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EXPORT BIG HITS

Self-discovery, demand shocks, or idiosyncratic?

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Export big hits : Self-discovery, demand shocks, or idiosyncratic?[1]

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Abstract

This paper identifies sudden surges in export value at the origin-destination-product-time level using international trade statistics combined with firm-level customs data for eight developing and emerging countries. These "big hits" are rare events (less than 5% of 7-year or more export spells), yet account for over half the growth of aggregate exports. We find that they are neither purely demand-driven nor purely supply-driven, although they seem to "cascade" within products across destinations. They typically generate strong bandwagon effects across firms without crowding in leading to price collapses; however, there is no evidence that firms involved in one big hit are any more likely to participate in another one in the future.

JEL codes: F13, F14, F15

Keywords: Export, big hits, firms, externalities.

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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 countries—jumped from \$7 million to over \$40 million per year, accounting for half of the group's sales; based on current investment plans, the group expect to export over \$100 million in coming years. It 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. Worse, a top-down approach identifying successes from trade statistics would entirely miss the Roofings' Group's success, as most of its export sales go to the Democratic Republic of Congo, South Sudan and Burundi through largely recordless overland border posts. The Roofings' Group does not exist in trade statistics. Is the Roofings' Group story representative of the utter unpredictability of export success?

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 there 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? Not so fast. For all the unpredictability of export success, a growing empirical literature shows that government intervention in the form of export promotion invariably 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 (2012) to define export surges at the aggregate level, we define origin-destination-product surges, which we call "big hits", that represent fewer than 5% of long (seven-year or more) origin-destination-product spells and a negligible proportion 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.

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 selectively use 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 them. 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 productivity improvements across destinations. In practice, the low frequency of our big hits limits, by construction, the scope for repetition.

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). Within firms, we do not find evidence of a spillover of big hits across products. That is, once we control for time-invariant firm-level unobservables, participating in a big hit does not seem to make a firm more likely to hit another time. Again, the low frequency of big hits limits, by construction, the power of the test.

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 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. Section describes the data and the criteria used to construct big hits. Section 3 explores their determinants. Section 4 explores the firm-level dynamics. 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 focus our analysis on eight developing countries, Bangladesh, Chile, Kenya, Mexico, Morocco, Rwanda and Uganda.Our sample period is determined by the availability of matching customs data (see below).

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 both from BACI and from COMTRADE's direct export data.[3] The sample size and sample period for the BACI and 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

Basic descriptive statistics for BACI data are shown in Table 2.

Table 2: Descriptive statistics, BACI export data

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

[3] 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.

Variable	# observations	Mean	Std. Dev.	Median	min	max
ln unit value	741,745	-4.4	2.6	-4.8	-19	10.8
ln number firm	742,469	0.6	0.9	0.0	0	7.8
ln GDPpc destination	704,669	9.2	1.3	9.3	5.8	11.2
ln GDPpc origin	742,469	9.0	0.6	9.1	7.0	9.6
ln real exchange rate	576,502	0.2	3.0	0.5	-8.3	7.7

Notes: Ln unit value and ln number of firms 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.

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 160,393 such spells, accounting for 62 per cent of total trade flows in the sample. On this subset of long spells, we define big hits as three-year sudden accelerations at the origin-destination-product level using five independent criteria. This strong array of criteria allows us to filter out many pathological situations.

Notation

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

$$g_{odpt} = \ln\left(v_{odpt}\right) - \ln\left(v_{odp,t-1}\right)$$

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.[4] Let

$$g^1_{odpt} = \ln\left(v_{odp,t+3}\right) - \ln\left(v_{odpt}\right)$$

be total growth between t and $t+2$. Let $\overline{g}^1_{odpt}$ be the average growth during the same period, and let $\overline{g}^0_{odpt}$ be the average growth from $t-3$ to $t-1$. The years after t identify a takeoff period and the three years before a baseline period. We define similarly $\overline{v}^1_{odpt}$ and $\overline{v}^0_{odpt}$, the average value of origin

[4] One issues with identifying big export hits, is the time we allow for exports of a given origin-destination-product flow to grow. By imposing that spell be at least 7 years and that big hits be initiated in the third year onward, we de facto exclude instances of export success that occur within less than three years, the so called "born big". In practice there are only few of such cases in our dataset. In addition, such instances are likely to correspond to foreign firms entry in the domestic market or firms mergers or acquisition, which we precisely want to filter out.

o's exports of product p to destination d in the take-off and baseline period, and s^1_{odpt} and s^0_{opdt}, origin o's market share in imports of product p in destination d.

Criteria

We define "big hits" as origin-destination-product (*odp*) spells satisfying the following five criteria: Criterion C1 requires average growth during a three-year (or more) take-off to be at least 6 per cent (see Freund and Pierola, 2012, for a discussion in the context of aggregate export surges).

C1 (growth over 6 per cent during take-off) $\bar{g}^1_{odpt} \geq 0.06$.

Criterion C2 requires average growth during take-off to be at least 30 per cent higher than during the baseline period.[5]

C2 (growth acceleration) $\bar{g}^1_{odpt} \geq 1.3\, \bar{g}^0_{odpt}$.

C3 requires country o's average market share in imports of product p into destination d during take-off to be at least 30 per cent higher than before, ruling out purely demand-driven surges:

C3 (market-share increase) $\bar{s}^1_{odpt} > 1.3\, \bar{s}^0_{odpt}$.

C4 requires that average export value during take-off be over a "significant size" cutoff λ set alternatively at U.S. $500'000 or one million, ruling out very small surges.

C4 (significant size)

$$\bar{v}^1_{odpt} \geq \lambda .$$

Finally, C5 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 $\tilde{v}^1_{odpt} = \min\left(v_{odp,t+1}, v_{odp,t+2}, v_{odp,t+3}\right)$, and $\tilde{v}^0_{odpt} = \max\left(v_{odp,t-1}, v_{odp,t-2}, v_{odp,t-3}\right)$.

C5 (stability) $\tilde{v}^1_{odpt} \geq \tilde{v}^0_{odpt}$.

Let τ_{odp} be the first year in the sample that meets C1-C5 for cell *odp*, and suppose that at least two years after τ_{odp} also meet C1-C5. Then cell *odp* is undergoing a big hit, and we define its take-off as τ_{odp} and the following two or more years. We call τ_{odp} the "initiation year", and the length of the big hit is at least six years (the three years making the baseline period, τ_{odp} itself, and the two following years during which take-off takes place). If more than two years after τ_{odp} meet C1-C5, the big hit is called a sustained one and its length is more than six years.

If two years meet criteria C1-C5 while being distant by over three years with a gap in between, we have a case of multiple big hits. That is, suppose that 2000 is the initiation year of a non-sustained

[5] 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.

big hit, 2001 and 2002 being its take-off years; suppose also that 2003 has no growth and 2004 sees again the initiation of a take-off. In that case, we have a sequence of two big hits for the same *odp* cell.

Criteria 1-5 limit the number of spells to 7,691 out of a total of 160,393 spells of seven years or more during our sample period (4.79 per cent). Their distribution in terms of duration is shown in Table 3. As noted, a given *odp* spell can have several big hits; thus, the first column reports data for the first big hit, the second for the second big hit, and so on. Most export spells have a single big hit: Only 8 per cent of the 7,691 spells have multiple episodes. Unsurprisingly, the frequency of take-offs in terms of their length drops very rapidly beyond three years. This is largely due to censoring, as we retain from BACI only those years for which we have customs data.

Table 3: Distribution of big hits, by length

Big hit takeoff period length (in years)	Multiple big hit spells			
	First in spell	Second in spell	Third in spell	All big hits
3	5,858	536	6	6,400
4	899	105	5	1,009
5	214	27	0	241
6	29	1	0	30
7	9	1	0	10
9	1	0	0	1
Total	7,010	670	11	7,691

How important are big hits in aggregate export performance? Table 4 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.[6] To clarify what Table 4 does, let $V_{ot} = \sum_p \sum_d v_{odpt}$ be aggregate exports (excluding commodities).[7] By construction, the net change in aggregate exports from t-1 to t is the sum of net changes at the destination-product level:

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

Note that, in (1), we take first differences of dollar values without taking logs. We do not treat product entries ($v_{odp,t-1} = 0$) and exits ($v_{odpt} = 0$) differently than intensive-margin variations. In

[6] By construction, big hits require seven years (three years for the baseline period and four years for the big hit itself) so censoring affects their share three years after the start of the sample period and three years before its end. Only years in the middle are uncensored.

[7] 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.

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 4 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, we do not report it when total aggregate export growth (big hits and non-big hits) G_{ot} is negative in order to avoid negative ratios. The omission of negative-export growth years at the country level 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 4 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 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, surprisingly, only 15% in Rwanda. Thus, all in all, big hits as we define them are rare but highly significant drivers of export growth.

Table 4: Contribution of big hits to export value and growth, by origin country

	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	0.03
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	neg. growth	neg. growth	neg. growth	neg. growth	neg. growth	neg. growth	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	-0.08	neg. growth	0.02	neg. growth	0.00	neg. growth	neg. growth
Average	*0.74*	*0.37*	*0.27*	*0.65*	*1.54*	*0.15*	*0.62*	*0.36*

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.

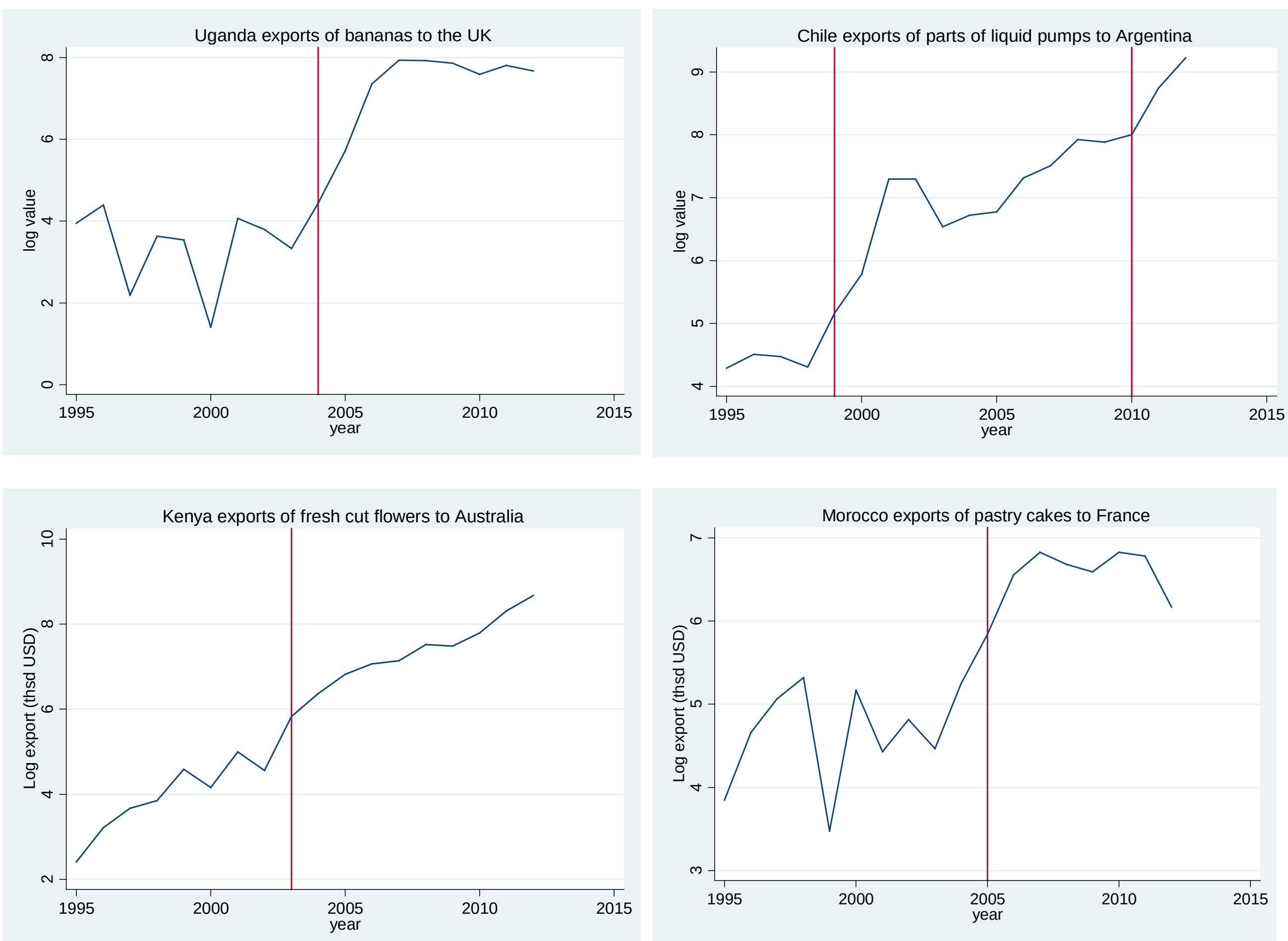
Table 5: Top big-hit sectors, by country

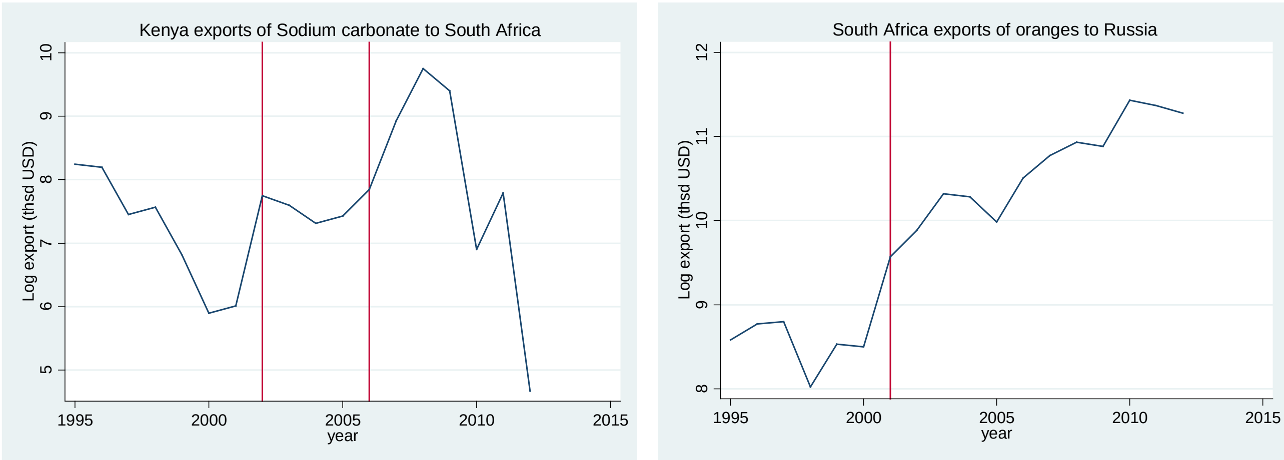
Origin country															
Bangladesh		Chile		Kenya		Morocco		Mexico		Rwanda		Uganda		South africa	
Textiles	1,051	Textiles	1,051	Vegetable Products	95	Textiles	441	Machinery / Electrical	2,342	Vegetable Products	9	Vegetable Products	40	Machinery / Electrical	795
Footwear / Headgear	48	Footwear / Headgear	48	Products of Chemicals	37	Vegetable Products	146	Products of Chemicals	933			Animal & Animal Product	21	Metals	739
Raw Hides, Skins, Leather	39	Raw Hides, Skins, Leather	39	Prepared Foodstuffs	31	Machinery / Electrical	137	Metals	588			Prepared Foodstuffs	16	Products of Chemicals	525
Animal & Animal Product	28	Animal & Animal Product	28	Textiles	22	Prepared Foodstuffs	68	Plastics / Rubbers	529			Metals	9	Prepared Foodstuffs	319
Prepared Foodstuffs	18	Prepared Foodstuffs	18	Metals	20	Animal & Animal Product	56	Optical & Medical Instruments	432			Products of Chemicals	5	Transportati on	318
Total # big hits	1,230		1,603		293		1,097		6,893		9		102		4,061
# opd spells > 7 years	5,889		15,810		5,265		10,795		46,905		90		889		56,469

Note: Commodities excluded from the analysis.

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-country level. The vertical line in each case is the "initiation year", i.e. the first year of the take-off period. The following two years are the take-off period over which criteria 1-5 apply, whereas the three preceding ones constitute the baseline 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 : Export values are computed at the origin-destination-hs6 product level.

How much of our big hits is accounted for by pure price variation vs. quantity variation? 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

$$g_{odpt} \equiv \Delta \ln v_{odpt} = \Delta \ln p_{odpt} + \Delta \ln q_{odpt} . \tag{2}$$

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.[8] Figure 2 shows a scatterplot of the RHS of (2) against its LHS. The fit is strikingly bad, but most of the noise is in relatively small items, so that cross-product averages of the two sides of (2) are not so far away from each other.

Figure 2: Product-level growth in quantity and unit value against growth in quantity

[8] 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.

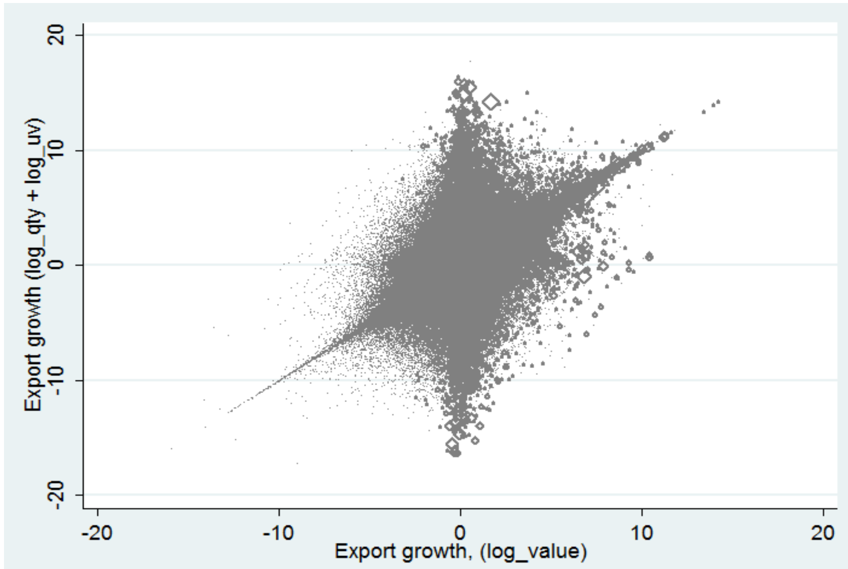


Table 6 shows the decomposition averaged over all products (first line) and big hits in the take-off phase only (second line). For all products, the RHS of (2) (the sum of the log-change in quantities and prices), i.e. 0.05 + 0.03, adds up to just the LHS (0.08), and quantity variation accounts for 56% 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% 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

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

To sum up, big hits (i) account for fewer than 5% of long spells (7 years or more) and a negligible fraction of all spells; (ii) account for more than half of aggregate export growth in all countries in the sample except Rwanda; (iii) are driven overwhelmingly by volume increases. Thus, they constitute a natural object of policy attention.

3 What drives big hits?

We now explore in an agnostic way where the possible drivers of big hits might lie. As explained in the introduction, 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 the nature of the fixed effects, to be demand-side or supply-side ones.

Consider first the following regression:

$$g_{odpt} = \delta_{odp} + \delta_{ot} + \delta_{dt} + \beta_1 e_{odt} + \beta_2 I_{odpt}^{\text{big hit}} + u_{odpt} \tag{3}$$

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 we constructed big hits so as to ensure that they had 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.) and 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. Table 7 shows the results for the whole sample (column 1) and by origin country. On average, export growth is 77.9 percentage points higher for big hits than normal.

Table 7: Baseline (tautological) specification

Sample Dep. Variable: g_{odpt}	All	Bangladesh (1)	Chile	Kenya	Morocco	Mexico	Rwanda	Uganda	South Africa
Big hit	0.779a	0.565a	0.705a	0.786a	0.737a	0.782a	0.350	0.814a	0.830a
	-0.02	-0.03	-0.05	-0.06	-0.05	-0.02	-0.81	-0.15	-0.02
ln (RER)	-0.007								
	-0.02								
ln (dest. GDP pc)	0.019								
	-0.07								
Observations	1'939'835	80'586	229'446	91'009	118'497	643'508	1'658	18'139	815'461
R-squared	0.133	0.198	0.157	0.186	0.21	0.133	0.411	0.26	0.134
Fixed effects									
Origin-destination-product (*odp*)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-year (*ot*)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-year (*dt*)	No	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

Against this baseline, consider a variant of (3) that includes destination-product-year fixed effects in order to control for unobservable time-variant demand shocks at the country-product level. That is,

$$g_{odpt} = \delta_{odp} + \delta_{ot} + \delta_{dpt} + \beta_1 e_{odt} + \beta_2 I_{odpt}^{\text{big hit}} + u_{odpt} . \tag{4}$$

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 with origin-product-year fixed effects:

$$g_{odpt} = \delta_{odp} + \delta_{opt} + \delta_{dt} + \beta_1 e_{odt} + \beta_2 I_{odpt}^{\text{big hit}} + u_{odpt} \,. \tag{5}$$

Again, if they kill the significance of $\hat{\beta}_2$, big hits are driven by unobservable product-level supply shocks in the origin country. Results are shown in Table 8. Column 3 corresponds exactly to estimation equation (4). Column 4 replaces *dpt* fixed effects by *dst* ones (destination-sector-year, where sector is defined at HS4 instead of HS6). Columns 5 and 6 omit *ot* fixed effects. Column 7 is close to estimation equation (5) 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 in addition to all the other ones is much more demanding than that of *ot* ones and exceeds the computational capabilities of a standard computer, even in OLS. The stability of coefficients across columns 3-6 makes it unlikely that this drives the sign and significance of the coefficient on the big-hit dummy.

Table 8: Supply or demand shocks?

Sample: All countries Dep. Variable: g_{odpt}	Baseline (1)	 (2)	 (3)	Demand shocks (4)	 (5)	 (6)	Supply shocks (7)
Big hit	0.810a	0.806a	0.751a	0.782a	0.754a	0.785a	0.743a
	(0.015)	(0.015)	(0.066)	(0.016)	(0.067)	(0.016)	(0.020)
ln (dest. RER)	0.015	-2.420	0.499	0.932	0.234	0.158b	0.005
	(0.064)	(278.9)	-45.73	-18.95	(0.181)	(0.073)	(0.061)
ln (dest. GDP pc)	-0.192						-0.200
	(0.166)						(0.186)
ln (orig. GDP pc)					-0.297	-0.011	
					(0.767)	(0.281)	
Observations	480'679	498'331	498'331	498'331	498'331	498'331	480'679
R-squared	0.255	0.261	0.918	0.362	0.917	0.361	0.445
N *odp* spells	80114	83345	83345	83345	83345	83345	80114
N *odp* big hits	6924	7048	7048	7048	7048	7048	6924
Fixed effects							
Origin-destination-product (*odp*)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-year (*ot*)	Yes	Yes	Yes	Yes			
Destination-year (*dt*)		Yes					
Destination-product-year (*dpt*)			Yes		Yes		
Destination-sector-year (dst)				Yes		Yes	
Origin-product-year (*opt*)							Yes

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 (column 7) kills 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 indeed.

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.

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 9.

Table 9: Cascading big hits

Sample: All countries	(1)	(2)
Dep. Var.: $\Pr\left(I_{odpt}^{\text{big hit}}=1\right)$		
Product p already exported to d from o'	0.003c	
	(0.002)	
Product p already exported to d from o' and was a big hit	-0.003	
	(0.022)	
Product p already exported by o to d'		0.011
		(0.093)
Product p already exported by o to d' and was a big hit		0.037a
		(0.014)
ln (RER)	0.012b	0.019
	(0.005)	(0.028)
ln (origin GDP pc)	0.049a	
	(0.014)	
ln (dest. GDP pc)		0.009
		(0.125)
Observations	562'509	582'172
R-squared	0.510	0.870
N *odp* spells	131'164	135'073
N *odp* big hits	5'666	5'777
Fixed effects		
Origin-Destination-Product (*odp*)	Yes	Yes
Origin-Product-Year (*opt*)	Yes	
Destination-Product-Year (*dpt*)		Yes

The result is very strong on within-product, cross-destination (i.e. supply-side) spillovers, where the probability of observing a big hit is raised at the 1% 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.

4. Big hits and firm-level exports

4.1 Value and unit-value patterns during take-offs

We now identify firm participation 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 11’568 to) 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, as those would cancel out at the product level.

Figure 3 shows the evolution of value and unit value at the firm-product-destination level (in logs) in relatively long windows around the take-off year, using parameter estimates on year effects (years being coded in “analysis time”, i.e. relative to the take-off year). That is, the regression equation for export values is

$$\ln v_{fpdt} = \sum\nolimits_{k=0}^{6} \delta_{\tau-k} + \sum\nolimits_{k=1}^{6} \delta_{\tau+k} + u_{fpdt} \tag{5}$$

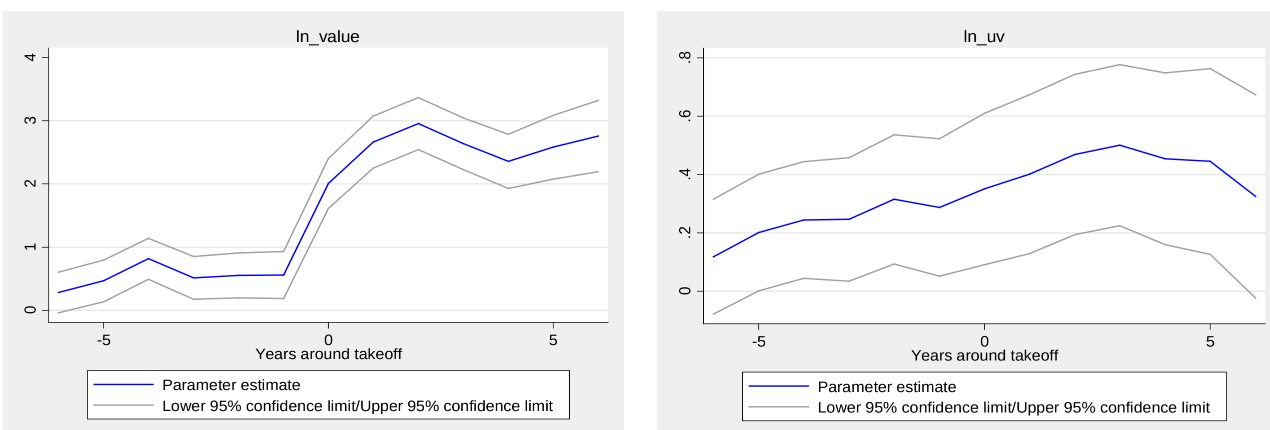
where $\delta_{\tau-k}$ and $\delta_{\tau+k}$ are dummy variables marking years around the take-off, defined by

$$\delta_{t-k} = \begin{cases} 1 & \text{if } t = \tau - k \text{ and } (pdt) \text{ is a big hit} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

and similarly for δ_{t+k}. The regression for unit values is the same. Panel (a) display the jump in export value apparent at the product level. Panel (b) suggests that unit values seem to grow slightly faster over the three-year take-off period (τ to $\tau + 3$, where τ is normalized at zero in the figure) than over the baseline period ($\tau - 3$ to τ).

Figure 3: Firm-product-destination value and unit value around the take-off year

(a) ln export value per firm (b) ln export unit value

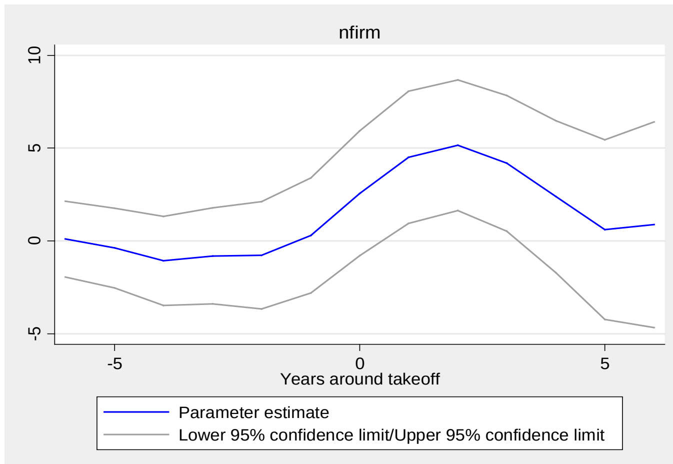


Note: Unbalanced sample. We also run regressions on a balanced sample of 7-year spells to avoid biasing our estimates. The results are qualitatively the same and are available upon request.

4.2 Identifying bandwagon effects

We now explore whether big hits display discernible patterns of single-firm export discovery followed by imitators or of simultaneous discovery by a group of firms. As a first pass, Figure 4 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 3. The line 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 4: Number of firms in a big-hit cell around the take-off year



We now test formally for the dynamics of entry, diffusion and exit into and out of big hits. In order to test for cross-firm spillovers, our three variables of interest are 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 10. 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.

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 11 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 of active firms.

Table 10: 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)
Interaction terms for BH						
= 1 if product *p* already exported from *o* to *d* as a BH 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

Table 11: 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* 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 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)		
$\ln\left(n_{odpt}^{-f}\right)$		0.008*** (0.00008)	0.002*** (0.0001)		0.008*** (0.00008)	0.002*** (0.0001)		-0.0009*** (0.00003)	0.0002*** (0.00005)
$\left[\ln\left(n_{odpt}^{-f}\right)\right]^2$			0.0008*** (0.00001)			0.001*** (0.00002)			-0.0002*** (7.89e-06)
$\ln\left(n_{odpt}^{-f}\right) \times I_{odpt}^{\text{big hit}}$		0.010*** (0.0005)	0.300*** (0.003)		0.043*** (0.0006)	0.175*** (0.003)		0.053*** (0.0004)	0.125*** (0.002)
$\left[\ln\left(n_{odpt}^{-f}\right)\right]^2 \times I_{odpt}^{\text{big hit}}$			-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
Fixed effects									
Origin-destination-product (*odp*)	yes	yes	yes	yes	yes	yes	yes	yes	yes

Interestingly, Table 12 shows that crowding in does not seem to lead, on average, to price collapses. In Table 12, 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, and particularly during the take-off phase, more exporters correlate with higher export prices, suggesting that crowding in does not undo the root causes of the big hit.

Table 12: Export prices and the number of participating firms

Dependent variable: ln (unit value)	(1)	(2)	(3)	(4)
ln (# of firms)	-0.113***	-0.167***	-0.110***	-0.164***
	(0.00646)	(0.00560)	(0.00637)	(0.00560)
ln (# of firms) × big hit	0.135***	0.0799***		
	(0.0209)	(0.0203)		
ln (# of firms) × big hit during take-off			0.0890***	0.0188***
			(0.00831)	(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
Fixed effects				
Origin-Destination-Product (*odp*)	Yes	Yes	Yes	Yes
Origin-year (*ot*)	No	Yes	No	Yes
Year (t)	Yes	No	Yes	No

Finally, we explore whether some firms are "repeat big-hitters", suggesting a learning effect across products (permanent, unobservable firm characteristics are absorbed by origin-destination-firm fixed effects). Results are shown in Table 13. Participation in a big hit reduces the probability of participating in another big hit, failing to support, at this stage, the notion of "learning from success".

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. The study of these events, if it can highlight some—even limited—stylized facts, can contribute to the ongoing debate about whether there is enough in export success that is deterministic and predictable to justify targeted government interventions.

Table 13: 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* 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 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)	0.017*** (0.0002)	0.016*** (0.0002)	0.023*** (0.0009)
Interaction terms for BH (= 1 if firm f already exported at least one BH product other than p from o to d in the past)	-0.078*** (0.001)	-0.071*** (0.002)	-0.088*** (0.002)
Obs	2888132	1834878	1053254
Adj R2	0.080	0.0136	0.1456
Fixed effects			
Origin-destination-firm (*ofd*)	yes	yes	yes

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 of any kind. 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. Third, 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. There may thus be a limited case for monitoring this kind of event 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—albeit at the risk of reducing the appropriability of export entrepreneurship.

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