Was Technology Skill-Biased in the Atlantic Merchant Marine, 1863 to 1913?

BINGLING KONG

Advisor: Dr. David Mitch

Instructor: Dr. Brad Humphreys

May 12, 2004

1. Introduction

Both economists and policy makers over the past twenty years have had great interest in the notion of skill-biased technical change and its impact on wage structure and income distribution between skilled and unskilled workers. Technical change is regarded as skilled-biased, if it increases the relative demand for skilled workers (Autor, Katz and Krueger, 1988). Previous studies, such as Nelson and Phelps (1967), Griliches (1969), Welch (1970), Schultz (1975), and Tinbergen (1975), argue that technical advances increase the demand for skills. A higher demand for skills would increase the wage premium for skilled workers, followed by a widening wage inequality between skilled and unskilled workers. For example, Krueger (1993) shows that in the US workers using computers in their work receive a wage premium. Using a longitudinal dataset from the UK, Bell (1996) shows that wages are positively related to technical skills (using computers, capable of mathematical calculations etc.).

However, technical change can be unskill-biased as well. During the nineteenth century in Britain, products normally made by skilled artisans started to be produced in factories by relatively unskilled workers using machines. Formerly complex tasks were greatly simplified with machines involved in the production, reducing the demand for skilled workers (James and Skinner, 1985; Goldin and Katz, 1998; Mokyr, 1990).

Hudgins and Mitch (2003) examined the trends in the premium to literacy in the Atlantic Merchant Marine from 1863 to 1913, and found that the premium was higher for steam crew than sail. Based on this trend, they argue that the introduction of steam could be viewed as skill-biased technical change. Nonetheless, they did not explain that the change in the wage premium to literacy was attributed to skill-biased technical change rather than some other factors. More important, they did not address why it is the case that technical change was skill-biased. This paper will mainly focus on whether technical change in the Atlantic Merchant Marine was skilled biased.

Adopting Acemoglu's (2002) model, which will be discussed formally in the next section, I will attempt to compare two different types of technologies in the Atlantic Merchant Marine, sail and steam, and examine whether technical change from sail to steam was skill biased, and within each technology, whether technical change over time was skilled biased.

2. Methodology and Hypothesis

Voyages (Y) can be seen as an output from a production process, in which given technology, physical capital and labor inputs are combined to transport cargo to a destination stipulated in voyage contracts. To simplify the analysis, I consider the vessel as the only physical capital in production, and there are two types of labor inputs, that is, skilled crew (H_1) and unskilled crew (H_2). Assume labor inputs can be separated from physical capital, and a two-factor constant-elasticity-of-substitution (CES) production function has the form, $Y = \left[(\alpha H_1)^{\rho} + (\beta H_2)^{\rho}\right]^{1/\rho}$, where α and β are technological augment factors, and $\rho \leq 1$. The elasticity of substitution between skilled and unskilled labor is $\sigma = 1/(1-\rho)$.

Suppose labor markets are perfectly competitive, that is, workers get paid equal to their marginal products. Then, the skilled wage W_1 is equal to the first derivative of Y with respect to H_1, that is, $W_1 = \partial Y / \partial H_1 = \alpha^\rho (\alpha^\rho + \beta^\rho (H_1 / H_2)^{-\rho})^{(1-\rho)/\rho}$. Similarly, the unskilled wage W_2 is defined as $W_2 = \partial Y / \partial H_2 = \beta^\rho (\beta^\rho + \alpha^\rho (H_1 / H_2)^\rho)^{(1-\rho)/\rho}$. The wage premium ω is

$$\omega = \frac{W_1}{W_2} = \left(\frac{\alpha}{\beta}\right)^\rho \left(\frac{H_1}{H_2}\right)^{\rho-1} \tag{1}$$

Taking natural logs of both sides of Equation (1) and substituting $\sigma = 1/(1-\rho)$, I obtain:[1]

$$\ln \omega = \frac{\sigma - 1}{\sigma} \ln\left(\frac{\alpha}{\beta}\right) - \frac{1}{\sigma} \ln\left(\frac{H_1}{H_2}\right). \tag{2}$$

In this model, the elasticity of substitution (σ) determines the slope of the relative labor demand and affects the intercept term. The relative labor demand curve is downward sloping, i.e., the skill premium decreases when the skilled labor is relatively more abundant. Mathematically,

$$\frac{\partial \ln \omega}{\partial \ln H_1 / H_2} = -\frac{1}{\sigma} < 0.$$

Graphically, the relationship between the wage premium and the relative labor demand is depicted in Figure 1. As the relative labor supply increases from $(H_1 / H_2)_0$ to $(H_1 / H_2)_1$, the wage premium decreases from ω_0 to ω_2. In a case study, Angrist (1995) shows that the sharp fall in the premium to college graduates relative to high school graduates in Palestine can be largely explained by a very large increase in the supply of

[1] *See* Acemoglu, D. (2002), 'Technical Change, Inequality, and the Labor Market,' *Journal of Economic Literature*, Vol. XL: 7–72.

skills.

The relationship between the wage premium and technology is obtained by differentiating $\ln \omega$ by $\ln(\alpha / \beta)$. That is,

$$\frac{\partial \ln \omega}{\partial \ln(\alpha / \beta)} = \frac{\sigma - 1}{\sigma}.$$

If $\sigma > 1$, technical change would shift the relative demand curve to the right, from D_0 to D_1, and increase the skill premium from ω_0 to ω_1. If $\sigma < 1$, technical change would move the relative demand curve to the left and reduce the skill premium.

Up to this point, it is clear that two forces are offsetting each other: An increase in the relative labor supply reduces the wage premium, holding the labor demand constant; a skill-biased technical change shifts the relative labor demand to the right and increases the wage premium, holding the labor supply constant. When both forces work at the same time, the outcome would depend on the relative strengths of both forces.

3. Data and Empirical Models

The datasets, compiled in 1998 by the Maritime History Archive based at the Memorial University of Newfoundland, Canada, consist of 85,600 crew agreements from 18,800 sea voyages between 1861 and 1913 on vessels registered in non-Canadian ports (mostly English). See Smith et al. (1998) and Maritime History Archive (1998) for further details.

The data are contained in four separate datasets: vessel registries, crew agreements, ship masters and ports. The vessel registry dataset provides records on whether a vessel was sail or steam (if the horsepower value for a given vessel is missing, then that vessel is treated as sail; otherwise steam), tonnage and horsepower, destinations for a given voyage and its duration, and the number of crew. The crew agreements dataset records seaman's specific characteristics such as age, birth place and signature ability (literacy), as well as detailed terms of agreements including monthly wages and occupations. Both of these two datasets have the common voyage identification number, which facilitates matching the datasets.

For the purpose of this study, I construct a dataset that only contains voyages by five-year intervals starting from 1863, i.e., 1863, 1868, 1873 … 1913 etc. Table 1 provides some descriptive statistics on the restricted dataset. The mean wages are calculated using a Consumer Price Index (CPI) with the prices in 1913 in the U.K. set as 100.[2]

Table 2 summarizes the distribution of voyages of non-Canadian ships in the sample years. Both sail and steam vessels existed during the period, but there was a clear trend of transition from sail to steam. Sail vessels were dominant before 1873, but declined at an increasing pace until completely eliminated by 1913. Given this technological change from sail to steam, it is interesting to compare technology in sail versus that in steam by examining the difference in technological parameters α / β. If $(\alpha / \beta)_{steam} > (\alpha / \beta)_{sail}$, I would argue that the technical change from sail to steam was skilled biased.

The first empirical model (Model 1) is derived from equation (2), specifically,

[2] This index is obtained from the Economic History website in www.eh.net.

(3a) for sail $\ln(W_1/W_2)_{it} = \theta_0 + \theta_1 \ln(H_1/H_2)_{it} + e_{it}$

(3b) for steam $\ln(W_1/W_2)_{jt} = \eta_0 + \eta_1 \ln(H_1/H_2)_{jt} + \varepsilon_{jt}$

where for a given sail voyage *i* or steam voyage *j* in year *t* (*t*=1863, 1868, 1873 …), W_1 and W_2 are average wages of skilled and unskilled crew, and H_1 and H_2 are the number of skilled and unskilled crew. The error terms are assumed to be normally distributed with mean zero and a constant standard error, i.e., $e \sim N(0, \sigma_e^2)$, and $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ The elasticity of substitutions are $\sigma_{sail} = 1/|\theta_1|$ and $\sigma_{steam} = 1/|\eta_1|$.

If it is assumed that technology (mainly physical equipment) on a vessel is mainly fixed once it has been built and will not change over time, then dummies identifying the year that a vessel was built would capture average technological level in that year. Then, a dummy variable fixed-effect model (Model 2) becomes,

(4a) for sail $\ln(W_1/W_2)_{it} = \theta_0 + \theta_1 \ln(H_1/H_2)_{it} + \beta T + e_{it}$

(4b) for steam $\ln(W_1/W_2)_{jt} = \eta_0 + \eta_1 \ln(H_1/H_2)_{jt} + \delta T + e_{jt}$

where *T* is a (1×10) vector of ten year dummies from 1868 through 1913 at five-year intervals. I use 1863 as the base year for both sail and steam. In particular, year dummies are assigned to unique vessels, equal one if a vessel starts its first voyage in that year and zero otherwise. By controlling vessel years, I will compare α/β in sail versus steam to address the issue of skilled-biased technical change.

Another econometric method to deal with fixed effect is the fully de-meaned model (Model 3), (5a) sail $\ln(W_1/W_2)_{it} - \overline{\ln(W_1/W_2)_i} = \theta_0 + \theta_1\left(\ln(H_1/H_2)_{it} - \overline{\ln(H_1/H_2)_i}\right) + (e_{it} - \overline{e}_i)$

(5b) steam $\ln(W_1/W_2)_{jt} - \overline{\ln(W_1/W_2)_j} = \eta_0 + \eta_1\left(\ln(H_1/H_2)_{jt} - \overline{\ln(H_1/H_2)_j}\right) + (\varepsilon_{jt} - \overline{\varepsilon}_j)$

with the fixed effect being the vessel effect. Using STATA, it is straightforward to run this fixed effect model and obtain results.

A critical issue centers on the definition of skilled versus unskilled labor. Generally, skills and wages are highly correlated; skilled workers earn a higher wage than unskilled workers. If it is true that certain occupations that offer a high average wage are generally the ones that demand more skills, then the laborers in those occupations are most likely to be classified as skilled workers and thus earn high wages. For example, in the sail dataset, an engineer, on average, earned 246 shillings a week, as compared to an average of 69 shillings across all occupations. It is obvious that engineer is an occupation that requires certain skills and engineers get commensurate rewards for the skills they provide on board. However, some occupations are less obvious. Surgeon, for instance, should be a skill-intensive job, but surgeons on sail voyages earned far less than 69 shillings. It may well be the case that some occupations offer higher wages, not because they require more skills, but because they are essentially more dangerous. In addition, some workers earn more simply because they are more experienced. Even though this classification is arbitrary, it is a feasible way to grouping crew into skilled and unskilled categories. Following this approach, in the sail dataset, the occupations with mean wages above 69 shillings a week are defined as ‘skilled’ occupations; in the steam dataset, the occupations with mean wages above 100 shillings a week are defined as ‘skilled’ occupations. Table 3 summarizes the proportion and the mean wage of each occupation in sail and steam. It is interesting to find that the proportion of high-paid occupations increased from sail to steam. For example, the proportion of engineer was 3.02 percent in steam as compared to only 0.09 percent in sail. This evidence may indicate that the technical change from sail to stem was skilled biased.

Since the substitution between skilled and unskilled labor is more plausible between related occupations than for broader occupation categories, I employ the following two approaches. The second approach to classifying crew into skilled and unskilled categories is to restrict the data by including only able-bodied seaman and ordinary seaman. Able-bodied seaman is defined as skilled and ordinary seaman as unskilled, not only because the former earns more on average, but also because 'able-bodied' indicates a higher skill level in the seaman occupation.

The last approach of grouping applies to crew on steam voyages only. Since the fireman on steam vessels maintained the furnace while the trimmer mainly shoveled coals, it makes sense that the fireman was more skilled than the trimmer. Therefore, fireman is defined as skilled crew whereas trimmer as unskilled.

Some descriptive statistics are summarized in Table 4. By comparing mean statistics between sail and steam in the first two approaches, the relative labor ratio (H1/H2) is higher in steam than in sail at a five percent significance level, and the relative wage ratio (W1/W2) is not significantly different between sail and steam. I.e., at a given level of wage premium, steam voyages would hire more skilled workers, which suggests that the technical change from sail to steam was skilled biased.

4. Empirical Results

Table 5 summarizes the empirical results. Derived from Equation (2) and Equation (3), $\ln(\alpha/\beta)$ is equal to $\theta_0/(1+\theta_1)$ for sail and $\eta_0/(1+\eta_1)$ for steam. In all models with skilled workers defined as those in high-paid occupations, intercepts and coefficients are significant at a five percent confidence level against a two-sided alternative. By calculation, I reported the value of $(\alpha/\beta)_{steam}$ and $(\alpha/\beta)_{sail}$ in all models. And testing the null hypothesis that $(\alpha/\beta)_{steam}$ is equal to $(\alpha/\beta)_{sail}$, I rejected the null hypothesis at one percent confidence level, that is, in all models, $(\alpha/\beta)_{steam}$ is greater than $(\alpha/\beta)_{sail}$, which indicates that technical change from sail to steam was skilled biased.

For steam voyages in all models, the coefficients on ln(H1/H2) have the expected sign, i.e. negative, since it is generally the case that labor demand should be negatively correlated to wages. However, for sail voyages, the coefficients are positive in all models. It might be interpreted as there is not much substitution between skilled and unskilled labor on sail voyages. One possibility is that occupations are mainly fixed on sail vessels: Skilled workers occupy the job by certain skills and experiences, and there is no simply rule to follow for an unskilled worker to complete a task that is normally assigned to a skilled worker. Even though steam produced a consistently negative estimate in all models, it translates into a very large value of the elasticity of substitution, that is, 6.33, 5.56 and 6.54 in the three models respectively, which are much larger than estimates ranging 1 to 2 that are normally reported in previous studies using more recent data. But since previous studies have used aggregate macro-data at a much broader level than a particular section in an industry as in this study, it could be the case that there is a very high substitution between skilled and unskilled workers when they producing the same good, that is, steam voyages.

It is worth noticing that technical change and elasticity of substitution have offsetting effects on the relative labor demand. A skill biased technical change, as captured by an increase in α / β, would boost the relative productivity of skilled labor, and therefore decrease the relative labor demand for skilled labor for a given output. But if elasticity of substitution is high, more skilled workers would be hired to substitute for unskilled workers since the former are more productive. In my empirical study, there is a skill biased technical change from sail to steam, and the elasticity of substitution on steam voyages is much greater than one, which means that the effect of elasticity of substitution would dominate and thus increase the relative demand for skilled labor and boost the wage premium on skills.

Most year dummies in Model 2 are not significant individually for both sail and steam. Estimates in some years even show a significantly negative effect, such as 1888. But if year dummies capture other factors besides technology that affect the relative labor demand, and they are stronger enough to offset the effect of technical advances, negative estimates on year dummies would be no surprise. Figure 3 plots the trends of technical change in sail and steam. The estimates on year dummies are reported using the first approach. It is interesting to find that the technical change in sail and steam over time followed a similar pattern. There might be some general shock affecting both sail and steam technology at the same time. However, I did not find a clear trend of technical change within each technology.

In comparison of OLS and the fixed effect models, the fixed effect model has controlled for factors that affect the labor demand pertaining to a unique vessel. The estimates from these two models are quite close for steam, but different for sail, which implies that the vessel-specific features on sail voyages have a significant impact on the relative demand. I.e. the fixed effect model accounts for important vessel-specific features and therefore provides a more accurate estimate of technical change as well as elasticity of substitution.

Using the second approach defining skilled as able-bodied seaman and unskilled as ordinary seaman, I found all coefficients on ln(H1/H2) are positive, and they are not significant in steam, which is quite different from the findings using the first approach. Contrary to my expectation, this finding suggests that there is little substitution between able-bodied seaman and ordinary seaman. OLS and the fixed effect models show that $(\alpha/\beta)_{steam}$ is larger than $(\alpha/\beta)_{sail}$ (which is significant at any confidence level), while the year dummies model presents the opposite, i.e., $(\alpha/\beta)_{steam}$ is significantly smaller than $(\alpha/\beta)_{sail}$. But generally, using a narrow approach, it still shows that technical change from sail to steam was skill biased.

Using the third approach, I found that there is not much substitution between fireman and trimmer, which bring forth the question whether narrow occupation classification is appropriate to define skilled versus unskilled labor.

Empirical practices show that elasticity of substitution between skilled and unskilled labor is sensitive to the definition of skills. I have tried both broad and narrow approaches by occupation. The broad approach generates significant estimates of elasticity of substitution, while the narrow approaches provide significant estimates on sail voyages only. Other definitions of skills may include education levels and age groups, which has not been done in this study.

5. Conclusions

Using the Atlantic Merchant Marine datasets, I found that technical change from sail to steam was skill biased in terms of a comparison of α / β. I also found that there is not much substitution between skilled and unskilled labor on sail voyages, while the substitution on steam is substantial. These findings imply that the skill-biased technical change from sail to steam in the non-Canadian sea voyage industry is a legitimate candidate to explain the change in wage structure and wage premium to literacy as Hudgins and Mitch (2003) argued in their paper.

Both technologies seemed to follow a similar pattern of changing in relative productivity over time. But within each technology, I did not find a clear trend of skill-biased technical change. It is worth noticing that α / β as well as elasticity of substitution are sensitive to the definition of skilled versus unskilled workers.

Further research is needed to implore technical changes in the Atlantic Merchant Marine. There are at least three aspects that can be improved. First, the model specifications need refinement. A more general model with more than two inputs may be useful to capture the elasticity of substitution between labor inputs, but this approach relies on measuring physical capital. In addition, destinations and ports may be used to control for shifts in the relative demand curve. Second, the definition of skilled versus unskilled labor should be further refined. Since empirical results are sensitive to the method of defining skilled and unskilled labor, it is important to define skilled versus unskilled labor carefully. For instance, using occupation classification, it is important to understand the nature of occupations in sea voyages industry to account for compensating differentials. It is also important to control for experiences, because experiences are highly correlated with wages. Finally, data quality is also a consideration. There may be some measurement errors in the datasets, which distorts the estimates. For example, wages below 1 shilling per week may not be legitimate. A careful examination of vessel agreements may improve the subsequent empirical results.

REFERENCES

Acemoglu, D. (2002), 'Technical Change, Inequality, and the Labor Market,' *Journal of Economic Literature*, Vol. XL: 7–72.

Allen, R. (1938), *Mathematical Analysis for Economists*, London: Macmillan.

Angrist, J.D. (1995), 'The Economics Returns to Schooling in the West Bank and Gaza Strip,' *The American Economic Review*, Vol. 85: 1065–87.

Autor, D.H., Katz, L.F. and Krueger, A.B. (1988), 'Computing Inequality: Have Computers Changed the Labor Market,' *The Quarterly Journal of Economics*: 1169 –1213.

Bell, B.D. (1996), 'Skill-Biased Technical Change and Wages: Evidence from a Longitudinal Data Set,' Economics Papers No. W25, Economics Group, Nuffield College, University of Oxford.

Goldin, C. and Katz, L.F. (1998), 'The Origins of Technology-Skill Complementarity,' *The Quarterly Journal of Economics*, 113: 693-732.

Griliches, Z. (1969), 'Capital-Skill Complementarity,' *The Review of Economics and Statistics*, 51: 465-68.

Hamermesh, D.S. and Gant, J. (1979), 'Econometric Studies of Labor-Labor Substitution and Their Implications for Policy,' *The Journal of Human Resources*, XIV: 518–42.

Hicks, J.R. (1970), 'Elasticity of Substitution again: Substitutes and Complements,' *Oxford Economic Papers*, 22: 289–96.

Hudgins, L. and Mitch, D. (2003), 'Trends in the Premium to Literacy and the Age Earnings Profile in the Atlantic Merchant Marine, 1863 to 1913: the Shift from Sail to Steam,' unpublished capstone paper in Department of Economics, University of Maryland Baltimore County.

James, J.A. and Skinner, J.S. (1985), 'The Resolution of the Labor-Scarcity Paradox,' *Journal of Economic History*, 45: 513-50.

Krueger, A.B. (1993), 'How Computers have changed the Wage Structure: Evidence from Microdata, 1984-1989,' *Journal of Political Economy*, 101: 410-42.

Maritime History Archive (1998), *Ships and Seafarers of Atlantic Canada*, CD-ROM, St. John's, Memorial University of Newfoundland.

Mokyr, J. (1990), *The Levers of Riches: Technological Creativity and Economic Progress*, NY, Oxford University Press.

Nelson, R. and Phelps, E. (1967), 'Investment in Humans, Technological Diffusion and Economic Growth,' *AEA Papers Proceedings*, 56: 69-75.

Sanders, M. and Weel, B. (2000) 'Skilled-Biased Technical Change: Theoretical Concepts, Empirical Problems and a Survey of the Evidence,' DRUID working paper, number 00-8.

Schultz, T. (1975), 'The Value of the Ability to Deal with Disequalibria,' *Journal of Economic Literature*, 13: 827-46.

Smith, K., Watts, C.T. and Watts, M.J. (1988), *Records of Merchant Shipping and Seamen*, PRO publications.

Tinbergen, J. (1975), *Income Difference: Recent Research*, Amsterdam, North-Holland.

Welch, F. (1970), 'Education in Production,' *Journal of Political Economics*, 78: 312-27.

Table 1: Descriptive Statistics on Non-Canadian Vessels

		Min	Max	Mean	Std. Dev.	# of obs
Sail						4128
	Age	12	68	29.17	9.56	
	Wage (1913 shilling)	0.9	295.95	69.19	31.08	
Steam						13947
	Age	12	88	31.32	9.2	
	Wage (1913 shilling)	0	1064.55	100.86	64.62	

Table 2: Distribution of Voyages, Non-Canadian Vessels

Year	% Sail	% Steam
1863	90.91	9.09
1868	79.65	20.35
1873	57.76	42.24
1878	41.88	58.12
1883	18.45	81.55
1888	18.3	81.7
1893	10.8	89.2
1898	10.72	89.28
1903	6.6	93.4
1908	8.9	91.1
1913	0	100

Table 3: Mean wages and proportions of each occupation in sail and steam

	Sail		Steam	
	Mean wage	%	Mean wage	%
Supercargo	1	0.02	35	0.02
Surgeon	1	0.07	116.21	0.57
Carpenter's Mate	10.67	0.07	1	0.01
Boy	11.95	1.98	22	0.45
Unknown	20	0.19	7.04	3.61
Purser	20.5	0.05	13.33	0.41
Assistant Steward	20.5	0.33	60.06	6.12
Assistant Cook	33	0.14	77.68	1.6
Ordinary Seaman	39.13	9.97	37.13	1.48
Painter/Seaman	40	0.02	120.5	0.01
Bosun/Mate	55	0.07	92.01	0.48
Storekeeper	60	0.02	90.02	0.31
Able-bodied Seaman	62.82	59.42	75.7	24.85
Lamp Trimmer	65	0.02	81.02	0.35

A.B. & Lamp Trimmer	65	0.02	87.74	0.69
3rd Mate	68.96	0.66	133.26	1
Trimmer (Steamer)	70	0.09	68.05	4.32
Cook/Steward	76.26	2.96	116.73	0.43
Cook	78.38	2.56	106.48	2.86
Fireman & Trimmer	80	0.12	86.18	2.49
A.B. & Donkey Man	80	0.07	90	0.01
Bosun & Sailmaker	80	0.02	200	0.01
Bosun	80.63	3.36	97.59	1.59
A.B. Steward	81.67	0.07	28	0.01
Steward	85.28	2.21	118.61	2.88
Fireman	88.33	0.42	83.54	18.49
Sailmaker	88.86	1.04	63.75	0.01
Bosun & Lamp Trimmer	90	0.02	104.47	0.84
Carpenter/A.B.	94.46	0.33	121	0.07
Donkey Man	95.38	0.31	94.47	2.31
2nd Mate	100.06	2.12	132.87	2.96
Carpenter	109.95	2.71	114.79	2.07
Master	120	0.02	100	0.01
1st Mate	122.35	6.23	173.23	3.1
3rd Engineer	125	0.05	162	2.31
Quartermaster	140	0.02	79.91	1.23
2nd Engineer	185	0.09	199.71	3.13
Engineer	255	0.09	275.03	3.02
Apprentice	29.14	0.16		
A.B. & Sailmaker	71.79	0.33		
Cook & Seaman	72.42	1.29		
Carpenter/Bosun	100	0.02		
Tindal	120	0.02		
Apprentice (Topaz)	180	0.16		
Distressed Br. Seaman			0.33	0.03
Stewardess			36.72	0.74
Mess Room Steward			46.98	0.97
Deck Hand			50.22	0.06
A.B. & Trimmer			62.19	0.11
Leading Fireman			104.77	0.08
Clerk			108.2	0.04
4th Mate			111.53	0.57
Oiler & Greaser			115.76	0.33
4th Engineer			153.24	0.94
Total	69.19	1	100.86	1

Table 4: Descriptive Statistics using three classification approaches

		Sail			Steam		
		# of obs	Mean	Std.	# of obs	Mean	Std.
Occupation	W1/W2	266	2.093	6.351	419	2.331	6.315
groups	H1/H2	266	0.443	0.311	419	0.779	0.548
Able-bodied	W1/W2	186	4.413	12.596	108	7.123	19.619
vs. ordinary	H1/H2	186	4.875	2.796	108	6.230	4.614
Fireman vs.	W1/W2				100	1.281	0.439
trimmer	H1/H2				100	2.010	1.441

Table 5: Comparison of Sail versus Steam Voyages

		Simple OLS		Year dummies		Fixed effect	
		Sail	Steam	Sail	Steam	Sail	Steam
Occupation	Constant	0.599*	0.594*	0.534*	0.614*	0.673*	0.597*
groups		(0.064)	(25.45)	(0.085)	(0.094)	(0.069)	(23.2)
	ln(H1/H2)	0.109*	-0.158*	0.108*	-0.180*	0.182*	-0.153*
		(0.054)	(-4.99)	(0.054)	(0.033)	(0.062)	(-3.47)
	ln(α/β)	0.540*	0.705*	0.482*	0.749*	0.569*	0.705*
		(0.081)	(0.048)	(0.093)	(0.122)	(0.087)	(0.063)
Able-bodied	Constant	0.360*	0.651*	0.393*	-0.068	0.446*	0.678*
seaman vs.		(0.098)	(0.256)	(0.148)	(0.539)	(0.124)	(0.334)
ordinary	ln(H1/H2)	0.241*	0.152	0.199*	0.207	0.170**	0.134
seaman		(0.065)	(0.147)	(0.071)	(0.172)	(0.097)	(0.202)
	ln(α/β)	0.290*	0.565*	0.328	-0.056	0.381*	0.598*
		(0.067)	(0.158)	(0.388)	(0.451)	(0.077)	(0.193)
Fireman vs.	Constant		0.176*		0.099		0.219*
trimmer			(0.030)		(0.010)		(0.023)
	ln(H1/H2)		0.079*		0.006		0.001
			(0.040)		(0.033)		(0.035)
	ln(α/β)		0.163*		0.098		0.219*
			(0.023)		(0.098)		(0.017)

Notes: Std. errors in parentheses;

Std. of ln(α/β) is calculated by the formula:

$$\left(\left[\frac{1}{1+\theta_1}\right]^2 \mathrm{var}(\theta_0)+\left[\frac{\theta_0}{(1+\theta_1)^2}\right]^2 \mathrm{var}(\theta_1)+2\left[\frac{1}{1+\theta_1}\right]\left[\frac{\theta_0}{(1+\theta_1)^2}\right]\mathrm{cov}(\theta_0,\theta_1)\right)^{1/2};$$

* significant at 5% against a two-sided alternative;

** significant at 10% against a two-sided alternative.

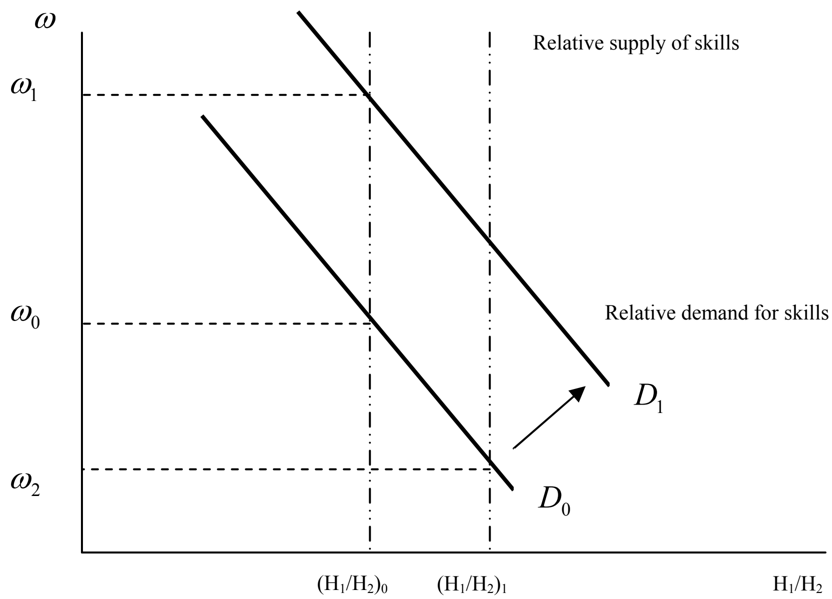

Figure 1: Skill Premium, Relative Labor Ratio and Labor Market in Equilibrium

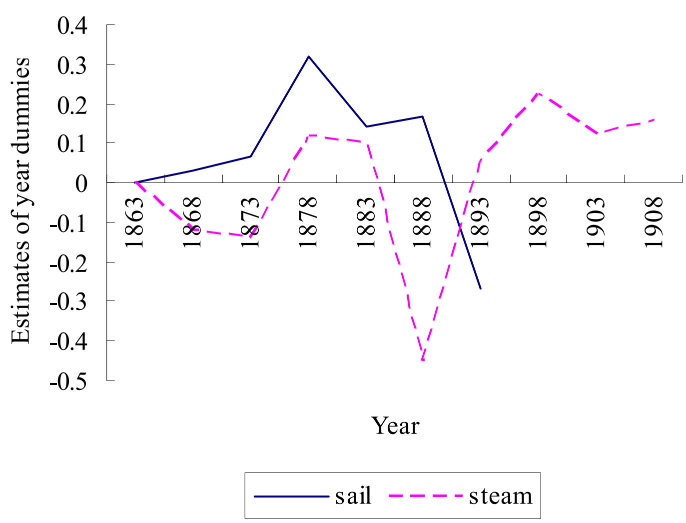

Figure 2: Trends of technical change in sail and steam, 1863-1908

Note: Estimates of year dummies are extracted from Table 3.