Do exporters learn from one-off exporting?

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Abstract

The internationalization of firms is regularly viewed through the lens of learning, yet the process is nonlinear, with frequent de- internationalization events. In our data, following 6,031 Danish firms over 20 years in administrative registers of monthly export transactions, we identify 870,221 newly started firm-country-product export spells, of which a stunning 35% are one-off (unprecedented and unrepeated) export events. We ask if these potentially costly but immediately abandoned engagements provide firms' an opportunity to improve future export prospects or if they are simply experimentation. We employ a mathematical formulation of learning to export in the country and the product dimension. Conceptually, we separate previous exporting into spells of successful (at least once) recurrent exporting and one-off exports and hypothesize that, from a learning perspective also the latter will affect (albeit at a lower level) the firm's probability of starting new export spells, but not so from an experimentation perspective. Using conditional probability analysis, we find that one-off exporting indeed improves future prospects. The effects are smaller than those from recurring exporting, but larger than the effects from import experience. Based on dynamic simulation we illustrate how effects from one-off exporting can accumulate to lasting internationalization.

Keywords: Learning; experiential knowledge; export duration; sporadic; unsolicited; experimentation; firm-level data; transactions data.

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1 Introduction

Johanson and Vahlne's (1977) seminal theoretical explanation of a firm's development of international operations has among many other things provided the foundations for viewing internationalization through the lens of learning processes and has trigged a rich stream of research (Vahlne and Johanson, 2017). In parallel, research has identified and studied export market exit, failed internationalisation strategies, false starts, sporadic or unsolicited exports and many other phenomena surrounding discontinued and short export engagements (Welch and Wiedersheim-Paul, 1980; Leonidou et al., 2010). With access to large-scale administrative data, such as customs data, researchers have documented a surprisingly high frequency of short and very short export spells (Békés and Muraközy, 2012).

The current study examines the phenomenon of short export spells in its extreme form and singles out episodes of one-off export sales (Geishecker, Schröder and Sørensen, 2019) in comparison to recurring export episodes. In order to do so, we employ detailed large-scale longitudinal administrative register data for 6,061 firms' exports at the monthly product-country transaction (shipment) level for Denmark in the period 2000 to 2019. We identify 870,221 newly started firm-country-product export spells of which 35% turn out to be one-off events: isolated single export transactions in the centre month of a 4-year period of non-exporting the same product to the same country by the same firm.[1] Surely, on first sight these abandoned export engagements could simply be the bad draws of substantial amounts of potentially costly export experimentation. Alternatively, it could be the case that firms learn even from one-off exporting and potentially improve their future export prospects. This is the question we set out to answer.

Our research complements existing literature by looking at one-off exporting as a potential source for export capability building, and accordingly relates to several strands of research. First, we speak to the well-known empirical evidence based on detailed administrative firm-level panel data and the high frequency of short export engagements. These patterns have for

[1] This scale is in line with previous findings presented in Geishecker et al. (2019), but will in the annualized data sets that are typically available to researchers be masked as year-long export relations. Our Data and methodology section elaborates on further descriptive statistics and data definitions. Notably, the precise scale of one-off spells and recurrent export spells in the data depends on the applied filtering rules, such as the aggregation level of the commodity (product) classification, or extending the required length of observed non-exporting from 4 to 10 years, or eliminating certain product groups (e.g., capital goods). For various conceivable permutations Geishecker et al. (2019) find that the share of one-off episodes in all new export spells varies between 25% to 40%.

example been linked to experimentation, (Eaton et al. 2011). Second, existing literature provides ample evidence of learning-by-exporting, for example in the sense that export experience from one destination spurs entry into additional destinations (Morales et al., 2019), may result in productivity gains (DeLoecker, 2013) and matters even for born global firms (Choquette et al., 2017). Third, the stage model literature has developed and applied a wide range of learning concepts, where the internationalization process is conceptualized as taking place over time, is path-dependent and is, inter alia, based in experiential learning (Andersen, 1993; Eriksson, et al., 1997; Casillas and Moreno-Menéndez, 2014). Fourth, intermitted exporting and re-entry is another important area of study and an empirical phenomenon that has received growing attention (Sousa et al., 2021). While the present paper does not address export re-entry, we nevertheless employ insights and theoretical foundations from this literature. Finally, our paper also relates to a literature that examines the role of non-export internationalization experience for export development. For example, Choquette (2019) examines the effect of import-based market experience (a potential source of market-specific knowledge) prior to export market entry – on the probability of a firm exiting an export market.[2]

Against this backdrop based on previous literature and the associated conceptual frameworks, the current study formalizes through mathematical expressions a stylized learning by exporting framework that structures our hypothesizes and informs our empirical design. Our framework unfolds the country and the product dimension of export expansion, i.e., the extensive margins. In other words, we allow previous country-product export experiences of a firm to have differential effects on the firms future exports on the specific foreign market and with the specific product in question. Moreover, we separate previous exporting into spells of successful (at least once) recurrent exporting and one-off exporting. The essence of our theory section and hypothesizes is as follows: learning by recurrent exporting increases the probability of export expansion on both the country and product margins in the future. To the extent that one-off episodes in the data simply are the bad draws of experimentation, an empirical observation of past one-off export sales should not increase the probability of future export expansion of the firm. Alternatively, if one-off export episodes hold the opportunity for experiential learning or other export capability building, then past one-off exporting should be able to predict future export success, albeit less so than past recurrent exporting.[3]

[2]Choquette (2019) finds little evidence of learning from importing, a result that we in part mirror in our empirical result section.

[3]Obviously it would be a logical fallacy to interpret an empirical confirmation of these

In our empirical section, we test these hypothesises. We explore a rich panel of administrative data on the universe of Danish firms. This administrative data has previously been used for different research questions (Hummels et al. 2014 ; Choquette et al., 2017; Choquette, 2019), and similar data are available in other countries (Love and Máñez, 2019). The Danish data allows us to identify firm-product-destination combinations of export transactions at the monthly level.[4] At this level of disaggregation computational restraints become an issue and we focus on exports of electric machinery and equipment (Denmark's largest export sector - and comprised of 214 unique product categories). Still, the total number of observations in our data exceeds 400 million. We sample all firms with registered wholesale business functions for the period 2000 to 2019 and for all possible export destinations (215). The resulting sample consists of 6061 firms with 13,723 feasible commodity-destination observations of potential or realised newly started export spells per firm and year. Across these dimensions we observe 870,221 newly started spells of which 324,517 (35%) are one-off. Moreover, as expected our descriptives show that firms have a fairly constant exposure to one-off export events per year, but build and expand their portfolio of recurrent export engagements over time.

With these data we can test the various hypotheses from above by econometric analysis of firms' conditional probability to expand their export activities. Our empirical model has as its depended variable the zero-one event of starting a new recurrent export spell at the firm-country-product-time dimensions. Thus for a given firm a new spell at a given point in time could be a new product, a new destination country or a new product-destination combination. Our independent variables are the past export spells – captured by zero-one indicator variables, and separated into the country-product dimension and recurrent versus one-off export spells – of the firm in question from three years earlier. This focus on historic experience, stacks the deck against our findings, but helps us to gain some causal indication and most importantly ensures that results are not contaminated by firm's potentially contemporaneous export expansion strategies.[5] Finally, we control for past importer status. Most importantly we include – depending on model spec-

hypothesises as a test for the absence of experimentation.

[4]To the best of our knowledge, the monthly dimension of the data has hitherto only been used by Geishecker, Schröder and Sørensen (2019). Moreover, the monthly transactions dimension is seldom available for research purposes in register data from other countries, but essential to our research design.

[5]Without a time lag, a firm that implements an aggressive export expansion strategy in terms of many new countries and products, but fails in some but not all would appear to have learned from it's failed episodes.

ifications – various fixed effect variables, such that all observable and unobservable firm-time, destination-time and product-time characteristics are controlled for.

Turning to the results, we find that – in line with previous literature - – internationalization experience raises the propensity to start new export spells. The effects are strongest for recurrent export and a factor 3 smaller for one-off experience and again a factor 3 smaller for previous import experience. Furthermore, previous export engagement, even if it is one-off, has a strong product- and destination-specific component, helping firms to expand their exports of a specific product across additional destinations and/or to expand their product portfolio within a given destination. To be precise: Even after controlling for firm-time as well as product- and country-time confounders, if a firm three years earlier has had one-off exports of a given product to some destination, the probability to start a new recurrent export spell of the same product elsewhere is raised by 0.35 percentage points; for the country dimension the increase from one-off experience is 0.31 percentage points. Accordingly, we conclude that both product specific and country specific learning is associated with one-off export events.

Finally, we provide an indication of the economic importance of these findings and parameters based on a dynamic simulation model calibrated to the real data and estimated coefficients. In the simulation we find that exposing a typical non-exporting firm to only two initial random isolated one-off export episode triggers a chain of accumulated learning by exporting. Within 12 years of simulation, the exposed firm's international reach expands to 10 distinct product categories serving 8 distinct destination countries with successful recurrent exports.

Understanding how and why firms expand their export portfolio has ample managerial implications and provides important insights for the design and evaluation of policies such as export promotion. Our findings challenge the otherwise implicit view of swift export market exits as costly, failed internationalization endeavours. We show that even singular, apparently failed, export engagements contribute experiental learning opportunities for firms. In size these effects are a third of the effects triggered by recurrent exporting. Obviously, longer and recurring export relations will be more valuable to the firm, but our findings suggest that it is worthwhile for firms and policy makers to reexamine their assessment of what are the successful stepping stones in the internationalisation path of a firm.

2 Theory and hypotheses development

2.1 Organization of thought

The stage model literature has developed and applied a wide range of learning concepts. A common denominator in the literature is that the internationalization process is conceptualized as taking place over time, is path-dependent and is based in experiential learning (Andersen, 1993; Eriksson, et al., 1997; Casillas and Moreno-Menéndez, 2014). In particular, we allure to a dissimilarity between experiential learning and simple experimentation. We take insights and theoretical foundations from the literature to conceptualise ideas on learning that guide our hypothesis development and structure our empirical investigation. For example, concepts of uncertainty, instability of environments, the accumulated resources within the firm, and firms' capabilities and learning over time are important themes in re-entry studies. Seminal works on re-entry have identified firms' competitive advantages through their previous networks or experiential knowledge as drivers for export re-entry (Bernini et al., 2016; Welch and Welch, 2009). Thus, in a setting of uncertainty, previous export experience provides information, say concerning product appeal, networks etc, and exporting is in the nature of an experiment as already suggested by Welch and Wiedersheim-Paul (1980). This is also the nature of exporting in testing-the-waters type explanations for the empirical regularity of high hazard rates for newly established export episodes (Eaton et al., 2011). Moreover, scholars have proposed organizational learning theory to explore how learning from past experiences can determine a firm's re-entry decision (Love and Máñez, 2019 or Surdu et al., 2018). Recently, Surdu et al. (2021) propose the application of behavioral theory of the firm to the understanding of the internationalization process and highlight both search and learning by doing as important elements. Our formalization in section 2.2 builds on the above arguments and theories.

The structure of our below formalisation and resulting hypotheses can be summarized as follows: Actions by the firm (e.g., export experimentation) or outside change agents (e.g., unsolicited export orders) may (1) reveal information, for example about market opportunities or own capabilities, that was previously undisclosed and/or may (2) contribute to experiential learning. In the latter case, - and that is the mechanism included in our mathematical representation - firms actually improve their capabilities and performance by directly reducing the firm's sunk export market penetration costs. Clearly, these two (and multiple other) channels will potentially be present in real data. Yet, none of these mechanisms are directly observable. Nevertheless, the phenomenon of one-off episodes in the data provides a unique opportunity to identify patterns that are compatible – or not – with experiential learning and other forms of learning by exporting. Clearly, firms also do learn from export experiments when new information is revealed. The obvious lesson a firm must have learned from a newly started but immediately discontinued export episode is that it not worthwhile or feasible to pursue a second sale. In this perspective, one-off episodes must, on average, constitute failed export attempts, where rewards do not match costs according to the objectives of the firm. For the same reason, recurring exports must, on average, constitute successful export episodes. Importantly, an export experiment that is deemed a success according to the firms objectives, would by definition become a recurrent export spell.

In order to take this argument to the data, we hypothesize in section 2.3. that learning by recurrent exporting episodes in the past increases the probability of export expansion on both extensive margins (product and country). However, to the extent that one-off episodes in the data only constitute the bad draws of experimentation, the empirical observation of past one-off export sales should not affect the probability of future export expansion of the firm. To see why assume for the moment that no experiential learning by exporting is taking place. Then any failed export episode (one-off) can only affect the firms future exporting by disclosing information that a given country-product export is unattractive for the firm in question. Hence, on average we should not expect the firm to be more likely to follow up on such one-off episode by expanding on the market in question (say with other products) or by pushing the same product to different markets. In other words: in the absence of any experiential learning observing a one-off episodes by a given firm with a specific country-product combination should, on average, not provide a statistical prediction of future exports by that firm to that market or with that product. In contrast, if one-off export episodes hold the opportunity for experiential learning, say the opportunity to build export capabilities or to develop valuable network, then past one-off exporting should to some extend predict future export success, albeit less so than past recurrent exporting.

2.2 An illustrative formalized learning model

A formal stylized framework assists the identification of testable hypotheses in Section 2.3 and structures our empirical approach in Section 3 and 4. The framework builds - based on the literature and ideas laid out above - on the notion of learning by previous export experience. We model learning here as improvements in the firms ability to overcome the costs of entering a new market, i.e., a reduction in fixed entry costs. As discussed above the literature has of course identified far richer and more complex learning types and learning outcome dimensions, yet for the purpose of formalization a reductions in fixed entry costs suffices.[6] Importantly, we go beyond the mere exporter status and add further granularity - reflecting our empirical data - by including both the destination and the product dimension. Firms add export destinations - i.e., firm-level export expansion on the extensive margin, and firms evolve their product range in their export sales mix by destination. In essence the export decision of the firm that we capture is thus the addition of product-destination combinations. This allows us to formally capture and distinguish learning by exporting to a given destination as well as learning by exporting a given product. Accordingly in the formalization the notion of a market refers to a destination-product combination. Finally, and at the core of the present paper, the mathematical representation adds the distinction into recurrent exporting and one-off exporting episodes. Thereby this framework is able to theoretically separate potentially differential learning outcome from these two distinct forms of international engagement and experience.

We apply a standard heterogeneous-firms modelling approach, see Melitz (2003) for a seminal contribution, with CES preferences and constant firm-level marginal costs. The reduced form flow profits for firm f in destination c for product p at time t can be written as $\pi_{f,c,p,t} = \varphi_{f,t}^{\sigma-1} D_{c,p,t}$, where $\varphi_{f,t}$ is a firm-time-specific productivity term, σ is the elasticity of demand, and $D_{c,p,t}$ is a destination-product-time-specific component capturing, for example, (Iceberg) trade costs, ad-valorem tariffs, local preferences for the product, local demand level, local competition, exchange rate fluctuations etc, and is assumed to follow a random walk.[7] Let firm-specific sunk costs to enter export destination c with product p at time t be given by $F^X_{f,c,p,t}$. Accordingly, the expected (E_t denoting the expectations operator) net-present value for firm f from entering destination c with product p at time t is

[6] Entry cost reductions are frequently identified in empirical work. Morales, Sheu and Zahler (2019) apply a structural (moment inequality) approach and firm-level data to document a substantial (69-90 %) reduction in destination-level entry costs due to extended gravity forces, i.e., due to similarities between new and existing export destinations of the firm, where geographical and linguistic proximity are key drivers. See also Schmeiser (2012) and Sheard (2014) for models where export experience reduces export market entry costs.

[7] With CES preferences

$$D_{c,p,t} = N_{c,p,t} P_{c,p,t}^{\sigma-1} \left(\frac{\sigma}{\sigma - 1} \right)^{-\sigma} (\tau_{c,p,t} w_t)^{1-\sigma},$$

where $N_{c,p,t}$ is aggregate nominal expenditure, $P_{c,p,t}$ is the price index, w_t is the wage rate, and $\tau_{c,p,t} \geq 1$ is the Iceberg trade friction.

$$\begin{aligned}
\Pi_{f,c,p,t} &= \sum_{k=0}^{\infty} \delta_f^k E_t\left(\pi_{f,c,p,t}\right) - F_{f,c,p,t}^X = \sum_{k=0}^{\infty} \delta_f^k E_t\left(\varphi_{f,t+k}^{\sigma-1} D_{c,p,t+k}\right) - F_{f,c,p,t}^X \\
&= \sum_{k=0}^{\infty} \delta_f^k E_t\left(D_{c,p,t+k}\right) E_t\left(\varphi_{f,t+k}^{\sigma-1}\right) - F_{f,c,p,t}^X \\
&= D_{c,p,t} \sum_{k=0}^{\infty} \delta_f^k E_t\left(\varphi_{f,t+k}^{\sigma-1}\right) - F_{f,c,p,t}^X, \qquad (1)
\end{aligned}$$

where δ_f is the discount rate (including a firm-level idiosyncratic risk of exogenous exit - possibly including immediate exit - from a given market), and k simply counts all future periods. The third equality follows as $\varphi_{f,t+k}$ and $D_{c,p,t+k}$ are assumed to be independent, i.e., firm-specific productivity is uncorrelated with market-specific demand and cost factors. The fourth equality follows since we assume that D, the composite of market-specific factors, follows a random walk, i.e., $E_t\left(D_{c,p,t+k}\right) = D_{c,p,t}$ for all $k \geq 1$.

Importantly, entry costs, $F_{f,c,p,t}^X$, are subject to learning such that cost of entering a given market depends on the previous export status of the firm. Formally, $F_{f,c,p,t}^X = g\left(X_{f,t-1}\right)$, where $X_{f,t-1}$ is export experience of firm f at time $t-1$.[8] More specifically, we assume that

$$\begin{aligned}
F_{f,c,p,t}^X = \hat{F}_{c,p,t}^X \exp(&- \alpha I_{f,t-1}^{rec} - \alpha_p I_{f,p,t-1}^{rec} - \alpha_c I_{f,c,t-1}^{rec} \\
&- \beta I_{f,t-1}^{one} - \beta_p I_{f,p,t-1}^{one} - \beta_c I_{f,c,t-1}^{one}), \qquad (2)
\end{aligned}$$

where $\hat{F}_{c,p,t}^X$ is common for all firms and the I's measure a specific firm's export experience at time $t-1$ at the level denoted by the subscript, for destinations, c, and products, p. The superscript distinguishes between one-off export experience (*one*) and recurrent export experience (*rec*). Hence we have arrived at a framework that allows us to distinguish between general learning-to-export and learning-to-export effects at the product and destination level as well as between learning from one-off episodes versus learning from successfully repeated export events. If learning is triggered by one of these types of export episodes, coefficients (α's and β's) are expected to be positive, else zero.

[8] Time in the formalisation refers to periods, not years. As a matter of fact, in our empirical application, we implement a time window of 3 years. Thus empirically we measure firm specific historic export status (for destinations and products) from thee years ago against the present day probability of adding new export destination-product combinations.

Firms are forward-looking in the sense that a firm pro-actively decides to enter a market when the expected net-present value of the cash flow from entry is positive.[9] Entry in destination c with product p for firm f at time t yields a positive expected net-present-value of cash-flow if and only if

$$\Pi_{f,c,p,t} > 0 \Longleftrightarrow D_{c,p,t} \sum_{k=0}^{\infty} \delta_f^k E_t \left(\varphi_{f,t+k}^{\sigma-1}\right) > F_{f,c,p,t}^X. \tag{3}$$

This condition can be rewritten as

$$A_{f,c,p,t} \equiv \ln D_{c,p,t} - \ln \hat{F}_{c,p,t}^X + \ln \left(\sum_{k=0}^{\infty} \delta_f^k E_t \left(\varphi_{f,t+k}^{\sigma-1}\right) \right) + L_{f,c,p,t} > 0, \tag{4}$$

with $L_{f,c,p,t}$ capturing the learning-to-export mechanism

$$L_{f,c,p,t} \equiv \alpha I_{f,t-1}^{rec} + \alpha_p I_{f,p,t-1}^{rec} + \alpha_c I_{f,c,t-1}^{rec} + \beta I_{f,t-1}^{one} + \beta_p I_{f,p,t-1}^{one} + \beta_c I_{f,c,t-1}^{one}. \tag{5}$$

Hence, expected net-present-value cash-flow from market entry is ceteris paribus more likely to be positive if the firm has (relevant) export market experience in terms of destination, product or both.

Clearly, $\Pi_{f,c,p,t}$ and $A_{f,c,p,t}$ are non-observable (latent) variables. However, what we as researchers can observe is whether firms enter a new export market (product destination combination) or not at a given point in time. Our empirical model in section 3 will therefore be a (linear) probability model. We have that

$$X_{f,c,p,t}^{rec} = \alpha_p I_{f,p,t-1}^{rec} + \alpha_c I_{f,c,t-1}^{rec} + \beta_p I_{f,p,t-1}^{one} + \beta_c I_{f,c,t-1}^{one} + \gamma_{f,t} + \gamma_{c,p,t} + \varepsilon_{f,c,p,t}, \tag{6}$$

where $X_{f,c,p,t}^{rec}$ takes the value of 1 if firm f starts to export product p to country c at time t and zero otherwise and $\varepsilon_{f,c,p,t}$ is an error term. The firm-time fixed effects, $\gamma_{f,t}$, capture both $\ln \left(\sum_{k=0}^{\infty} \delta_f^k E_t \left(\varphi_{f,t+k}^{\sigma-1}\right)\right)$ as well as the terms $\alpha I_{f,t-1}^{rec}$ and $\beta I_{f,t-1}^{one}$, which includes potential learning effects from recurrent or one-off exporting that apply equally to all markets, i.e., general competence building and learning-to-export mechanisms, as well as the expected firm-level productivity path (for example underlying performance improvements at the firm). The country-product-time, i.e., the market-time, fixed effects, $\gamma_{c,p,t}$, capture $\ln D_{c,p,t} - \ln \hat{F}_{c,p,t}^E$, i.e., the variation in general attractiveness of a market, the competitive environment, etc.

[9] However, we assume that firms do not internalize the learning-to-export mechanism in the export decision. Accounting for such dynamics implies a highly complicated dynamic optimization problem and bounded rationality of the firm is a well-established concept in the literature that has emerged from Johanson and Vahlne (1977).

In conclusion, we have hence arrived at a formulation, where the estimate of, for example, α_p measures how the previous experience of recurrent exporting of product p increases the probability that the firm today will start exporting the same product to another destination, i.e., learning at the product level. Similarly, the estimate of α_c measures how repeated successful experience of exporting to country c increases the probability that a firm will start exporting other products to country c. By the same logic, β_p and β_c, inform us how much - if anything - firms do learn from one-off export episodes.

2.3 Testable Hypotheses

Based on the above formalization, the existing empirical literature as well as the well-known theories of international business reviewed above we state the core hypothesizes on learning dimensions to be investigated in our empirical section.

Hypothesis 1a: *The probability to expand the export product portfolio in a given destination country increases when a firm has previously had recurrent exports to the destination in question.*

Hypothesis 1b: *The probability to expand the export country portfolio for a given product increases when a firm has previously had recurrent exports of the product in question.*

Hypothesis 2a: *The probability to expand the export product portfolio in a given destination country increases, but by less than in H1a, when a firm has previously had one-off exports to the destination in question.*

Hypothesis 2b: *The probability to expand the export country portfolio for a given product increases, but by less than in H1b, when a firm has previously had one-off exports of the product in question.*

In addition to our theoretical probability model from above the empirical specification includes a number of controls and high-dimensional fixed effects. Possible elements of learning from importing (see, e.g., Choquette, 2019) are included by import controls but not introduced by separate hypotheses. Similarly, the various other export drivers that clearly must be present in the data are contained in the fixed effect specification of our empirical design (see also our discussion of methods below). Accordingly, a vast multitude of other dimensions that affect export performance and the probability to start a new recurrent export engagement - that register data in principle could permit to investigate - are not hypothesized in this paper and accordingly muted in our empirical section via the inclusion of fixed effects.[10]

3 Data and Empirical Methodology

3.1 Sample

We draw on Danish firm-level register data and business account information for the years 2000 to 2019 provided by Statistics Denmark.[11] We start from the universe of all Danish firms but focus on wholesale businesses (Industry, NACE, rev. 2: 46). We thus exclude, e.g., pure manufacturing firms, since international expansion could in the short run be affected by production capacity constraints that we cannot observe in the data. Importantly, manufacturing firms that register part of their business activity as wholesale will be included in our sample. We further condition on firms having yearly sales exceeding DKK 100,000 (about USD 14,000, in constant prices) to exclude erroneous negligible ultra small firms. Table 1 gives a detailed account of our sample constraints and their consequences.

These data are merged with monthly destination- and commodity-specific export and import information for each sampled firm from the *External trade of Denmark* database which essentially covers all measurable export and import events of Danish firms and allows us to identify newly started export spells as well as past export and import experience.[12]

We distinguish among all previous trade episodes between spells that are single one-off events and those that are successful recurrent trade relationships. In order to do so, we building on the classification developed in

[10]Note, that even though we in Section 2.1 contrast potential learning from one-off exporting (say through experiential learning) to simple bad draws in export experimentation one can not hypothesize on the absence of experimentation, nor could such claim of absence be meaningfully verified with data.

[11]Recent publications exploiting comparable Danish firm-level register data include: Hummels, Jorgensen, Munch and Xiang (2014), Choquette (2019) and Bernard, Fort, Smeets and Warzynski (2020).

[12]For our analysis we exclude transactions with Greenland and the Faroe Islands which are autonomous destinations closely tied to Denmark and governed by special trade and reporting regulation. Furthermore, we consolidate a number of small trade destinations that we consider to be closely connected politically or geographically with a larger entity. Examples in case are Gibraltar which although a British territory is consolidated with Spain or French Guiana and Reunion which are overseas departments and thus consolidated with France. The key point is that such a consolidation makes our definition of one-off exporting, explained in what follows, more conservative as several trade spells are aggregated.

Geishecker, Schröder and Sørensen (2019) applied at the six-digit commodity level (CN6).[13]

Specifically, we classify a firm-product-destination export episode as an one-off event when we observe a single-month trade transaction that is preceded and followed by 24 months of non-trade, i.e., a 4-year window of non-trade with a single export transaction in the center month. This rule eliminates even the most sporadic export and import patterns that are known from the lumpiness of trade literature (see e.g., Alessandria, Kaboski and Midrigan, 2010; Hornok and Koren, 2015), and leaves us with conservatively identified one-off episodes. Everything else we label - by definition - as recurrent trade. To be explicit, this means that, for example, already a trade spell that is composed from only two consecutive months of trade shipments is not classified as one-off but as a recurrent trade engagement. Similarly, a trade spell that has only one month of transaction, can violate the filtering rule of 24 months of non-exporting before and after and thus would also not be classified as one-off, but as recurring instead. Clearly, this unique level of granularity is only possible because we employ the actual monthly transaction level that is available to researchers in Danish register based data and is accessed by us for the longitudinal dimension of 20 years. Once true one-off export events are identified there is no further need for monthly trade information and we aggregate our monthly to yearly data to ease computational requirements.

According to the definition of one-off export spells we need to observe firms' product-destination specific export and import activities for at least 49 consecutive months (i.e., more than 4 years) and, correspondingly, we limit our sample to firms that meet our sample restriction regarding sales for at least five consecutive years. Furthermore, to avoid right truncation of one-off export or import spells, we must observe at least 24 months in the data after a trade spell has potentially ended. Since our date contain matched yearly firm-level register data and monthly trade transactions data up until 2019, our firm-commodity-country panel available for analysis ends in 2017. This yields an unbalanced panel of 17,224 firms between 2005 and 2017.

[13] The (CN6) level thus reports product categories and not specific brands or makes of products. We use the terms product, product category and commodity interchangeably. To account for several changes in the commodity classification during our sample period (the CN is continuously updated), we apply the concordance scheme of Van Beveren, Bernard and Vandenbussche (2012) adopted to the most recent changes in the CN and to the 6-digit commodity level. Note that all concording steps make our one-off export identification more conservative. In principle, recurrent trade episodes can be further divided according to the duration of the engagement, as in Békés and Muraközy (2012) and Geishecker Schröder and Sørensen (2019).

Furthermore, this data structure allows to identify past trade experience (one-off or not) of up to three years, i.e., from 2002 onwards.[14]

It is important to note that for the analysis of export learning our interest lies not only in firms' realised export transactions but equally so in firms' potentially export transactions that do not materialise. To illustrate, each and every firm (observed by us for between 5 to 20 years) potentially could export in each year to any of 215 export destinations any of the 4321 commodities (defined at the concorded six-digit level). Our data, thus, would need to entail at least 80,006,771,800 observations which is computational unfeasible.

We, thus, reduce the dimensions in our data. First of all, we limit our analysis to exports of commodities that fall under chapter 85 of the combined nomenclature, that is exports of electrical machinery and equipment and the likes, and features 214 different product categories at the six-digit commodity level. Importantly, chapter 85 is the main export category in Danish exports in terms of volume.[15] We then define a set of viable commodities and destinations, i.e., our permitted cells are the Cartesian product of all chapter 85 commodities ever exported and all destinations ever served. We include all firms that exported a Chapter 85 product at least once during the sample period. Furthermore, as our focus lies on firms' extensive export margin we only analyse newly started spells and thus follow firm-product-destination cells over time only until a cell is served for the first time, i.e., non-exporting is exited. The resulting unbalanced panel consists of 6061 firms with exports of 214 possible six-digit products to 215 possible destinations and 13723 feasible commodity-destination observations of potential or realised newly started export spells per firm and year, for at least 5 consecutive years. Across these dimensions we observe 870,221 newly started spells of which 324,517 are one-off and, thus, 545,704 recurrent. The total number of observations in our data, however, still by far exceeds 415,875,515.[16] Despite the reduced dimensionality the resulting sample at full size still outruns available computing power. Instead we opt for repeatedly estimating our empirical model for 10 per cent block-samples of firms for which we compile the data across all dimensions which amount to about 73,000,000 observations per random draw.

[14] Following the classification scheme previously described, the earliest one-off trade events can be identified in 2002.

[15] $https://ec.europa.eu/eurostat/ramon/nomenclatures$

[16] The exact number of theoretically required observations remains unknown as the panel is unbalanced with a varying number of years per firm and the full data set is never generated for computational reasons, see Table 1.

Table 1: Sample and Sample Constraints

	Firms	Country-Product	Observations
Full Wholesale Population	70811		
sales $\geq$ 100,000 DKK	47716		
$\geq$ 5 years	24772		
$t-3$ one-off exports (i.e., $\geq$ 12 years)	17224	215 countries 4321 products	$\geq$80,006,771,800
Chapter 85 export once	6061	feasible product-countries 13723	$\geq$415,875,515

3.2 Descriptives

Figure 1 shows the evolution of the number of export markets over time averaged over all exporting firms over their respective first five years in our sample.[17]

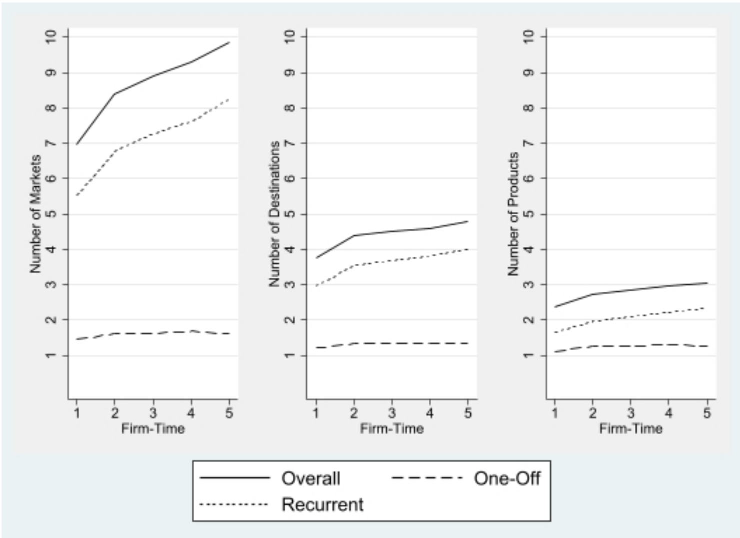
While in the first firm-specific year exporting firms on average serve about 7 product-country markets, this number evolves over time suggesting significant path dependency of wholesale exporting such that after 5 years exporters on average serve about 10 markets.[18] This expansion of the extensive margin materializes along the country as well as product dimension. One-off exports appear to contribute to this expansion by continuously introducing export destinations and products, that by definition are new, i.e., expand firms' export portfolio. In line with our formalized learning model and hypotheses 2a and 2b, one-off export experience, thus, translates into steadily increasing numbers of products and destinations in recurrent exporting.

Moreover, one-off exports are not rare, they are omnipresent in firms' export activities as has been already shown in Geishecker et al. (2019). Table 2 reports newly started export activities from the firm perspective for our sample. On average Chapter 85 wholesaling firms start about 16 new export

[17] We focus on the first five years as by sample design all firms are included for at least five years such that we can rule out compositional changes.

[18] These descriptives are limited to a balanced sample of the first 5 years of firm-observations to rule out the impact of compositional changes.

Figure 1: **Average Number of Firms' Export Markets over Time**



Note: Authors calculations. Constrained to five consecutive years per firm to rule out compositional changes due to firm attrition.

spells per year, of which about 6 are one-off, i.e., only occur once in a 49 months interval. However, these average figures clearly are driven by the right tail of the distribution. The median firm starts only 2 new export spells per year of which 1 is one-off. In terms of volume, new one-off export spells on average account for 44 per cent of firms' overall newly started export activity and thus clearly matter for the average firm. However, at the aggregate we calculate that the importance is somewhat lower, with one-off exports accounting for about 17 per cent of total sales volume of all newly started exports among Chapter 85 firms in our sample.

Table 2: New Export Spells per Firm

	Mean	10th percentile	Median	90th percentile
New Spells ALL	16.42	0	2	31
New Spells One-Off	5.70	0	1	12
New Spells Recurrent	10.72	0	1	18
Annual export volume share one-off	0.44	0.00	0.33	1.00
Number of firms			6061	

3.3 Empirical Model

Our model assesses the conditional probability $P(X_{fpct} = 1|.)$ that firm f starts to recurrently export a product in commodity category p (defined at the six-digit concorded CN) to destination c at time t. Our four dimensional panel data by far exceeds 415,875,515 firm-product-destination-time observations (see Table 1). Accordingly, we repeatedly draw 10 per cent random block-samples of firms (with replacement) which allows us to identify mean model parameters and corresponding bootstrapped standard errors. To accommodate our four dimensional panel structure, i.e., to simultaneously control for firm-, destination- and product-specific confounding factors we estimate a linear probability model.[19]

$$
\begin{aligned}
X_{fpct} &= \alpha_{ft} + \iota_{ct} + \rho_{pt} \\
&+ \beta_1 XP^{rec}_{fpt-j} + \beta_2 XP^{one}_{fpt-j} + \beta_3 XC^{rec}_{fct-j} + \beta_4 XC^{one}_{fct-j} \\
&+ \beta_5 MP_{fpt-j} + \beta_6 MC_{fct-j} + \\
&+ \beta_7 dur_{0-1} + \beta_8 dur_{1-2} + \beta_9 dur_{2-3} + \beta_{10} dur_{3-4} + \epsilon_{fpct}
\end{aligned}
\tag{7}
$$

with X being an indicator variable for whether a new recurrent export spell starts. Following from our formalization in Section 2, firm-time-specific α_{ft}, destination-time-specific ι_{ct} and product-time-specific ρ_{pt} observable and unobservable characteristics are controlled for. Importantly, α_{ft} not only captures firm-time-specific shocks, productivity and size but also controls for

[19]We reject the hypothesis that unobserved error components are uncorrelated with explanatory variables and thus do not estimate any of the mixed models popular in duration analysis. However to assess robustness, we also estimate a conditional logistic model controlling firm-time confounders (which turn out to be most relevant), which also can be seen as a special discrete time Cox-proportional-hazard model with firm-time frailty.

firms' total number of product-destination markets, i.e., firms' scope for further expanding their extensive export margin. Note that ι_{ct} controls for standard gravity controls such as distance, market size as well as the destination-specific export experience of other firms and related externalities as discussed, albeit partly in a different context, in the literature (Cadot, Iacovone and Pierola, 2012; Fernandes and Tang, 2014, Choquette and Meinen, 2015; Choquette, 2019).

XP_{fpt-j} and XC_{fct-j} represent indicator variables for whether the firm previously has exported commodity p to anywhere ($c' \neq c$) or previously has exported any other commodity ($p' \neq p$) to destination c. The two variables, thus, capture previous product- and destination-specific export experience, respectively. The superscripts rec and one respectively denote whether such previous export experience has been in the mode of recurrent or one-off exporting. To reflect on the importance of imports for firms' extensive export margin discussed in the literature (Choquette, 2019) we also control for product specific MP and destination specific MC import experience, however, without differentiating between recurrent and one-off imports. Duration dependence (of non-exporting) is captured by a set of yearly duration dummies dur with duration > 4 years being the default category. The remaining error term ϵ_{fpct} is independently distributed but allowed to be correlated across the panel dimensions as we bootstrap standard errors.

4 Results

Table 3 shows average parameter estimates across 100 random 10 per cent firm-block samples with replacement and corresponding bootstrapped standard errors. Since we estimate a linear probability model and all explanatory variables are discrete, coefficients correspond to pseudo marginal effects. We assess the economic significance of these results with a dynamic simulation of export learning in Section 4.1.

We present three empirical models. Model I constrains firm-time, destination-time and product-time-specific controls to zero. Model II controls for destination-time and product-time-specific confounders while Model III is the most conservative as it simultaneously controls for firm-time, destination-time and product-time-specific confounders.

While we focus on our most conservative Model III, differences in coefficients between Models I and Model III are informative about prevalent channels or modes of export learning which we will discuss later. For now it is worth mentioning that in all model specifications previous export experience, regardless of recurrent or one-off, is found to raise a firm's probability to start a new recurrent export spell in a new destination or new product, i.e., to expand the extensive export margin. Accordingly, all four hypotheses (H1a, H1b, H2a, H2b) are unambiguously supported by all model specifications. Previous import experience, in general, also raises the probability to start a new recurrent export spell, however the effect is considerably less pronounced. We also find a negative duration dependence of starting a new export, i.e., the longer non-exporting lasts, the lower the probability to exit that state.

Let's start the discussion with the product-specific learning effect β_1 in Model III: If a firm previously has recurrently exported a given product to some destination, the probability to start a new recurrent export spell of the same product somewhere else is raised by 0.97 percentage points, supporting hypothesis H1b. If previous export experience of the same product has been only one-off, the conditional probability to start successful recurrent exports of the same product elsewhere is raised by 0.35 percentage points (β_2 in Column III, Table 3). While both effects are positive and highly statistically significant the effects of recurrent and one-off export experience differ by about factor three, supporting hypotheses H2b.

In addition, destination specific export experience plays a significant role. In line with H1a, previous export experience in a given destination raises the probability to export a new product to the same destination by 0.83 percentage points (β_3 in Model III). This also holds in principle when the destination specific export experience has been only one-off. Thus, even an ultrashort, unsuccessful, and likely unsolicited export event helps firms to build export capabilities, raising the probability to start recurrent exports of other products to the same destination by 0.31 percentage points (β_4, Model III). Again, the effects of export learning differ by about factor three between recurrent and one-off exporting, supporting H1b.

Turning our attention to import experience we also find positive statistically significant coefficients, i.e., support for export learning from import experience along the product as well as country dimension. However as the coefficients β_5 and β_6 in Model III of Table 3 indicate, effects are much lower in magnitude. For instance, experience in importing a specific product raises the probability to start a new recurrent export of the same product by merely 0.10 percentage points. Thus, the effect is about 10 (3) times smaller than that of recurrent (one-off) export experience. The same essentially holds when comparing the effect of destination specific import experience β_6 to the effects of destination specific export experiences β_3 and β_4.

Arguably, it is good practice to control for as much confounding factors as possible to avoid potential omitted variable bias and thus focus on the most conservative unconstrained Model III. However, by comparing coefficient estimates between Models I to III, i.e., by assessing the bias, we can infer more about relevant learning channels.

Model I does not control for firm-time α_{ft}, destination-time ι_{ct} and product-time-specific confounders ρ_{pt} and coefficient estimates, thus, must be biased. Model II controls for ι_{ct} and ρ_{pt} (but not α_{ft}) capturing country-specific and product-specific factors found to be important predictors of firms' export activities in the literature. Yet, coefficient estimates hardly differ between Model I and Model II, i.e., the bias is not affected for any of the estimated coefficients β_1 to β_4. Accordingly, ι_{ct} and ρ_{pt} appear not to be correlated with our experience variables. If they were, controlling for them should reduce the bias. We can thus infer, that since ι_{ct} and ρ_{pt} are uncorrelated with export experience, learning about product-specific as well as destination-specific factors does not appear to be particularly relevant for expanding firms' extensive export margin. However, when comparing Models I and II to Model III we see significant differences in estimated coefficients β_1 to β_4, with a consistent upward bias of at least 26 per cent in Models I and II. Thus, firm-time-specific factors α_{ft} that foster (hamper) new exports are positively (negatively) correlated with firms' export experience.[20] In line with these findings we infer that in addition to match-specific, i.e., firm-destination-product-specific learning as identified in Model III, firms also build their general firm-specific export capabilities across products and destinations.

[20]To illustrate, using matrix notation our Model (Equ 7) becomes: $X = C\beta + Z\gamma + \iota + \rho + \epsilon$ with X being a $(N \times 1)$ vector of our dependent variable, C being a $(N \times k)$ matrix of all included control variables (i.e., k=10), β the $(k \times 1)$ coefficient vector and ι and ρ representing $(N \times 1)$ vectors corresponding to destination-time and product-time controls. Z represents α which is omitted in Models I and II. The asymptotic bias of estimated coefficients $\widehat{\beta}$ then is $\delta\gamma$ with δ representing the coefficient vector from regressing Z on the full set of included variables C (Angrist and Pischke, 2009, Chapter 3.2). Accordingly, with $\gamma > 0$ and $\delta_k > 0$ we have that the coefficient estimate $\widehat{\beta_k}$ corresponding to a specific control variable k is upward biased.

Table 3: Mean Parameter Estimates

			(I)	(II)	(III)
β_1	export	recurrent same product	0.0123 ***	0.0122 ***	0.0097 ***
			(0.0020)	(0.0020)	(0.0015)
β_2	export	one-off same product	0.0053***	0.0052***	0.0035***
			(0.0018)	(0.0018)	(0.0013)
β_3	export	recurrent same country	0.0106***	0.0106***	0.0083***
			(0.0017)	(0.0017)	(0.0013)
β_4	export	one-off same country	0.0054***	0.0054***	0.0031***
			(0.0013)	(0.0013)	(0.0010)
β_5	import	same product	0.0015***	0.0014***	0.0010***
			(0.0005)	(0.0005)	(0.0003)
β_6	import	same country	0.0008**	0.0008**	0.0007***
			(0.0004)	(0.0004)	(0.0003)
β_7	duration	$\leq$ 1 year	0.0002***	0.0005***	0.1459***
			(0.0001)	(0.0002)	(0.0207)
β_8	duration	$\leq$ 2 years	0.0001***	0.0003***	0.0894***
			(0.0000)	(0.0001)	(0.0089)
β_9	duration	$\leq$ 3 years	0.0001***	0.0002***	0.0545***
			(0.0000)	(0.0001)	(0.0091)
β_{10}	duration	$\leq$ 4 years	0.0000***	0.0001***	0.0359***
			(0.0000)	(0.0000)	(0.0075)
α_{ft}	firm-time FE		NO	NO	YES
ρ_{pt}	product-time FE		NO	YES	YES
ι_{ct}	country-time FE		NO	YES	YES

Notes: ***, **, ** statistically significant at 1, 5 and 10 percent error probability respectively. Average parameter estimates across 100 estimations for 10 per cent random firm block-samples with replacement and bootstrapped standard errors in parentheses. Duration >4 years as default category.

4.1 Illustration of economic significance by dynamic simulation

What is the economic significance of the above found increases of probabilities? At first sight the coefficient estimates presented in Section 4 albeit statistically significant appear modest. This is a misperception. In what follows we will show what dynamic effects, in terms of learning and triggering further export events, one can expect from initial export episodes, particularly if these initial export episodes are one-off? To find an answer to this question we carry out a thought experiment to quantify the expected extension of the extensive export margin through learning from previous export episodes.

Let us start with a firm that initially does not export anything and receives a number of unsolicited export orders from anywhere of anything, but all of these orders turn out to be unsuccessful (are not repeated) and thus one-off episodes. On average each firm in our sample carries out about 6 such one-off exports each year (see Table 2). We impose in the simulation a conservative two initial one-off export events corresponding to up to two different products to up to two different destinations with $\overline{p_0}$ and $\overline{c_0}$ denoting the respective vectors of involved products and destinations in $t = 0$.[21] With our most conservative Model 3 from Equation 7 and Column III of Table 3 we can now assess what number of new recurrent export spells of new products to new destinations to expect in $t+3$ and thereafter. To do so we randomly initiate two one-off export events and draw model parameters from a normal distribution around the mean point estimates and follow the model predictions through time. We repeat this exercise 100 times.

Equation 8 gives the expected number of new successful recurrent export destinations, as product specific learning raises the probability that the products which initially are exported one-off now are recurrently exported to any of 215 different export destinations.

$$E(C)_3 \;=\; \beta_2 \sum 1_p, \text{ with } 1_p = \begin{cases} 1 & \text{for} \quad p \in \overline{p_0} \\ 0 & \text{for} \quad p \notin \overline{p_0} \end{cases} \tag{8}$$

Similarly Equation 9 gives the expected number of new recurrently exported products to anywhere, as through destination specific learning from one-off exporting the probability that the firm recurrently exports within the same country is raised for all 214 available products.

[21] As the product and destination dimensions can overlap it is possible to observe two different products and one destination or two destinations and one product or any combination in between.

$$E(P)_3 \quad = \quad \beta_4 \sum 1_c, \text{with } 1_c = \begin{cases} 1 & \text{for} \quad c \in \overline{c_0} \\ 0 & \text{for} \quad c \notin \overline{c_0} \end{cases} \tag{9}$$

Analytically assessing the extensive export margins in $t = 6$ and thereafter, however, becomes slightly more evolved as firm's extensive product and destination margin overlap, that is, not every *new* product can be expected to be exported to a *new* destination. For our simulation, however, we do not need an analytical solution but simply repeatedly apply the estimated probabilities from the real data to predict and randomly assign newly started recurrent export events across the extensive margins while allowing for overlaps.

Our simulation shows that over time also the small probabilities for improved export performance from learning through past frustrated one-off experience do accumulate and transfer the non-exporting firm, hit by a few one-off export orders, to become an established exporter within a decade. Calibrated with the probabilities from the most conservative Model III specification, we find (see Table 4) that 12 years after the initial exposure to two one-off episodes the typical median firm sells to a visible portion of the global market place in our simulation, namely 10 distinct products to 8 distinct countries. Needless to say that this simulation is only an illustration. Obviously, in reality changes in the competitive environment, technological change or other events will affect and potentially curtail firms' internationalisation journey. Nevertheless, despite the reactive and stochastic nature of one-off exporting (Geishecker, Schröder and Sørensen, 2019), through learning one-off exports can be crucial for firms' internationalization.

Table 4: Simulated Extensive Margin Expansion, Model III

		New recurrent exports			
		mean	10th percentile	median	90th percentile
t=0	2005	1.52	1	2	2
t=3	2008	3.08	2	3	5
t=6	2011	4.92	2	5	8
t=9	2014	7.44	4	7	12
t=12	2017	11.36	6	12	18
		New recurrent destinations			
		mean	10th percentile	median	90th percentile
t=0	2005	1.48	1	2	2
t=3	2008	2.50	1	2	4
t=6	2011	3.98	2	4	7
t=9	2014	6.14	3	5	10
t=12	2017	9.02	5	8	14
		New recurrent products			
		mean	10th percentile	median	90th percentile
t=0	2005	1.52	1	2	2
t=3	2008	2.68	2	3	4
t=6	2011	4.22	2	4	7
t=9	2014	6.08	3	6	9
t=12	2017	9.12	5	10	14

Notes: 100 Simulations with 2 random initial one-off export events and model parameters drawn from normal distribution around mean.

5 Discussion and conclusion

Understanding how and why firms expand their export portfolio has ample managerial implications and provides important insights for the design and evaluation of policies such as export promotion. Our findings challenge the otherwise implicit view of swift export market exits as costly, failed internationalization endeavours. We show that even singular, apparently failed, export engagements contribute experiental learning opportunities for firms. In size these effects are a third of the effects triggered by recurrent exporting. Obviously, longer and recurring export relations will be more valuable to the firm, but our findings suggest that it is worthwhile for firms and policy makers to reexamine their assessment of what are the successful stepping stones in the internationalisation path of a firm.

5.1 Conclusion

This study takes its outset at the empirical regularity of frequent de-internationalization events. Short and very short export spells pose important questions for our understanding of the role of experimentation and experiential learning in the internationalization process of the firm. We contribute on several dimensions. Firstly we document in detailed administrative Danish firm-level data that extremely short one-off export episodes account for 35% of all newly started firm-country-product export spells (870,221) found in the data. One-off exporting is defined by a filtering rule such that a single country-product export transaction by a given firm for a given month is identified as one-off if the firm in question has for a full two years prior and two years after the observed transaction not engaged in the same country-product export relation. Second, based on the reasoning that even with the mildest of export fixed or sunk costs this amount of one-off transactions would constitute a substantial expenditure for failed export experimentation, we explore alternative routs and theories found in the literature. Third, based on exiting theories and concepts we present a mathematical formulation of learning by exporting (such as for example proposed in the stage model literature). This formalisation distinguishes the extensive export growth margins at the country dimension (the firm's ability to add additional export destinations) and the product dimension (the firm's ability to add additional product categories). Furthermore, we separate the firm's previous export experience into recurrent exporting (repeated at least once) and strict one-off exporting. Fourth, we present hypothesis such that our empirical data is fit to identify if any - and if how much - learning (say experiential learning or other export capability building) is triggered by one-off exporting compared to recurring exporting (and compared to international experience from importing). Fifth, using conditional probability analysis on our sample of firms and export spells, we find that previous one-off exporting by firms' indeed improves their future prospects of launching successful new country-product export spells. The effects from one-off experience are by a factor 3 smaller than those from recurring exporting, but larger than the effects from import experience. Sixth, we provide a dynamic simulation model, calibrated to the real data and seeded with only two one-off export episodes. The simulation shows that an initial non-exporter, will – only driven by the accumulated experiential learning effects estimated above – arrive at 8 distinct export destinations and 10 distinct export products within 12 rounds(years) of the simulation.

These findings challenge the otherwise implicit view of swift export market exits as costly and simply experimental, and suggest that firms indeed do learn from one-off exporting, and that these effects - although small in the first instance - are sizable and valuable to the firm in the long run.

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