Leader-follower dynamics in real historical time: a Markovian test of non-linear causality between sail and steam (co-)development

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Leader-follower dynamics in real historical time: A Markovian test of non-linear causality between sail and steam (co-)development

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ABSTRACT
The most dramatic changes in modern shipping occurred with the application of new industrial-age technologies to oceanic transportation. As metal-hulled and engine-powered trading platforms, industrial-age steamers (especially tramps and liners) lead to marked increases in the average tonnage of the typical vessel crossing the seas of an expanding global economy. Some of the most important developments had to do with the substitution of the traditional wind-driven ships by successive cohorts of vessels exploiting the comparative advantages of mechanisation. In this paper we deploy a set of both established and less-orthodox quantitative approaches to historical commercial shipping time-series so as to model the (complex) relationship between steam and sail performance. We find that, indeed, there is evidence of leader-follower dynamics during the later part of 19th century. This process of "creative destruction" was non-linear.

KEYWORDS
economic history, cliometrics, technological competition, sailing ships, steamships, vector autoregression, multivariate Markov chains.

1. Introduction

Structural change in ocean-going merchant transportation capital goods was a crucial dimension in the rise of shipping productivity during the second half of the 19th century. In the process, Britain became the shipyard of the world. The new generation of vessels being pushed out of its wharves and rivers became the prime carriers of the inter-continental commerce (Harley, 2004). The steamer was "the first key transport-related invention" of the industrial era; and it was the central chain of transmission of impacts elsewhere (Findlay and O'Rourke 2009, pp. 381). This research contributes to the appraisal of this transformative period with a quantitative assessment of the disruptive deployment of mechanisation in seafaring.

Recent scholarly work in the emerging field of "global economic history" has underlined just how innovation was integral to the the enhancement of markets, the deepening of international specialisation, and the promotion of economic growth (see

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Allen (2011)). Innovation and globalisation are the fundamental textbook causes of economic growth in the long-run. This study probes the ways in which the Industrial Revolution was pushed into the maritime scene and matured to deny the most profitable trading waters to the technologies of the Ancient Regime. In particular, this paper focuses on the dynamic competition patterns taking place between the new technology of steam and the old tradition of sail in the British mercantile fleet in the second half of the 19th century. We aim at understanding the key features that defined the relationship between steamers and sailing ships between the early 1860s (when the steamship finally became an able platform for longer-haul freight) and the 1910s (when the size of the mature sailing ship defied the imagination of the previous generation of mariners). How did the technical leadership of the steam-driven solution impacted the sail incumbency? To answer this question we take the average carrying capacity of British steam ships and sailing ships and seek to model the cross-effects overtime. The specific research question thus becomes: are the average tonnages of the different types of technical solutions (steam/sail) linked in any statistical (and meaningful) way?

Adding answers drawn from a quantitative appraisal of economic history of innovation is meaningful both methodologically and substantively. An analytical starting point for testing the Schumpeterian hypothesis of "creative destruction" in a context of multivariate processes is the VAR-family set of techniques. However, the results derived here from the deployment of this well-known econometric approach suggest that the two technologies evolve disjointly and independently, since no relationship between them can be detected. This lack of statistical success in detecting (linear) causality may be due to three reasons. First, no causality relationships exist and hence cannot be detected. Second, a relationship exists but is not detected by this modelling apparatus since the link can only be detected somewhere at higher moments of the probabilistic structure of the process, that is, not at its conditional mean. Third, there are non-linearities in the conditional mean of the processes and hence these are not captured by a VAR model; in this scenario the conditional mean was misspecified but an alternative approach could yield a working model. To investigate the latter conjecture, the original processes were reconstructed into a 5-state multivariate Markov chain. With this angle of analysis we show that, in fact, there is evidence of leadership-followership dynamics. Our findings also represent a tentative contribution to the substance of those debates ranging in the fields of cliometrics regarding the driving forces behind the process of globalisation taking shape in the late 19th century (see (Diebolt and Hagemann 2019)). Indeed, new have of literature has emerged trying to understand the full role of technological advances in ocean shipping and, more generally, the competitive interplay of alternative (complex and expensive) capital products co-evolving in a market characterised by uncertainty (see Madureira (2010); Mendonça (2013); Pascali (2017); Hanlon (2019); Ferreiro (2020); Ardelean et al. (2022)). This paper presents a number of econometric exercises that deepen the insights of studies which have documented the significance of product-level heterogeneity (technology, size) and its effect on the international maritime sector (structural change and growth).

The article is organised as follows. The next section fleshes out the argument from what is a rich but neglected body of, mostly qualitative, literature. The following section points to the modelling approaches and the empirical materials. Section 4 appreciates the results and contrasts them with the received wisdom, both in the fields of economy history and the economics technical change. Section 5 is the conclusion; it reviews the results, points to the limitations of the study, highlights the work needed to further extend this attempt, and the identifies some implications for theory as well as practice.

2. Historical background and conceptual context

Shipping is no stranger in the line-up of prime suspects for the critical sources of expansion and improvement of the European economy. That was surely the case during the 1500s, 1600s and in the aftermath of the Portuguese breakthroughs of ocean-going sail for the exploration and exploitation of new navigable routes (Unger 2011; Polónia, Bracht, and Conceição 2019). Regarding the ships themselves, naval architecture and construction have warranted the effort as a rich subject on which to pour new perspectives, new methods, and new archival resources (Ferreiro and McGee 2006; Reid 2017; Solar and de Zwart 2017).

For all its vital importance, modern-age shipbuilding as received scant attention from economists and historians (see Armstrong and Williams (2011)). This is surprising since by the end of the 1800s the western world's dominance was dependent on the services of the international shipping industry, an hegemony made more undisputed as the metal-made mechanised ship became the defining paradigm of efficient and robust sea transport ((Ojala and Tenold 2017)).

Fortunately, as of late, the eventful story of the ocean-going trader got new life thanks to a gust of favourable fresh research.

This burst of work includes new key books (most notably Smith (2018), and Ferreiro (2020)), but also a cluster of new research papers. Smith (2018) produces an outstanding account, and rarely detailed and polyhedral treatment, of the steamship as a central component of an world system which gained a new coherence in the transition to the 20th century. Ferreiro (2020) gives a magnificent moving picture of the interaction of science and technology as designers and institutions successively shaped and introduced marine steam-engines, paddles, propellers, iron and steel. These two comprehensive volumes make rare justice to the topic of steam at sea, and greatly complement, extend and update the insights of a previous generation of monographs who kept the subject afloat as sea-related topics felt out of favour among scholars (notably, Pollard and Robertson (1979); Allington and Greenhill (1997); Craig (2004))

Recent research also includes a number of papers that have probed new directions, namely by systematically perusing quantitative data. Kelly and O'Grada (2018) revisited the issue of British sailing ship speeds and found evidence of significant gains in early days of early industrialisation. Damásio and Mendonça (2019) stretched the time-frame from the beginning to mid-19th century and found evidence of rapid and marked technical progress in sailing ships, even in comparison to that of steamships. Pascali (2017) showed how the steamer decoupled trade routes from the age-old wind patterns and unleashed a major re-wiring of the world trade in the later part of the century. Hanlon (2019) has re-examined the persistent competitiveness of British steam shipbuilders in the late 1800s/early 1900s, vis-a-vis the American industry which had access to similar input and demand conditions.

The first 50 years of steam navigation were characterised by a steep learning curve (see Armstrong and Williams (2011)). Steamboats were experimented on rivers and lakes first, steam-propulsion was introduced into lower-cost applications such as ferrying and tugging, different configurations of ship deign were subjected to trial and error in higher-end uses such as the liner and the mail-carrying trades. By the the 1850's enough knowledge was held by the British engineers and shipbuilders, by far the most advanced in the world (see Craig (2004)). A generally accepted architectural solution emerged, and one that was suitable to a great variety of waters (technical fitness landscapes) and business (economic requirements). That template, or "dominant design", was the iron-screw combination (Mendonça 2013).

Conventional wisdom in innovation studies (that is, evolutionary economics, and the field of industrial dynamics in particular) would predict that upon the formation of a "consensus configuration" (dominant design) the market is expected to enter a new phase. The establishment of such a template causes dynamic effects among competing alternatives that are hardly reversible. Such phenomena have been modelled as complex co-evolutionary processes (Castellacci 2018); see also Robert, Yoguel, and Lerena (2017); Filatrella and De Liso (2020); De Liso, Arima, and Filatrella (2021); Filatrella and De Liso (2021).

In the case at hand, as the dominant design emerged the steamship gained its mature features and substantive uncertainty regarding that new alternative gave ground to a head-to-head competition with the traditional sail. More than anything else, the key capability of the merchant fleet that were fit for selection was servicing cargo cheaply and reliably, not speedily (the same is valid today, see Stopford (2009, p. 28); see also Basberg (1998)).

Indeed, a classic technological clash of the 19th century is the competition between sail and steam. However popular, this story is often superficially assumed rather than properly understood (see Mendonça (2013)); for a modelling approach to the phenomena of delayed diffusion see De Liso and Filatrella (2008)). In light of the need to better grasp the nature of the transition of sail to steam this paper will investigate the relationship between such competing platforms in terms of they relative performance over. What type of vessel, what followed, in which way, with want cross-inter-dependencies, if any, in that most important economically-relevant variable: cargo usable tonnage.

3. Modelling the interactions between old and new technologies

3.1. *Data and sources*

Our data refers to the complete fleet of British working ships (i.e. non-naval) from 1865 to 1914. The evidence is taken from Mitchell (1988), a well-known general source for long-time series on economically relevant statistics. The original data is number and tonnage for both British-built sail and steam merchant fleets, from which we get the average net tonnage figures. This provides us with an indicator of economically relevant technical progress which we can study over time and comparatively. As the shipbuilding activity is very dependent of economic expansions and contractions, as its products are expensive investment goods for the shipping services industries, we also take the real GDP of Britain as a control variable (the Maddison Project being the source).

Vessel size is a well-known variable in the economics of seaborne trade. Larger hulls carry higher volumes of cargo at a lower cost. It is also an engineering feature that, as time went by, steamers made the most of the metal materials needed to ensuring ever greater size (e.g. very bulky steel-built windjammers were built at the turn of the 20th century, but these were difficult to maneuver and fend off in storms given the very large canvas structures needed to power them). Moreover, higher and higher tonnages posed non-linear design challenges for builders. Progress along higher average tonnage fleet profiles was inherently intensive in trial-and-error, thus establishing a path-dependent nature in the dynamics of learning and innovation.

3.2. *A Vector Autorregression Approach*

The vectorial autorregressive (VAR) model is probably one of the most used techniques to describe the dynamics, and to forecast, a $K-$dimensional multivariate stochastic process. Hence, with Sims' critique (Sims 1980) the VAR framework emerged as the standard technique in time-series econometrics. VAR models are commonly employed either for analyzing the dynamic structural relationships between a system of interrelated variables and for forecasting purposes. The VAR approach explains the endogenous variables in the system as a function of the lagged values of all of the endogenous variables in the same system. As follows.

$$\mathbf{y}_t = \boldsymbol{\nu} + \mathbf{A}_1\mathbf{y}_{t-1} + \ldots + \mathbf{A}_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\mathbf{y}_t = (y_{1t}, \cdots, y_{Kt})'$ is a k-dimensional vector of endogenous variables, $\mathbf{A}_j,\ j = 1, \cdots, p$ are k-dimensional squared matrices of lag coefficients to be estimated, $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \cdots, \varepsilon_{Kt})'$ is a k-dimensional white noise process such that $\mathrm{E}[\boldsymbol{\varepsilon}_t] = \mathbf{0}$, $\mathrm{E}[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'] = \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}$, with $\mathrm{E}[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_s'] = 0$ for $t \neq s$ This approach postulates an efficient way to capture linear dynamics in multivariate processes. Hence, in our case, this approach is a natural choice for the assessment of the impact of Historical random disturbances of one technology on the performance of the other, and vice-versa. It may well be that Granger-type causality goes from one type of technological solution to the other, but not the other way around. In many respects, impulse-response analysis seems an appropriate angle of analysis through causal inference can be conducted. So as to investigate the dynamics of the relationship between sail and steam in the latter part of the 1800s, we make use of the standard detection and modelling procedures. Concerning the estimation of VAR order, i.e., the parameter p, several formal statistical procedures are usually considered. Probably, the most widely used is the sequential modified LR test, grounded on a general-to-specific (GTS) strategy, (Lütkepohl 2005). As follows. First, we consider an arbitrarily large number of lags, M; second we evaluate $H_0 : \mathbf{A}_M = \mathbf{0}$ versus a bilateral alternative hypothesis. If the null is rejected we set $p = M$, otherwise the hypothesis $H_0 : \mathbf{A}_{M-1} = \mathbf{0}$ is rehearsed. We consider (Sims 1980) small sample modification LR statistic

$$LR = (T - Kp - 1)\left(\log\left|\widetilde{\Sigma}_u^r\right| - \log\left|\widetilde{\Sigma}_u\right|\right) \sim \chi^2_{(k^2)} \tag{2}$$

For the sake of robustness, other procedures were also considered, namely the Final Prediction Error (FPE) and the Akaike's information criterion (AIC). The FPE

$$\mathrm{FPE}(m) = \left[\frac{T + Km + 1}{T - Km - 1}\right]^K \left|\widetilde{\Sigma}_u(m)\right| \tag{3}$$

p is estimated in order to minimize the FPE, that is $p = arg\min\{FPE(m)|m = 0, 1, \ldots, M\}$

Regarding the AIC

$$\mathrm{AIC}(m) = \log\left|\widetilde{\Sigma}_u(m)\right| + \frac{2mK^2}{T} \tag{4}$$

p is also chosen in such a way the AIC is minimized.

3.3. *Deploying the standard VAR estimation techniques*

We consider a trivariate VAR where, besides sail and steam's average tonnage, GDP was also considered as a control variable (as explained above). As the unit root tests suggest the nonstationary behaviour of our processes, we considered log-differentiated series. All procedures suggest a first-order VAR model, see Table 1, in other words:

$$\mathbf{y}_t = \boldsymbol{\nu} + \mathbf{A}_1 \mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t. \tag{5}$$

where $\mathbf{y}_t = \begin{pmatrix} SAIL_t & STEAM_t & GDP_t \end{pmatrix}'$ with all series expressed in (continuous) growth rates; and

$$\mathbf{A}_1 = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

Table 1. Lag Lenght Criteria

Lag	LogL	LR	FPE	AIC
0	64.78702	NA	1.29e-05	-2.746090
1	76.25529*	20.89773*	1.16e-05*	-2.855791*
2	80.20265	6.666653	1.46e-05	-2.631229
3	90.45433	15.94706	1.40e-05	-2.686859
4	96.25515	8.250045	1.66e-05	-2.544673

Table 2 reports the Granger linear causality tests. We find, indeed, and to be sure, no causality in either direction. The null hypothesis of "no Granger causality" is not rejected either for steam being influenced by events in sail in the previous period or vice-versa. That is, no pattern of cross-influence emerges from the analysis. This absence of evidence supporting the existence of effects from past technological events in one technology on the other may be due to several possible reasons. First, no link exists and hence it is not detected (absence of statistical evidence may be due to unexisting relationships). Second, a connection does exist but is not captured because, for example, the date is not appropriate or because the patters have not been modelled correctly (absence of statistical evidence may be due modelling techniques being unable to pick up the dynamics present in the data structure).

Finally, Table 3 summarises the VAR estimation results. The development of steamship technology, i.e. the growth in the size of this type of vessels, is highly correlated with itself but not with the putative competing technology or with the economic context. Overall, besides path-dependence in steam nothing detected at the conventional statistical significance levels. However, chances are that much is being missed by these exercises. Linear techniques may be overlooking non-linear phenomena.

Our next step is to try an alternative probabilistic approach. The aim is to capture and model the underlying structure of interdependencies as a stochastic, non-linear process, and to appreciate the (quantitative) results in the light of the broader evidence that (qualitative) maritime economic history research has accumulated over the years.

Table 2. Granger Linear Causality Tests

	H_0 : **does not Granger Cause**	
Variable	Steam	Sail
Steam	–	0.4682
Sail	0.6097	–
GDP	0.7864	0.7924
Joint Wald	0.8521	0.7870

p-values are reported

Table 3. VAR Model

Variable	**Coefficient**	**(Std. Err.)**
Equation 1: Steam		
Steam(-1)	-0.496020	(0.13597)
Sail(-1)	-0.142787	(0.20411)
GDP(-1)	-1.113202	(2.94835)
Intercept	0.040303	(0.06986)
Equation 2: Sail		
Steam(-1)	-0.053722	(0.10254)
Sail(-1)	0.150845	(0.15393)
GDP(-1)	1.278942	(2.22354)
Intercept	-0.024006	(0.05268)

Estimates are presented, se's between parentheses.

** denotes statistical significance at the 5% level

3.4. *Multivariate Markov Chain Methodology*

In the previous sections the traditional econometric tools for modelling the joint dynamics of multivariate processes were articulated and shown to lead to unsatisfactory results when tested. More precisely, sail and steam appear to be processes that develop without an apparent relationship. There is no systemic story behind the descriptive technological facts under appraisal, if linear approaches are our lenses.

It is important to note that the VAR approach only models one aspect of a process' probabilistic structure - the conditional mean, which is assumed to be linear. This inability to detect relationships may, however, be due to three distinct circumstances. First, in fact there is no relationship between sail and steam and therefore the results of the VAR approach are correct. Second, the conditional mean was poorly specified in the VAR model due to the presence of non-linear relationships, see Psaradakis, Ravn, and Sola (2005); Droumaguet, Warne, and Woźniak (2017). Third, sail and steam are related but not at the conditionally mean, i.e. this relationship occurs at other/higher moments of the probabilistic structure (variance, kurtosis, etc.). That is, there are complex relationships between these two variables that are not captured by the VAR model (see, e.g. Comte and Lieberman (2000); Lee and Yang (2012)). To answer this question, we tackle the sail and steam scene from a multivariate Markov chain perspective.

Markov chain models are increasingly proficiently and interdisciplinary used. To be specific, in Finance (Siu et al. 2005; Fung and Siu 2012), Financial Markets (Maskawa 2003; Nicolau 2014; Nicolau and Riedlinger 2015), Biology (Gottschau 1992; Raftery and Tavaré 1994; Berchtold 2001), Environmental Sciences (Turchin 1986; Sahin and Sen 2001), Linguistics(Markov 1913), Medicine (Li et al. 2014), Forecasting (Damásio and Nicolau 2013), Management (Ching, Fung, and Ng 2002; Horvath, Autry, and Wilcox 2005; Zhu and Ching 2010), Macroeconomics (Nicolau 2017; Damásio, Louçã, and Nicolau 2018), Economic History (Damásio and Mendonça 2019), among others; see, e.g. (Ching and Ng 2006; Sericola 2013).

The multivariate stochastic process $\{(S_{1t}, \cdots, S_{st})\,; t = 0, 1, 2, ...\}$ is said a MMC when

$$P\left(S_{jt} = i_0 | \mathcal{F}_{t-1}\right) = P\left(S_{jt} = k | S_{1t-1} = i_1, \cdots, S_{st-1} = i_s\right) \tag{6}$$

where S_{jt} $(j = 1, \cdots, s)$ can take values in the set $E = \{1, \cdots, m\}$, and $\mathcal{F}_{t-1}$ is the σ-algebra generated by the available information until $t - 1$.

However, despite its relevance and flexibility, an MMC cannot be estimated using the conventional theory for univariate markov chains. In fact, modeling probabilities (6) is impractical to the extent that there are m^s states and therefore the total number of states of the process growth exponentially with s. To address this issue (Raftery 1985) proposed the mixture transition distribution model (MTD)[1]. However, the MTD-Probit model (Nicolau 2014; Damásio and Nicolau 2013) stood out because it has the best properties in terms of efficiency, ease of implementation and robustness of results (it can be proved that the probabilities estimated by this model are closer to the true probabilities than the MTD).

The quantity $P\left(S_{jt} = i_0 | S_{1t-1} = i_1, \cdots, S_{st-1} = i_s\right)$ is taken as a non-linear com-

[1]some improvements to this model have been proposed by Raftery and Tavaré (1994); Lèbre and Bourguignon (2008); Chen and Lio (2009)

bination of bivariate conditional probabilities as follows:

$$P\left(S_{jt}=i_0|\,S_{1t-1}=i_1,\cdots,S_{st-1}=i_s\right)^{\Phi}\equiv \frac{\Phi\left[\eta_{j0}+\eta_{j1}P\left(S_{jt}=i_0|\,S_{1t-1}=i_1\right)+\cdots+\eta_{js}P\left(S_{jt}=i_0|\,S_{st-1}=i_s\right)\right]}{A} \quad (7)$$

where $A=\sum_{k=1}^{m}\Phi\left[\eta_{j0}+\eta_{j1}P\left(S_{jt}=k|\,S_{1t-1}=i_1\right)+\cdots+\eta_{js}P\left(S_{jt}=k|\,S_{st-1}=i_s\right)\right]$ is a normalizing constant that ensures that

$$\sum_{j=1}^{s}P\left(S_{jt}=i_0|\,S_{1t-1}=i_1,\cdots,S_{st-1}=i_s\right)^{\Phi}=1 \quad (8)$$

Once the quantities $P\left(S_{jt}=i_0|\,S_{kt-1}=i_k\right)$ $k=1,...,s$ are easily estimated using the consistent estimators

$$\widehat{P}\left(S_{jt}=i_0|\,S_{kt-1}=i_k\right)=\frac{n_{i_1i_0}}{\sum_{i_0=1}^{n}n_{i_1i_0}} \quad (9)$$

where $n_{i_1i_0}$ represents the number of transitions from $S_{k,t-1}=i_k$ to $S_{jt}=i_0$; the parameters η_{jk} are thereafter estimated using the maximum likelihood principle. Considering, without any lost of generality the dependent variable in 7 maximum likelihood the estimator is:

$$\log L=\sum_{i_1i_2...i_{i_s}i_0}n_{i_1i_2...i_{i_s}i_0}\log\left(P_j^{\Phi}\left(i_0|\,i_1,...,i_s\right)\right). \quad (10)$$

where, to ease the notation

$$P_j^{\Phi}\left(i_0|\,i_1,...,i_s\right)\equiv P\left(S_{jt}=i_o|\,S_{1t-1}=i_1,\cdots,S_{st-1}=i_s\right)^{\Phi} \quad (11)$$

One of the advantages of our methodology is that it allows statistical inference under the parameters, η_{jk} the weights of the non-linear combination. This means that the relevance of a specific bivariate probability, that depicts a concrete variable, can be tested from a statistical point of view. Put otherwise, a non-linear form of causality test is proposed in such a way that this approach allows us to test whether or not the density of a process depends on the density of the other process, as we will show in the next section.

3.5. *Modelling the dynamic relationship between incumbent and insurgent technologies*

Econometric research frequently synthesises discrete random variables that were composed from some original continuous random variable y_t. Let y_{1t} and y_{2t} the yearly growth rates of the average tonnage (the ratio tonnage/number of ships) of sail and steam, respectively. Let also y_{3t} represent the UK GDP annual growth rate. Given the continuous nature of the above variables, the first step is a reconstruction of the discrete processes that characterize the MMC. There are several methodologies for reconstructing stochastic processes, see for example (Harding and Pagan 2011). In our case the processes were reconstructed into a 5-state trivaritate Markov chain in accordance with the following rule:

$$S_{jt} \quad = \quad \begin{cases} 1 \text{ if} & y_{jt} < \hat{q}_{j,0.2} \\ 2 \text{ if} & \hat{q}_{j,0.2} < y_{jt} < \hat{q}_{j,0.4} \\ 3 \text{ if} & \hat{q}_{j,0.4} < y_{jt} < \hat{q}_{j,0.6} \\ 4 \text{ if} & \hat{q}_{j,0.6} < y_{jt} < \hat{q}_{j,0.8} \\ 5 \text{ if} & y_{jt} > \hat{q}_{j,0.8} \end{cases} \tag{12}$$

where $\hat{q}_{j,\alpha}$ is the estimated quantile of order α of the marginal distribution of y_{jt}. As for sail and steam, this 5-state process labels the technology into five categories of innovation accordingly to its development prowess: 1- very slow movement, 2 - slow movement, 3 - standard movement, 4 - fast movement, 5 - very fast movement. The same reasoning applies to GDP: economic contraction (state 1 and 2); economic stabilisation (state 3); or economic expansion (states 4 and 5).

Although the fundamental interest of this specification is to test for non-linear interdependent relationships between sail and steam, the GDP was considered, as in the VAR model, as a control variable such that the the forces underlying the interdependence pattern of these technologies is accommodated.

Hence for each $j-th, j = 1, 2, 3$ series the model can be expressed as

$$\begin{aligned} & P\left(S_{jt} = i_0 \middle| S_{1t-1} = i_1, S_{2t-1} = i_2, S_{3t-1} = i_3\right)^{\Phi} \equiv \\ & \qquad \frac{\Phi\left[\eta_{j0} + \eta_{j1} P\left(S_{jt} = i_0 \middle| S_{1t-1} = i_1\right) + \right.}{\sum_{k=1}^{5} \Phi\left[\eta_{j0} + \eta_{j1} P\left(S_{jt} = k \middle| S_{1t-1} = i_1\right) + \right.} \\ & \qquad \frac{\left.\eta_{j2}\, P\left(S_{jt} = i_0 \middle| S_{2t-1} = i_2\right) + \eta_{j3} P\left(S_{jt} = i_0 \middle| S_{3t-1} = i_3\right)\right]}{\left.\eta_{j2}\, P\left(S_{jt} = k \middle| S_{2t-1} = i_2\right) + \eta_{j3} P\left(S_{jt} = k \middle| S_{3t-1} = i_3\right)\right]}, \end{aligned} \tag{13}$$

a trivariate MMC ($s = 3$) with domain $E = \{1, 2, ..., 5\}$, $m = 5$.

It is important to emphasize the indispensability of the specification MTD-Probit. In fact, given the characteristics of MMC, 5 states and 3 series, a fully parameterised model, i.e. a traditional Markov chain, will involve $m^s = 125$ different states and $m^s(s-1) = 250$ independent parameters. Obviously this estimation problem was impossible due to our the sample size.

Once again, we draw attention to the parameters $\eta_{jl}, j = 1, 2, 3; l = 1, 2, 3$. This parameters measure the the contribution of each variable past state (or relative strength) to the $j-th$ variable current state (or relative strength). For the sake of clarity, suppose without any lost of generality that we are interested in explaining sail's technology current strength. In this circunstance the equation will be

$$P\left(S_{1t} = i_0 \middle| S_{1t-1} = i_1, S_{2t-1} = i_2, S_{3t-1} = i_3\right). \tag{14}$$

With this approach we are explaining not only the conditional mean of sail as a linear function of GDP and steam, but also all sail's probabilistic structure is a (non-linear) function of sail, steam and gdp probabilistic structure:

$$\begin{aligned} \eta_{j1} P\left(S_{jt} = i_0 \middle| S_{1t-1} = i_1\right) \quad & + \eta_{j2} P\left(S_{jt} = i_0 \middle| S_{3t-1} = i_2\right) \quad + \\ \eta_{j3} P\left(S_{jt} = i_0 \middle| S_{3t-1} = i_3\right). & \end{aligned} \tag{15}$$

It should be mentioned that all variables on the right-hand side are reported at $t-1$, which ensures that there is no simultaneity-bias. On the other hand, with this specification we are modeling the probabilistic structure of the variables, which assures us that there are no endogeneity problems, i.e., the MLE remains consistent, (see eg (Billingsley 1961; Basawa 2014)). Furthermore, this methodology allows us to test a general form of non-linear causality. For example, an implication of a rejection of the null $H_0 : \eta_{11} = 0$ and a non-rejection of the null $H_0 : \eta_{12} = 0$ is that sail's current strength does not depend on steam's past strength. Therefore sail is a dominated technology, given that its current performance only depends on the past performance of steam. Although the parameters η_{j0} have no economic interpretation, their inclusion in the model is justified because they have been shown to improve fit; the respective estimates are also reported.

The estimation results of the equation 13 are depicted in Table 4. The estimates $\hat{\eta}_{j1}$ and η_{j2} measure, respectively, the impact of sail's and steam's past performance on the technology j current performance.

Table 4. MTD Probit Estimation

Equation	$\hat{\eta}_{j0}$ (Intercept)	$\hat{\eta}_{j1}$ (Sail)	$\hat{\eta}_{j2}$ (Steam)	$\hat{\eta}_{j3}$ (GDP)	*Mean LL*
1 Sail	-3.9969^{**}	4.6599	5.4739^{*}	4.4748	-0.0815224
	(0.8011)	(2.5736)	(1.9553)	(2.8614)	
2 Steam	-3.9667^{**}	7.0723	7.8941^{*}	5.3751	-0.0813727
	(1.1094)	(4.0263)	(3.7212)	(2.6918)	

Coefficient estimates are presented, standard errors between parentheses.

Mean LL represents the mean of the log-likelihood function.

** and * indicates the statistical significance level, respectively, for 1% and 5%

In this paper we find evidence that steam technology is (statistically) at the centre of a broader story at sea on the second half of the 19th century, and this is a story of systemic change. Steam is found to push along a technological trajectory that is determined by its own previous technological events (the estimate 7.8941 is significant, and points to the power of the past in the case of steam). However, the impact of changes in steam are felt beyond this technology. This is important. Maritime history documents that the increase in the average vessel capacity of both types of ships was a secular trend, something driven by new hull materials and framing methods that could be applied to steamships and sailing ships alike (Slaven 1980). However, the co-evolutionary patterns have remained persistently obscure.

Thus, the connection with sail is telling. Not only its own technological events seem not to induce changes in its own performance, there seems to be an external source of impact at play. The present dynamics of sail is driven by the past dynamics of steam: the estimate 5.4739 is significant, and shows how past technological changes in steam drive follow-up changes in sail.

All in all, shocks in the performance of steam are found to have happened ahead, and been linked, to statistical changes in the performance of sail. Innovation in steamship design and architecture, measured by the stream of qualitative changes captured by the average capacity of vessels, thereby seem to lead whatever was happening in the sailing shipbuilding; changes in the technical specifications in sail effectively came in the wake of those of steam, i.e. sail followed steam in the variables and methods studies here are concerned.

Our findings offer a picture of the steamship as a robust, consolidated, and even imposing, techno-economic platform. Indeed, we are examining steam navigation after its dominant design (the screw-iron template) was established. We also can perceive the sailing ship as a dynamic type of vessel, albeit on the defensive, reacting to steam, but seemingly unable of building on its own technological trajectory. This stylised fact is consistent with what the available industrial dynamics literature, and also from what we grasp from the extant scholarship of industrialisation at sea in the 19th century. Our approach provides a test of these insights, and brings into sharper focus a fundamental aspect of structural change.

Moreover, the strong persistence of growth in the average capacity of steam vessels appeals to the notion of endogenous technical change (as distinct from the conjecture of discrete and finite exogenous technological shocks). This observation should encourage the investigation of theoretical models of technological progress in new product industries that explicitly bring to the centre concepts such as learning and other cumulative intangible factors.

4. Conclusions

This paper advances a combination of a classic history case with cutting-edge quantitative methodologies. It employs data from a well-known statistical source, cushioned with an awareness of the maritime context provided by the specialised literature. It also attempts to deploy standard (VAR) and less-conventional (MMC) modelling approaches.

As globalising industrial capitalism progressed in the second half of the 1800s, the technologies of oceanic commercial carriage interacted. The multivariate Markov chain (MMC) approach provides a persuasive quantitative account, which is well in line with the qualitative insights that can be gleaned from the extant maritime economic history. Whereas a vector auto-regressive (VAR) approach is unable to detect dynamic relationships between sail and stem, the MMC approach adds to our understanding that complex cross-technology effects were indeed at work. Technical progress is systemic: change in one front produces impacts on other fronts of the technological system.

As the Victorian age was marching toward maturity, we witness steam technology being propelled by its own past developments. We also see that progress in steam is not without significance elsewhere: the performance of sail technology as a viable economic alternative is impacted by events in the steam-based mode of transportation. However, the reverse is not true: not only events in sail are steam-dependent, progress in sail is not driven by progress in sail. In other words, steamship innovation is the central factor leading to further (ever cumulative) innovation in steamships whereas the alternative of sail becomes ever more peripheral, as if unable even to produce meaningful technological influence onto itself.

Our paper emphasises the usefulness of combining non-linear approaches and economics. This promise should invite more testing, namely, by considering other variables of economic and technical performance. The lessons learned matter not only to historical research (see Rosenberg (1972); Madureira (2010); Mendonça (2013)) but also to policy-makers, strategists and analysts dealing with contemporary disruptive innovation. Understanding the cross-dynamics of substitute and complementing technologies will remain an empirical task likely to yield fresh insights as long as innovation remains a creative, destructive, systemic and, in a word, Schumpeterian phenomenon.

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