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Modeling insurgent-incumbent dynamics: Vector autoregressions, multivariate Markov chains, and the nature of technological competition

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ABSTRACT
The struggle between sail and steam is a long-standing theme in economic history. But this technological competition story has only partly tackled, since most studies have appreciated the rivalry between the two alternative modes of commercial sea carriage in the late 19th century while the early period has remained relatively under-analysed. This paper models the early dynamics between the two capital goods using a vector autoregression approach (VAR) and a Multivariate Markov Chain approach (MMC). We find evidence that the relationship was nonlinear, with a strong indication of complementarities and cross-technology learning effects.

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

1. Introduction

At least since Schumpeter, modernisation carries the connotation of "creative destruction". The superior newcomer technology makes the old one redundant. In economic history technological competition has been epitomised by the replacement of sail by steam (see, e.g., Craig 2004; Geels 2002). This momentous change in the profile of mercantile marine paved the way to the rise of the west and the triumph of industrial progress.

Most studies, however, have covered the process of transformation of sea-related activity in the late 19th century, when the steamer was already a stand-alone fully viable alternative (see Pollard and Robertson (1979), Mohammed and Williamson (2004)). Since the classic findings of North (1958), through the insights of Harley (1971) to the most recent work by Pascali (2017), steam navigation has been taken to be a major driving force behind the sharp reduction of transport times and costs that ushered the first era of globalisation.

Less known is the period before machinery and metallurgy reined supreme, when accommodation was the main feature of a maritime world in transition. This paper

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looks into this earlier period so as to unpack the dynamics of technological co-existence between the two alternatives until the time in which they became clear substitutes (1860s onwards). This empirical work assesses the first five decades of ascendancy of the insurgent, but still experimental technology of steam when sail dominance was overwhelming and yet advancing its performance.

We find that while a vector autoregression approach would be an obvious choice for modelling structural relationships in multivariate processes the results are quite unsatisfactory. Additionally, there is no trace of Granger causality. One reason for these failures to identify interactions may have to do with the presence of non-linear dynamics. To investigate this hypothesis a multi-variate Markov chain approach is applied, to check if density functions (not only first moments) are time-dependent between variables. This modelling strategy succeeds in picking up directional powers between the historical paths of sail and steam. In particular, we detect that while the insurgent (steam) does not impact the incumbent (sail) some effects are produced from the incumbent (sail) to the insurgent (steam) technology. However paradoxical, this finding makes sense in the light of the existing literature on technical change in maritime history.

2. Argument and approach

The industrial revolution at sea is a relatively little explored issue. Clearly, it was a slow process at first. On the one hand, the old technology was more efficient than is usually assumed: sailing ships were pushing ahead in terms of speed and strength comparing with their immediate predecessors (Solar 2013; Kelly and O'Grada 2018). On the other hand, steamships were not competing on established trades and routes as they were handicapped by difficulties of range and efficiency (Allen 2011), see also Mendonça (2013).

Surely both technologies advanced over time; what is less clear is how they influenced each other in this early period in which sail was a dynamic incumbent and steam was still an uncertain insurgent. One way to investigate this issue is by applying conventional time-series techniques that inquire causality and interdependencies between variables, and by taking into consideration a proxy of economically useful ship sophistication (average tonnage). Here we focus on the British merchant sail and steam fleets between 1814 (the earliest datapoint) and 1865 (a cut-off point generally taken to mark the beginning the of the end of sail and the end of the begging of steam; see, e.g. Harley (1971)).

3. Modelling the interactions between old and new technologies

3.1. *Metrics and materials*

In this paper, we start by proposing a vector-autoregression approach to model the evolution of the two technologies between 1814 and 1865. We then try to get extra leverage through a multivariate Markov chain approach. The aim is to characterise the key features of sail-steam dynamic interdependencies.

The dataset is taken from Mitchell (1988), a source that makes available for historians long series of economic and technological statistics. Although providing yearly information about number and tonnage for both British-built sail and steamships, this source has remained under-exploited. This study takes the average net tonnage of the sail and steam fleets as a comparative indicator of economically useful technical progress and monitors growth rates over time. As shipbuilding is highly sensitive to the business cycle and to the expansion of trading opportunities British real GDP is taken as a control variable (the Maddison Project is the source here).

It should be pointed out that, given the non-stationary nature of the processes, we considered the log-difference of series (growth rates) of the average tonnage of sail and steam vessels. This is intended to enforce stationarity (both in mean and in variance) as it is confirmed by augmented Dickey-Fuller tests.

3.2. *A Vector Autorregression Approach*

In applied econometrics the joint dynamics of variables invites the development of a vector autoregression (VAR) methodology. Since the Sims critique (Sims 1980) that modelling $K-$dimensional multivariate stochastic process $\{(\boldsymbol{y}_t), t = 1, 2, 3, \cdots\}$ in the VAR framework has established itself as a standard tool in econometrics.

VAR models explain a multivariate set of endogenous variables uniquely by their own history, exploring the dynamics of the linear interactions between such variables. Therefore, this approach provides a systematic way to capture linear dynamics in multivariate processes. Past shocks to the growth rate in the average tonnage of one type of ship may impact the performance of the other, and/or vice-versa, with years of delay. It may be that Granger-type causality flows from one sort of technology to the other, but not the other way around. In many respects, impulse-response analysis seems an apt perspective through which to conduct causal inference. In order to investigate the dynamics of the relationship between sail and steam in the earlier part of the 19^{th} century, we consider the standard detection and modelling procedures.

Mathematically speaking, a VAR model of order p can be defined as

$$\boldsymbol{y}_t = \boldsymbol{c} + \sum_{j=1}^{p} \boldsymbol{\Phi}_j \boldsymbol{y}_{t-j} + \boldsymbol{\varepsilon}_t$$

where $\boldsymbol{y}_t = [y_{1t}, \cdots, y_{kt}]'$ is a $K-$dimensional vector of random variables; $\boldsymbol{c}$ is a fixed $K-$dimensional vector of intercepts controlling for a non-zero mean possibility; $\boldsymbol{\Phi}_j$ are $K \times K$ coefficient matrices (for $j = 1, \cdots, p$) and $\boldsymbol{\varepsilon}_t$ is a $K-$dimensional white noise process such that $E[\boldsymbol{\varepsilon}_t] = \boldsymbol{0}_k$, $E[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'] = \Sigma$ (a nonsingular matrix), and, for $v \neq s$ $E[\boldsymbol{\varepsilon}_v \boldsymbol{\varepsilon}_s'] = \boldsymbol{0}$

In order to deploy this linear estimation apparatus on the first moments of the time-series we start by establishing the length of the time-lag. Lag length is usually selected using formal statistical criteria like the likelihood ratio (LR), log-likelihood (LogL), Akaike's information criterion (AIC), Schwarz's information criterion (SIC), Hannan-Quinn (HQ), or the Final Prediction Error (FPE). The diagnostic tests point to a restricted model using a minimally-lagged VAR since the LR, FPE, AIC and HQ tests suggest just one time period (1 year) as lag. It is reassuring that many criteria are convergent, as a single criterion is a weak basis from which to judge a model, and that the AIC and the FPE, which are more appropriate when observations are small (60 or less), point in the same direction. LogL and SIC provide conflicting results, but not convergent. Table 1 displays the conventional lag length criteria tests.

Table 2 reports the Granger linear causality tests. We find that no causality is detected in either direction. That is, no pattern of cross-influence emerges: the null

Table 1. Lag Lenght Criteria

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	147.6038	NA	9.87e-06	-3.012579	-2.932443*	-2.980187
1	162.9642	29.44080*	8.64e-06*	-3.145088*	-2.824544	-3.015519*
2	170.9529	14.81242	8.83e-06	-3.124020	-2.563068	-2.897274
3	177.7178	12.12040	9.27e-06	-3.077455	-2.276096	-2.753532
4	185.2677	13.05495	9.58e-06	-3.047243	-2.005477	-2.626144

hypothesis of "no Granger causation" is not rejected either for steam being influenced by events in sail in the previous period or vice-versa. This lack of statistical success in picking up the effect the past technological events of one technology on the other may be due to two reasons. First, no connection exists and hence it is not detected. Second, it does exist but is not being modelled correctly.

Finally, Table 3 summarises the VAR estimation results. The development of steamship technology, i.e. the growth is ship size, is highly correlated with itself but nothing else. Results for the other variables are void. Overall, little is learnt from these (linear) exercises. The stage is now set for proposing another (non-linear) probabilistic approach to capture and model a latent structure of interdependencies as a stochastic process.

3.3. *Multivariate Markov Chain Methodology*

A Markov chain is a sequence of random variables $S_t, S_{t-1}, ..., S_0$, defined into a countable space state $E = \{1, 2, ..., m\}$, that is characterised by the Markov property that given the present, the future does not depend on the past as follows:

$$P(S_t = k_0 | \mathcal{F}_{t-1}) = P(S_t = k_0 | S_{t-1} = k_1) \quad (1)$$

Where $\mathcal{F}_{t-1}$ is the $\sigma - algebra$ generated by the available information until $t-1$. The multivariate stochastic process $\{(S_{1t}, \cdots, S_{st}); t = 0, 1, 2, ...\}$ is said to be a multivariate Markov chain process (MMC) if an only if

$$P(S_{jt} = k | \mathcal{F}_{t-1}) = P(S_{jt} = k | S_{1t-1} = i_1, \cdots, S_{st-1} = i_s) \quad (2)$$

Despite its limited usage, this approach configures a substantial advantage with respect to alternative econometric methods; estimating a MMC *tout court* is an impossible task because the total number of independent parameters grows exponentially with the number of categorical series (following $m^s(s-1)$). To address this issue the mixture transition distribution model (MTD) (Raftery 1985) has been proposed. Some improvements to this model have been proposed in the literature, notably by Chen and Lio (2009); Ching, Fung, and Ng (2002); Ching and Ng (2006); Lèbre and Bourguignon (2008); Raftery and Tavaré (1994); Zhu and Ching (2010).

A salient model is the MTD-Probit model (Nicolau 2014; Damásio and Nicolau 2013). The quantity $P(S_{jt} = i_o | S_{1t-1} = i_1, \cdots, S_{st-1} = i_s)$ is taken as a nonlinear combination of bivariate conditional probabilities as follows:

$$P\left(\left.S_{jt}=i_o\right|S_{1t-1}=i_1,\cdots,S_{st-1}=i_s\right)^{\Phi}\equiv \frac{\Phi\left[\eta_{j0}+\eta_{j1}P\left(\left.S_{jt}=i_o\right|S_{1t-1}=i_1\right)+\cdots+\eta_{js}P\left(\left.S_{jt}=i_o\right|S_{st-1}=i_s\right)\right]}{\sum_{k=1}^{m}\Phi\left[\eta_{j0}+\eta_{j1}P\left(\left.S_{jt}=k\right|S_{1t-1}=i_1\right)+\cdots+\eta_{js}P\left(\left.S_{jt}=k\right|S_{st-1}=i_s\right)\right]} \tag{3}$$

$\sum_{k=1}^{m}\Phi\left[\eta_{j0}+\eta_{j1}P\left(\left.S_{jt}=k\right|S_{1t-1}=i_1\right)+\cdots+\eta_{js}P\left(\left.S_{jt}=k\right|S_{st-1}=i_s\right)\right]$ is a normalising constant. The estimation technique is a two-step procedure. The quantities $P_{jk}\left(\left.i_0\right|i_1\right),\ k=1,,...,s$ are estimated nonparametrically through the consistent estimators $\hat{P}_{jk}\left(\left.i_0\right|i_1\right)=\frac{n_{i_1i_0}}{\sum_{i_0=1}^{n}n_{i_1i_0}}$ where $n_{i_1i_0}$ represents the number of transitions from $S_{k,t-1}=i_1$ to $S_{jt}=i_0$. The parameters η_{jk} are thereafter estimated using the maximum likelihood method. For the variable S_{jt} the MLE is

$$\log L=\sum_{i_1i_2...i_{i_s}i_0}n_{i_1i_2...i_{i_s}i_0}\log\left(P_j^{\Phi}\left(\left.i_0\right|i_1,...,i_s\right)\right). \tag{4}$$

It can easily be proved that $\hat{P}_{jk}$ is a consistent estimator of P_{jk} and then it is straightforward to show that $\hat{\eta}_{jk}\xrightarrow{p}\eta_{jk}$.

The parameters η_{jk} represent the weights of the nonlinear combination: the higher the coefficient, in absolute value, the higher the importance of the respective variable $P\left(S_{jt-1}=k\right)$. As the model is estimated through the ML estimator the inference problem is addressed. This means that the relevance of a specific bivariate probability, that depicts a concrete variable, can be tested from a statistical point of view.

As we will show in the next sub-section, the multivariate Markov chain methodology and the MTD-Probit specification can be used to capture the multivariate relationships and dependences between two technologies. In fact, unlike some traditional parametric econometric techniques, such as vector autorregressions that only capture linear relationships between variables, the purpose of nonlinear methodologies is to capture complex relationships that go beyond the first moment (conditional mean) or even the second moment (conditional variance) as in multivariate GARCH family models. Notice that the absence of parametric assumptions and constrains (the MTD-Probit model is completely free of super-imposed restrictions) underlying the model allows us to capture a wide range of associations between a set of variables that can only be captured using nonparametric approaches.

3.4. *Modelling the dynamic relationship between incumbent and insurgent technologies in the early days of steam*

Let y_{1t} and y_{2t} denote respectively the yearly growth rates of the average tonnage (the ratio tonnage/number of ships) of sail and steam. Let also y_{3t} represents the UK gdp annual growth rate. The MMC process was reconstructed accordingly to the following rule:

$$S_{jt} = \begin{cases} 1 \text{ if } & y_{jt} \leq q_{20} \\ 2 \text{ if } & q_{20} < y_{jt} \leq q_{40} \\ 3 \text{ if } & q_{40} < y_{jt} \leq q_{60} \\ 4 \text{ if } & q_{60} < y_{jt} \leq q_{80} \\ 5 \text{ if } & y_{jt} > q_{80} \end{cases}$$

where q_l represents the $l - th$ percentile of the process y_{jt}. Regarding the two technologies, the rationale behind this transformation is as follows. Each technology is labeled into five categories or states 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 rationale can be applied to the GDP to economic contraction (state 1 and 2), economic stabilisation (state 3) or economic expansion (states 4 and 5). The main interest here is to analyse the relationships between these two technologies: sail and steam. Information regarding GDP was considered as control and to accommodate the forces that give context to the interdependence pattern that governs the bivariate dynamics under scrutiny. Therefore, $\mathcal{F}_{t-1}$, the $\sigma - algebra$ generated by the available information until period $t-1$ was expanded. For each period the model for the $j-th, j = 1, 2, 3$ category is

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

Therefore, the space state is $E = \{1, 2, ..., 5\}$, $m = 5$ and $s = 3$. It should be pointed out the fact that, here, a fully parameterised MMC involves $m^s(s-1)$ independent parameters, circumstance which, in our case, leads to 500 independent parameters which is an untractable problem due to our data span.

The quantities $\eta_{jl}, j = 1, 2, 3; l = 0, 1, 2, 3, 4$ represent the contribution of each past variable for the $j-th$ variable current state. For instance, suppose that we are analysing sail technology. The dependent variable

$$P\left(S_{1t} = i_o \middle| S_{1t-1} = i_1, S_{2t-1} = i_2, S_{3t-1} = i_3 \right) \tag{6}$$

is a nonlinear function of sail, steam and gdp past states:

$$\eta_{j1} P\left(S_{jt} = i_o \middle| S_{1t-1} = i_1 \right) + \eta_{j2} P\left(S_{jt} = i_o \middle| S_{3t-1} = i_2 \right) + \eta_{j3} P\left(S_{jt} = i_o \middle| S_{3t-1} = i_3 \right) \tag{7}$$

If we fail to reject the null $H_0 : \eta_{12} = 0$ but we reject $H_0 : \eta_{11} = 0$ this means that sail does not depend on steam and, moreover, the current power of sail is not determined by steam's power and thus sail is a dominant technology, given that the current performance of sail only depends on its own past performance. The intercepts η_{j0}, although they have no interpretation, are included in the model as they have been shown to improve fit (Nicolau 2014, p.1127), so the respective estimates $\hat{\eta}_{j0}$ are reported.

4. Estimation Results

This section depicts the estimation results of the equation 5 for the period 1814-1865. Table 4 points out that the estimates $\hat{\eta}_{j1}$ and η_{j2} measure, respectively, the impact of sail's and steam's past power on the technology j current power.

On the one hand, it can be noticed that the dynamics that governs sail technology is characterised by a dependence on its own past states ($\hat{\eta}_{11}$=6.7794, significant at the 5% significance level, indicating a strong persistent behaviour) and an absence of influence by what has been going on before in steam ($\hat{\eta}_{12}$ not significant at any of the traditional significance levels). On the other hand, steam technology is strongly shaped by prior events in sail ($\hat{\eta}_{21}$ is high and significant). This effect happens to be even stronger (both statistically and substantially) than the influence of steam's own past dynamics on itself ($\hat{\eta}_{22}$ is lower and only significant at the 10% level). Both sail and steam dynamics appear to be coordinated with the general economic environment.

Therefore, one may infer an asymmetrical technological relationship. Against heroic or linear representations of innovation, leadership during the rise of the "insurgent" technology was on the side of "incumbent", that is, the vintage solution of sail. Sail's performance does predict steam's, and this circumstance implies a (statistical) dominant influence of the old on the newcomer. The transfer of leadership to steam, in the sense of the impact of the new technology on the old technology, would only occur beyond the period under analysis, and with devastating consequences for sail (Craig 2004; Mendonça 2013). At the core of the transformation of transport there was a complex relationship between contending technologies, a switch later amplified by the continuous investment in invention (see Ferreiro and Pollara 2016) and deployment of new infrastructures (see Gray 2015).

5. Conclusions

This paper addresses, analyses and comments the intriguing relationship between sail and steam at the dawn of globalising industrial capitalism. This paper presents evidence that improvements in the incumbent and insurgent technologies appear interrelated. Statistical results suggest that the mix of technologies in the British merchant marine had co-evolutionary characteristics from early on. That a multivariate Markov chain approach brings some fresh and history-friendly insight is testimony to the need for experimenting with new empirical approaches and for keeping the methodological toolbox plural.

Contrary to explanations that would see sail technology reacting to the competing threat posed by steam, we see that technological relations do not simply appear to be zero-sum. Positive, synergic relationships emerge with the arrival of steam to a maritime world dominated by sail. Moreover, the dynamics was not symmetrical. Evidence is somewhat elusive but tentatively points to a major influence from sail to steamship performance (as measured by average carrying capacity). That steam received an indirect payoff from its co-existence with sail resonates with maritime economic history and systemic visions of technical change. These views have emphasised the importance of technological complementarities: the old/incumbent technology, which was in fact quite alive in terms of innovation, re-invigorated the possibilities of the new/insurgent technology (see, e.g. Rosenberg (1972); Madureira (2010); Mendonça (2013). Such a stylised fact should be remembered by industrial policy analysts.

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Table 2. Granger Linear Causality Tests

	H_0 : **does not Granger Cause**		
Variable	Steam	Sail	GDP
Steam	–	0.9421	0.0149
Sail	0.5934	–	0.7915
GDP	0.2456	0.4891	–
Joint Wald	0.4732	0.7851	0.0514

p-values are reported

Table 3. VAR Model

Variable	**Coefficient**	**(Std. Err.)**
Equation 1: Steam		
Steam(-1)	-0.395**	(0.127)
Sail(-1)	0.489	(0.404)
GDP(-1)	0.643	(1.155)
Intercept	3.473	(4.856)
Equation 2: Sail		
Steam(-1)	-0.003	(0.046)
Sail(-1)	-0.081	(0.146)
GDP(-1)	-0.301	(0.418)
Intercept	2.028	(1.756)

Estimates are presented, se's between parentheses.

** denotes statistical significance at the 5% level

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	-4.6688^{***} (1.6422)	6.7794^{**} (3.3522)	7.9404 (4.9772)	5.2054^{**} (2.3467)	-0.0864203
2 Steam	-5.7473^{***} (1.8180)	10.2751^{**} (4.7123)	5.8173^{*} (3.1724)	9.3844^{**} (3.9230)	-0.0901025

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%, 5% and 10%