies from 68 pp for Bangladesh to 150 pp in the case of Uganda.

¹³ The effect is calculated as $e^{(0.81)} - 1 = 1.25$. This estimate is higher than the growth boost suggested by the descriptive statistics in Table 3 (91% on average, with a range from 76% for Bangladesh and 102% for South Africa) but in a similar range. Again, the two numbers are not fully comparable because of the inclusion of fixed effects and covariates.

Table 9: Baseline (tautological) specification

Dep. Var.: export growth	All countries			Bangladesh	Chile	Kenya	Morocco	Mexico	Uganda	South Africa
	(1)	(2)	(3)							
big hits	0.810a (0.016)	0.810a (0.015)	0.806a (0.015)	0.520a (0.040)	0.702a (0.032)	0.897a (0.144)	0.662a (0.064)	0.836a (0.024)	0.929a (0.240)	0.861a (0.028)
ln RER	0.015 (0.065)	0.111 (0.068)								
ln dest. GDPpc	-0.192 (0.169)									
ln orig. GDPpc		0.399 (0.280)								
Observations	501,926	520,013	520,013	16,583	65,004	19,649	33,899	159,112	3,978	221,389
R-squared	0.317	0.319	0.321	0.376	0.329	0.403	0.332	0.298	0.48	0.328
# spells	153,680	158,442	158,442	6,021	19,846	8,736	11,280	44,189	2,003	66,140
# big hits	5,703	5,815	5,815	382	679	93	198	2,739	36	1,688
Fixed Effects										
Origin-destination-product (<i>odp</i>)	Yes									
Origin-year (<i>ot</i>)	Yes		Yes							
Destination-year (<i>dt</i>)		Yes								

Note: BACI trade data is used but the sample countries and years are restricted to those available in the customs data. Mineral products are excluded from the analysis. Robust standard errors in parentheses. a: $p < 0.01$, b: $p < 0.05$, c: $p < 0.1$.

Against this baseline, consider a variant of (4) that includes destination-product-year fixed effects in order to control for unobservable time-variant demand shocks at the country-product level. Our estimation equation is now

$$g_{odpt} = \delta_{odp} + \delta_{ot} + \delta_{dpt} + \beta_1 e_{odt} + \beta_2 I_{odpt}^{\text{big hit}} + u_{odpt}. \quad (5)$$

If the introduction of δ_{dpt} kills the significance of $\hat{\beta}_2$, big hits are driven by unobservable product-level demand shocks in the destination country. Conversely, consider a variant of equation (4) with origin-product-year fixed effects:

$$g_{odpt} = \delta_{odp} + \delta_{opt} + \delta_{dt} + \beta_1 e_{odt} + \beta_2 I_{odpt}^{\text{big hit}} + u_{odpt}. \quad (6)$$

Again, if the inclusion of *opt* fixed effects destroys the significance of $\hat{\beta}_2$, big hits are driven by unobservable product-level supply shocks in the origin country.

Results are reported in Table 10. Columns (1) and (2) report our baseline results (the same as those in columns 2 and 3 of Table 9); Columns (3) to (6) report results when controlling for product-specific demand shocks (in various combinations with other fixed effects), and columns (7) and (8) report results when controlling for product-specific supply shocks.

Column (4) corresponds exactly to equation (5). Column (5) replaces *dpt* fixed effects by *dst* ones (destination-sector-year, where sector is defined at HS2 instead of HS6). Columns (3) and (5) omit *ot* fixed effects. Column (7) is close to estimation equation (6) but not exactly identical as it omits

dt fixed effects. The reason is that our database is asymmetric, with many more destinations than origins, so the inclusion of *dt* fixed effects in addition to all the other ones is much more demanding than the inclusion of *ot* ones and exceeds the computational capabilities of a standard computer, even in OLS. Column (8) replicates column (7) replacing *opt* fixed effect with *ost* ones. The stability of coefficients across columns (3) to (6) suggest that the inclusion of *ot* fixed effects does not drive the coefficient on our big hit dummy. Thus we can infer that the inclusion of *dt* fixed effects in columns (7) and (8) would be unlikely to affect the sign and significance of the coefficient on the big-hit dummy.

Table 10: Explaining take-off performance: Supply or demand shocks?

Dep. Var.: export growth	Baseline		Controlling for demand shocks				Controlling for supply shocks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
big hits	0.810a (0.016)	0.806a (0.015)	0.754a (0.068)	0.751a (0.067)	0.785a (0.016)	0.782a (0.016)	0.743a (0.020)	0.798a (0.016)
ln RER	0.015 (0.065)	-1.354 (214.485)	0.234 (0.185)	0.442 (38.930)	0.158b (0.074)	0.306 (17.471)	0.005 (0.062)	0.016 (0.065)
ln dest. GDPpc	-0.192 (0.169)						-0.200 (0.190)	-0.180 (0.172)
Observations	501926	520013	520013	520013	520013	520013	501926	501926
R-squared	0.317	0.321	0.924	0.924	0.412	0.413	0.490	0.328
N opd spells	153,680	158,442	158,442	158,442	158,442	158,442	153,680	153,680
N opd big hits	5,703	5,815	5,815	5,815	5,815	5,815	5,703	5,703
Fixed Effects								
Origin-destination-product (<i>odp</i>)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-year (<i>ot</i>)	Yes	Yes		Yes		Yes		
Destination-year (<i>dt</i>)		Yes						
Destination-product-year (<i>dpt</i>)			Yes	Yes				
Destination-sector-year (<i>dst</i>)					Yes	Yes		
Origin-product-year (<i>opt</i>)							Yes	
Origin-sector-year (<i>ost</i>)								Yes

Note: Robust standard errors in parentheses, a: $p < 0.01$, b: $p < 0.05$, c: $p < 0.1$.

Surprisingly, neither controlling for demand shocks (columns 3-6) nor for supply ones (columns 7-8) eliminates the significance of the big-hit dummy. Thus, the sharply higher growth of big hits seems to be driven by unobservable factors at the *odpt* level rather than either *opt* or *dpt*. They have to do not just with producer efficiency (capabilities) or consumer preference changes, but with the adequation of a given product with the demands of a given market at a given time, something very idiosyncratic.

It is possible that our test is too demanding in the following sense. Fixed effects at the *dpt* level capture demand shocks transmitted *simultaneously* to exporters in all origin countries. Similarly, fixed effects at the *opt* level capture supply shocks transmitted simultaneously to exports to all

destination countries. They might miss the sequential nature of shock diffusion. For instance, a demand surge in market d might be noticed first by well-informed exporters in origin o , after which other exporting countries discover the opportunity, possibly following spatial patterns of information diffusion and imitation (see e.g. Bahar, Hausmann and Hidalgo 2012). Similarly, a productivity shock at the opt level might generate first a breakthrough in market d , after which it diffuses to all other destinations. In both cases, one would expect to observe “cascading” big hits either across origin countries (for demand shocks) or across destinations (for supply shocks) within a few years.

Table 11: Cascading big hits

Dep. Var.: export growth	Cascading supply shocks				Cascading demand shocks	
	(1)	(2)	(3)	(4)	(5)	(6)
Product p already exported by o to d'	0.011 (0.100)	0.010 (0.102)	-0.002 (0.007)	-0.004 (0.007)		
Product p already exported by o to d' and was a big hit	0.037b (0.015)	0.034b (0.015)	0.034a (0.003)	0.034a (0.003)		
Product p already exported to d from o'					0.003c (0.002)	0.003c (0.002)
Product p already exported to d from o' and was a big hit					-0.003 (0.023)	0.002 (0.022)
ln RER	0.019 (0.030)	0.011 (2.594)	0.016a (0.006)	-0.319 (0.276)	0.012b (0.005)	0.011b (0.005)
ln orig. GDPpc	0.009 (0.135)		-0.036 (0.025)			
ln dest. GDPpc					0.049a (0.015)	0.050a (0.012)
Observations	673026	673026	673026	673026	651357	651357
R-squared	0.871	0.872	0.467	0.467	0.515	0.427
N opd spells	267,641	267,641	267,641	267,641	267,641	267,641
N opd big hits	5,815	5,815	5,815	5,815	5,815	5,815
Fixed Effects						
Origin-destination-product (odp)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-year (ot)		Yes		Yes		
Destination-product-year (dpt)	Yes	Yes				
Destination-sector-year (dst)			Yes	Yes		
Origin-product-year (opt)					Yes	
Origin-sector-year (ost)						Yes

We test for cascading demand shocks by estimating the probability of a big hit in the $odpt$ cell conditional on the occurrence of a big hit in a different cell $o'dpt'$ with $o' \neq o$ and $t' < t$, and for cascading supply shocks by estimating this probability conditional on the occurrence of a big hit in cell $od'pt'$ with $d' \neq d$ and $t' < t$. Given the large number of dummies, we estimate a linear probability model (i.e. OLS). Results are shown in Table 11.

The results are very strong on within-product, cross-destination, i.e. supply-side spillovers (columns 1-4), where the probability of observing a big hit is raised at the one-percent level of significance by the occurrence of a big hit for the same product in a different destination. Thus, our data suggests that big hits do spread, albeit slowly (the coefficient is small, although it must be interpreted cautiously since it is from an LPM) along supply-side lines. Columns (5)-(6) report no significant evidence of demand-shock diffusion across source countries for big hits. However this is not very surprising given the limited number of origin countries in our sample and the relative large distance (geography, languages etc...) between them. It would be surprising if a Mexican big hit in tomatoes on the US market trickled down to Kenya and trigger a big hit in that same destination market for that same product after just a few years.

3.2 Post-take off performance

We now carry over our approach to an analysis of post-take off performance, by running regressions similar to (5) and (6) but including dummy variables for post-take off periods and further decomposing post-take off periods to distinguish collapsing big hits from others. We say that a big hit collapses when the average export value during the post take-off period $[\tau + 3, \tau + 4, \tau + 5]$, \bar{v}_{odpt}^2 , is less than its average during the take-off, \bar{v}_{odpt}^1 . For spells that die before $\tau + 5$, we count the first year after death as zero value so as to take into account the drop in export value due to exit. Formally, let

$$I_{odpt}^- = \begin{cases} 1 & \text{if } \tau + 3 \leq t \leq \tau + 5 \text{ and } \bar{v}_{odpt}^2 < \bar{v}_{odpt}^1 \\ 0 & \text{otherwise} \end{cases}$$

and similarly for I_{odpt}^+ with the inequality sign reversed. The equivalent of (5) is

$$g_{odpt} = \delta_{odp} + \delta_{ot} + \delta_{dpt} + \beta_1 e_{odt} + \underbrace{\beta_2 I_{odpt}^{\text{big hit}}}_{\text{take-off}} + \underbrace{\beta_3 I_{odpt}^- + \beta_4 I_{odpt}^+}_{\text{post-take off}} + u_{odpt} \quad (7)$$

and the equivalent of (6) is the same equation with δ_{dpt} replaced by δ_{opt} . Results are shown in Table 12. The big-hit dummy, which marks take-off years, is always positive and significant, as before. The post-take off dummy, which marks the three years after the take-off, is negative and significant, showing that average growth after a take-off cools down to a level lower than the average level of the control group (big-hit spells in years other than take-off or post-take off and all other spells). This is consistent with Figure 3(a). The inclusion of either dpt or opt fixed effects (columns 2 and 4 respectively) fails to kill its significance, suggesting that neither universal demand

shocks (affecting all origins in the same way) nor universal supply shocks (affecting all destinations in the same way) explain the variation in post-take off performance.

Splitting big hits between collapsing ones and others does not change the result. The magnitude and significance of the dummies marking collapsing and non-collapsing post-take off periods (bust and boom respectively) is unaffected by the inclusion of *dpt* or *opt* fixed effects.

Table 12: Explaining post-take off performance: Supply or demand shocks?

Dep. Var.: export growth	(1)	(2)	(3)	(4)	(5)	(6)
big hit	0.791a (0.015)	0.746a (0.074)	0.728a (0.021)	0.775a (0.015)	0.727a (0.076)	0.714a (0.021)
bh post take-off	-0.057a (0.014)	-0.025 (0.066)	-0.054a (0.018)			
bh post take-off boom				0.123a (0.014)	0.130b (0.066)	0.104a (0.018)
bh post take-off bust				-0.414a (0.028)	-0.394a (0.130)	-0.389a (0.034)
ln RER		0.235 (0.185)	0.005 (0.062)		0.230 (0.185)	0.004 (0.062)
ln dest. GDPpc			-0.200 (0.190)			-0.207 (0.189)
ln orig. GDPpc		-0.301 (0.784)			-0.308 (0.782)	
Observations	520013	520013	501926	520013	520013	501926
R-squared	0.321	0.924	0.49	0.321	0.924	0.491
# spells	158'442	158'442	153'680	158'442	158'442	153'680
# big hits	5'815	5'815	5'703	5'815	5'815	5'703
Fixed Effects						
Origin-destination-product (<i>odp</i>)	Yes	Yes	Yes	Yes	Yes	Yes
Origin-year (<i>ot</i>)	Yes			Yes		
Destination-year (<i>dt</i>)	Yes			Yes		
Destination-product-year (<i>dpt</i>)		Yes			Yes	
Origin-product-year (<i>opt</i>)			Yes			Yes

Thus again, post-take off performance seems to be driven by idiosyncratic factors at the *odpt* level, although the same caveat applies, i.e. that *dpt* and *opt* fixed effects may be too stringent to capture shocks spreading over time on either the demand or the supply side.

4. Big hits and firm-level exports

In this section we rely on the firm-level data and examine the participation decisions of firms in big hits by matching spells identified as big hits in BACI data with customs data. We make the conservative choice of keeping only those spells meeting big-hit criteria in both datasets. This reduces drastically their number from 1,542,974 to 340,586 because of the data inconsistencies discussed in Section 2.1. Identifying big hits from product- rather than firm-level data spells filters out mergers and acquisitions (which could create artificial big-hits at the firm level) and volatility in firm-level exports due to the activity of trading houses which would cancel out at the product level.

4.1 Firm-level export growth during take-offs

Figure 5 shows the evolution of export value at the firm-product-destination level (in logs) in windows around the take-off year that are a little shorter than in Figure 3, because firm-level export spells are systematically shorter than product-level spells. Again, we use parameter estimates on year effects (years being coded in “analysis time”, i.e. relative to the take-off year). That is, the regression equation is

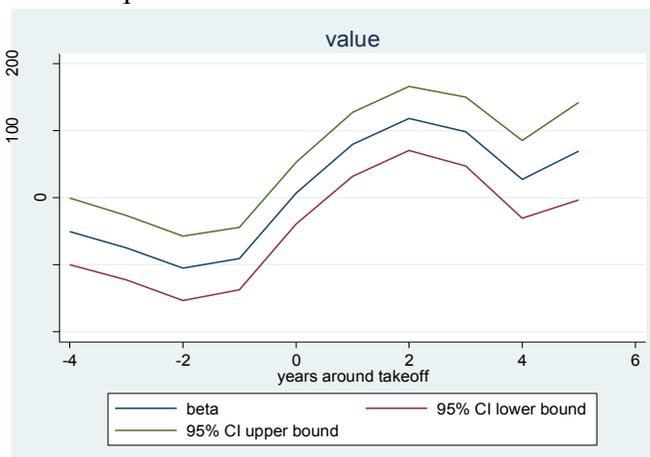
$$\ln v_{fpdt} = \sum_{k=-4}^5 I_{o(f)pdt}^k + \delta_t + \delta_{odp} + u_{fpdt} \quad (7)$$

where $o(f)$ is firm f 's origin country and $I_{o(f)pdt}^k$ is a dummy variable marking years around the take-off of big hit opd , defined by

$$I_{o(f)pdt}^k = \begin{cases} 1 & \text{if } t = \tau + k \text{ and } o(f)pdt \text{ is a big hit} \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Figure 5 shows a jump in export value similar to that of Figure 3, although there seems to be a topping off toward the end of the take-off period, against continued growth (albeit at a slower rate) at the product level.

Figure 5: Firm-product-destination value around the take-off year



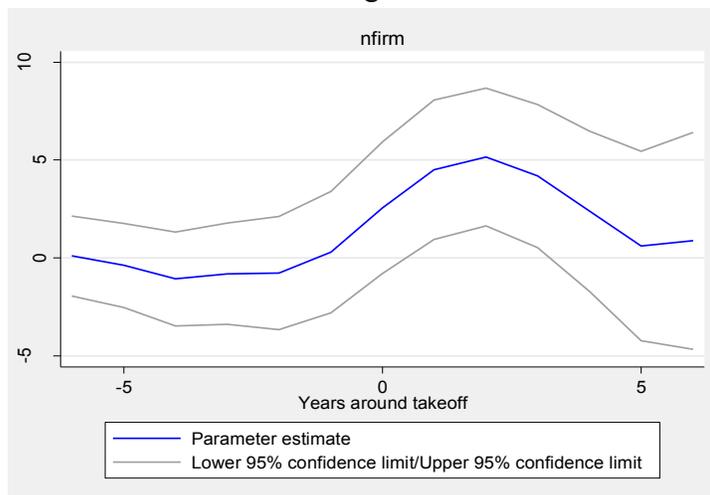
Note: Unbalanced sample. We also run regressions on a balanced sample of 7-year spells to avoid biasing our estimates. The results are qualitatively the same and are available upon request.

Thus, within firms, export values explode during the typical big hit, which is not entirely dissipated by entry, although the number of firms active in a big hit also rises during the take-off period, as we will see in the next section.

4.2 Identifying bandwagon effects

We now explore formally the dynamics of entry, diffusion and exit into and out of big hits. As a first pass, Figure 6 shows the number of firms exporting a big-hit product around the take-off year as the coefficient of a regression of the number of firms by *odpt* cell on analytical-time dummies as in Figure 5. The curve is suggestive of an increase in the number of firms involved in exporting big-hit products before and during its take-off followed by a reversal following year $t + 3$, possibly suggesting excessive entry and crowding out.

Figure 6: Number of firms in a big-hit cell around the take-off year



In order to test for cross-firm spillovers, our three variables of interest will be respectively the unconditional probability that firm f participates in a big-hit spell *odpt*, the probability that it does so conditional on the fact that it did not export big-hit product p before (entry), and the probability that it does so conditional on the fact that it already exported product p before (non-exit). We are interested in testing whether these probabilities correlate with the participation of another firm f' in a given big hit. Results are shown in Table 13. The probability that firm f exports product p to destination d goes up if another firm (of the same country) already does the same thing, but the effect is fifty times larger if product p is a big hit on d . Similarly, the probability that firm f enters market d with product p is higher if there is another firm of the same country already exports it, but the effect is twenty seven times larger if it is a big hit.

Table 13: Spillovers across firms, within product-destination

Dependent variable:	Prob that firm f exports BH product p from o to d in year t		Prob that f starts exporting BH product p from o to d at t (for the first time)		Prob that f continues to export BH product p from o to d at t (conditional on past export)	
	(1)	(2)	(3)	(4)	(5)	(6)
Regressors of interest (dummy variables)						
= 1 if product p already exported from o to d by at least one firm other than f , 0 otherwise	0.010*** (0.0001)	0.010*** (0.0001)	0.010*** (0.0001)	0.010*** (0.0001)	0.00004 (0.00003)	0.0002*** (0.00003)
<u>Interaction terms for BH</u>						
= 1 if product p already exported from o to d as a <u>BH</u> by at least one firm other than f	0.546*** (0.002)		0.277*** (0.003)		0.270*** (0.002)	
First year of take-off		0.766*** (0.002)		0.494*** (0.003)		0.273*** (0.003)
Second year of take-off		0.765*** (0.002)		0.366*** (0.004)		0.400*** (0.003)
Third year or post-take-off		-0.108*** (0.003)		-0.177*** (0.003)		0.069*** (0.002)
Obs.	2'888'132	2'888'132	2'888'132	2'888'132	2'888'132	2'888'132
Adj R2	0.577	0.720	0.364	0.458	0.236	0.305
Fixed effects	opd	opd	opd	Opd	opd	opd

Note: Robust standard errors in parentheses, a: $p < 0.01$, b: $p < 0.05$, c: $p < 0.1$.

Table 14: Bandwagon effects and crowding in

Dependent variable:	Prob that firm f exports BH product p from o to d in year t			Prob that f <u>starts</u> exporting BH product p from o to d at t (for the first time)			Prob that f <u>continues</u> to export BH product p from o to d at t (conditional on past export of opd)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
n_{odpt}^{-f}	4.32e-06*** (6.79e-08)			5.01e-06*** (6.91e-08)			-6.96e-07*** (1.72e-08)		
$n_{odpt}^{-f} \times I_{odpt}^{\text{big hit}}$	0.001*** (0.00001)			0.0005*** (0.00001)			0.0007*** (7.25e-06)		
$\ln(n_{odpt}^{-f})$		0.008*** (0.00008)	0.002*** (0.0001)		0.008*** (0.00008)	0.002*** (0.0001)		-0.0009*** (0.00003)	0.0002*** (0.00005)
$[\ln(n_{odpt}^{-f})]^2$			0.0008*** (0.00001)			0.001*** (0.00002)			-0.0002*** (7.89e-06)
$\ln(n_{odpt}^{-f}) \times I_{odpt}^{\text{big hit}}$		0.010*** (0.0005)	0.300*** (0.003)		0.043*** (0.0006)	0.175*** (0.003)		0.053*** (0.0004)	0.125*** (0.002)
$[\ln(n_{odpt}^{-f})]^2 \times I_{odpt}^{\text{big hit}}$			-0.039*** (0.0005)			-0.025*** (0.0006)			-0.014*** (0.0004)
Obs.	2'888'132	2'294'195	2'294'195	2'888'132	2'294'195	2'294'195	2'888'132	2'294'195	2'294'195
Adj R2	0.468	0.590	0.607	0.321	0.400	0.409	0.230	0.256	0.265
<u>Fixed effects</u>									
Origin-destination-product (odp)	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: Robust standard errors in parentheses, a: $p < 0.01$, b: $p < 0.05$, c: $p < 0.1$.

What is the size of the bandwagon effect? Let n_{odpt}^{-f} be the number of firms other than f having exported product p from o to d in the past. Table 14 explores the shape of the bandwagon effect as a function of the number of active exporters by fitting a second-degree polynomial in the log number of active firms. The estimates suggest that the bandwagon effect largely levels off at about a dozen active firms.

Interestingly, Table 15 shows that crowding in does not seem to lead, on average, to price collapses or to aggravate negative pecuniary externalities due to competition between national exporters. In Table 15, the dependent variable is the log of product p 's unit value when exported from origin o to destination d , using BACI's unit-value data. On average, a larger number of exporters of product p from origin o correlates with a lower unit value (first line), suggesting some degree of price-cutting competition between national exporters (economies of scale and other macro factors are likely to be absorbed by origin-destination-product and origin-year fixed effects). However, in the case of big hits, the effect is mitigated, although it is reversed only in column (1) which does not control for aggregate supply shocks (ot fixed effects). The interaction term's effect is weakened when limited to the take-off phase (columns 3 and 4) suggesting that it is strongest during the post-take off phase.

Table 15: Export prices and the number of participating firms

Dependent variable: ln (unit value)	(1)	(2)	(3)	(4)
ln (# of firms)	-0.113*** (0.00646)	-0.167*** (0.00560)	-0.110*** (0.00637)	-0.164*** (0.00560)
ln (# of firms) × big hit	0.135*** (0.0209)	0.0799*** (0.0203)		
ln (# of firms) × big hit during take-off			0.0890*** (0.00831)	0.0188*** (0.00626)
Observations	267,452	267,452	267,452	267,452
R-squared	0.003	0.047	0.004	0.047
Number of opd cells	32,923	32,923	32,923	32,923
<u>Fixed effects</u>				
Origin-Destination-Product (odp)	Yes	Yes	Yes	Yes
Origin-year (ot)	No	Yes	No	Yes
Year (t)	Yes	No	Yes	No

Note: Robust standard errors in parentheses, a: $p < 0.01$, b: $p < 0.05$, c: $p < 0.1$.

Table 16 revisits the issue of whether big hits are driven by unobservable supply-side events (technology adoption or improved management practices) but at the firm level, by regressing the same three dependent variables (probability of participation in, entry into and non-exit from a big hit) on (i) past export of the same product by the same firm in a different destination and (ii) past participation of the same firm in a big hit of the same product in a different destination. The experiment controls for heterogeneity between firm-destination pairs (say, whether a firm has a distribution network in a destination but not in another) through origin-firm-destination fixed effects; i.e. it is carried out “within firm-destination”, and measures how much does the probability

of product p being a big hit in a given destination rises after p becomes a big hit in a different destination. At 0.046 (column 2, second line), the probability of entry into a new big hit is eight times higher if firm f already participated in a big hit of the same product in a different destination than if it had just exported that product somewhere else without it being a big hit. Thus, there is some evidence, at the firm level, that a firm that introduced a big hit in a destination is more likely to introduce the same product in a different destination and to participate again in a big hit, confirming the “cascading” of big hits in Table 11.

Table 16: Supply-side big hits revisited

Dependent variable:	Prob that firm f exports BH product p from o to d in year t	Prob that f <u>starts</u> exporting BH product p from o to d at t (for the first time)	Prob that f <u>continues</u> to export BH product p from o to d at t (conditional on past export of opd)
	(1)	(2)	(3)
= 1 if firm f from o already exported product p to at least one other destination d' other than d in the past (0 otherwise)	0.009*** (0.0003)	0.006*** (0.0007)	0.006*** (0.0007)
<u>Interaction terms for BH</u> (= 1 if firm f from o already exported BH product p to at least one other destination d' other than d in the past)	0.016*** (0.001)	0.046*** (0.003)	0.014*** (0.001)
Obs	2888132	1834878	1053254
Adj R2	0.071	0.020	0.134
<u>Fixed effects</u>			
Origin-firm-product (ofd)	yes	yes	yes

Note: Robust standard errors in parentheses, a: $p < 0.01$, b: $p < 0.05$, c: $p < 0.1$.

At this stage, we cannot distinguish between two narratives: one in which a firm simply participates in a big hit and one in which it is responsible for the big hit. As a first pass at the issue, we ask whether firms learn from past success. If they do, participation in a big hit is not entirely passive. Table 17 reports the results of regressions of the probability of export, entry and non-exit (as before) on past export and past big-hit export of a different product to the same destination. The experiment, which mirrors the previous one (different product in the same destination instead of same product in a different destination) controls for heterogeneity between firm-product pairs (“capabilities”) through origin-firm-product fixed effects.¹⁴ Past export in the same destination raises the probability of participating in a big hit, but past participation in a big hit in that destination raises it much more, the effect being again highly significant and large in spite of the

¹⁴ These firm-level unobservables may be crucial determinants of a firm’s ability to introduce big hits (think of Apple introducing repeatedly big-hit products such as the ipod, iphone etc.) and would deserve in themselves a separate examination; however, this would require data on firm characteristics going beyond our customs data.

infrequency of big hits. For instance, the probability of direct entry into a big hit (column 2) conditional on past participation in a big hit is five times higher than the same probability conditioned only on past export to the same destination. Thus, so far the evidence is suggestive of strong “learning from success”.

Table 17: Jumping from one big hit to another?

Dependent variable:	Prob that firm f exports BH product p from o to d in year t	Prob that f <u>starts</u> exporting BH product p from o to d at t (for the first time)	Prob that f <u>continues</u> to export BH product p from o to d at t (conditional on past export of opd)
	(1)	(2)	(3)
= 1 if firm f already exported at least one product other than p from o to d in the past (0 otherwise)	0.009*** (0.0003)	0.010*** (0.0007)	0.005*** (0.0007)
<u>Interaction terms for BH</u> (= 1 if firm f already exported at least one BH product other than p from o to d in the past)	0.013*** (0.001)	0.049*** (0.004)	0.029*** (0.002)
Obs	2888132	1834878	1053254
Adj R2	0.192	0.175	0.155
<u>Fixed effects</u>			
Origin-firm-product (ofp)	yes	yes	yes

5. Concluding remarks

Our approach has allowed us to identify events that are at the same time rare and policy-relevant by their large influence on aggregate export growth rates. In itself, the finding that aggregate export growth proceeds in discrete leaps and bounds at the product-destination level is worth noting. So far, the literature on the composition of exports had highlighted the extreme concentration of export *levels* in terms of products (Easterly and Resheff 2009) and in terms of firms (Freund and Pierola 2012a). We find that the dynamics of export *growth* displays a similarly disproportionate influence of rare surge events at the product-destination level.

Being rare, these events are difficult to predict *ex ante*; however, *ex post*, they become easy to identify and may thus be realistic objects of policy attention. If their study could highlight some—even limited—stylized facts, it could help identify policy interventions that could, for instance, enhance their sustainability or prevent their collapse.

Being based on a limited sample by data and computational limitations, our exploration can only be preliminary. At this stage, it suggests the following observations. First, the typical big hit does not

involve multiple exporting countries at the same time because a “generic” business opportunity has appeared in a given foreign market. Nor does it happen simultaneously in several destination markets for a given exporting country because it is undergoing a technology transition or a positive supply shock in any given sector. Big hits seem to be idiosyncratic to origin-destination-product cells. Second, and as a slight counterpoint to the first observation, once an exporting country has undergone a big hit in a product-destination pair, it is more likely to undergo another big hit for the same product in other destination markets in the future, even after controlling for aggregate supply conditions by exporter-time fixed effects. Thus, there seems to be something both supply-side and product-specific in big hits.

At the firm level, big hits generate strong bandwagon effects across firms in their first years, and the crowding-in, on average, does not lead to a price collapse. Firms seem to learn from success, as the probability of placing a big hit rises cumulatively after controlling for time-invariant unobservables at the firm-product-destination level. Similarly, placing a big hit rises the probability that a firm will participate in a big hit with the same product in a different destination. All these results are derived with powerful arrays of fixed effects and are highly significant.

Thus, although big hits may be difficult or impossible to predict *ex ante*, once they are rolling, being rare events, they should be easy to identify from a simple real-time watch of export statistics. As seem to generate externalities and learning effects, there may thus be a case for actively monitoring big hits *ex post*, and, in view of the observation in Cadot et al. (2012) that clustering of exporters seems to improve their survival, to encourage the dissemination of information about export success.

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