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Abstract

I set forth a generalized stochastic time trend approach, based upon the Kalman filter, as an alternative to the general index approach to measure technological change. Technology is treated as a latent variable in a state-space model of the production function. In data sparse settings, where panel data are unavailable, the method provides results which encompass insights from the general index approach, but provides more detailed estimates. I revisit an analysis of technological change in the Lofoten fishery. The estimated technology time profiles agree to some extent between the methods, but my more detailed results demand a new historical interpretation. (JEL C22, O33, Q22)

1 Introduction

A common problem in economics is the presence of latent variables in empirical models. In particular, the problem applies to technological change in production functions. Technological change is believed to be an important source of growth, but little agreement exists regarding its nature and, under scrutiny here, measurement (Squires and Vestergaard 2009 provide an extensive discussion). Typical remedies for empirical measurement embody inclusion of a trend or proxy variables such as R&D expenditures (Slade 1989, p. 363), or time dummies (Baltagi and Griffin 1988; Hannesson et al. 2010). The latter is known as the general index number approach. The typical remedies certainly shed light on the issue and are better than pure ignorance, but more appropriate methods can improve the understanding and measurement of technological change. State-space models and the Kalman filter are ideal statistical tools for models with unobserved variables (Slade 1989, p. 364, Streibel and Harvey 1993, p. 264) and their use in economics should be well established. See Rausser and Howitt (1975) for an early application. Slade (1989, p. 364) reviews the earliest development in economics and further discusses how the Kalman filter approach to technological change measurement relates to traditional approaches. In the particular setup discussed here, the Kalman filter approach can be viewed as a stochastic generalization of the standard linear time trend approach.

Hannesson et al. (2010) examine technological change in the Lofoten fishery in order to discuss the interaction between the fish stock and changes in total factor productivity. While there are ample, anecdotal evidence of technological progress in the fishery, its role in the production function proves difficult to pin down. Hannesson et al. (2010), inspired by the Baltagi and Griffin (1988) general index number approach and later developments, introduce time period dummies into the production function $Y_t = A_t E_t^{\alpha} S_t^{\beta}$, where Y_t is the fish production (catch), E_t the input effort, S_t the fish stock level, and A_t reflects technology. Each dummy variable represents six years and the technology measure is equivalently crude. On the contrary, a finer resolution, which otherwise would be desirable, leads to more parameters entering the estimation equation and there is also a potential for a downward bias in the fish stock elasticity β (Hannesson et al. 2010, pp. 756-757). Further, the time dummy approach has problems with serial correlation.

I suggest an alternative approach. In a Kalman filter framework, I treat the technology parameter as latent and behaving according to the law of motion $A_{t+1} = \delta_1 A_t^{\delta_2}$. The law of motion is a generalization of the linear time trend model. First, I restrict the model to the purely exponential model, $\delta_1 = 1$, next, δ_1 varies with time. The Kalman filter yields an exact expression for the likelihood function, and parameters are estimated via maximum likelihood estimation. The time profiles of the estimated technology parameters for different gears are consistent with the results of Hannesson et al. (2010). Estimated factor elasticities and the level of the technology parameter differ somewhat, however. For some gears, I estimate a higher resource elasticity (β) and a lower technology level (A_t), while for other gear types, the opposite occurs. While my elasticity estimates are less than two standard deviations away from the Hannesson et al. (2010) estimates, there are larger discrepancies when it comes to the level of the technology parameter.

The Kalman filter approach has some advantages. First of all, the Kalman filter provides yearly estimates of the level of technology. With yearly estimates, sharp shifts in the technology development become apparent. In comparison, six year period estimates smooth out the effects of sharp shifts, and the shifts become more difficult, if not impossible, to detect. Thus, while the period estimates give rise to an understanding of the long term technological development, the yearly estimates also make the year-to-year development apparent. When compared to the historical and anecdotal evidence of technological change, the yearly estimates can ultimately reveal whether and to what extent certain innovations made an impact on the productivity. Finally, serial correlation is less of an issue with the Kalman filter than with the time dummy approach. Let me add that in situations where panel data are available for firms in an industry, the general index number approach (Baltagi and Griffin 1988) may prove less restrictive when it comes to the nature of technical progress; while it in the Kalman filter is necessary to model the technology process, the general index approach is model free. But when panels are unavailable or insufficient and time period dummies must be introduced to make a general index approach viable, as is the case in the Lofoten data, the Kalman filter provides estimates which capture the behavior of the time dummy estimates without sacrificing resolution.

Let me hasten to add that while I aim to improve on the estimation of technological development in the Lofoten fishery, Hannesson et al. (2010) has a wider agenda. They aim to understand why labor productivity in the fishery remained low for a long time, lagging behind the development in agriculture and manufacturing. For productivity growth rates, my alternative empirical approach does not make much difference and I have not pursued productivity growth rates here. That is, their final analysis still stands. Further, Hannesson et al. (2010) provide a history of the Lofoten fishery which has been exploited at least since the eight century. They also discuss the modern time historical development of institutions in the fishery.

In the fisheries economics literature, little attention has been devoted to measurement of technological change. Lack of relevant data is a part of the explanation, but the normative understanding of technological change in renewable resource industries is also underdeveloped (Squires 2009, Squires and Vestergaard 2009). Notwithstanding, Kirkley et al. (2004) used a rich dataset to evaluate contributions of technical change to catch rates in the French sète trawl fishery; see Squires (2009) for a comprehensive review of the emerging literature on fisheries technical change measurement. Squires (1992) extended the standard total factor productivity measurement framework to include the effect of fluctuating stock abundance, and a number of studies have followed. Key contributions are Fox et al. (2003), Hannesson (2007), and Jin et al. (2002).

2 Data and Background Information

I use the same data set which Hannesson et al. (2010) use. They describe and discuss the data thoroughly, so here I limit myself to a short description of the data and the fishery. The data on catches and effort were collected from the annual reports on the Lofoten fishery. The reports go back to 1859. Four different gear types are observed; gill nets, long lines, hand lines, and since 1959, Danish seine. Further different gear types have been used in the fishery for shorter periods, but most of them are not included in the data. There are some observations on the use of the highly effective purse seine, but it was outlawed in 1958, and the observations are too few to use in estimation. For each gear type, two measures of input effort exist: the number of men and the number of boats. The numbers are based upon a census of men and boats around the peak of the season. Physical characteristics such as boat length would be helpful, but does not exist. The correlation between men and boats is high and it does not make sense to include both in the same equation. As Hannesson et al. (2010), I focus on the boat variable as a reasonable proxy for effort.

The fish stock data goes back to 1900 and were obtained from the Institute of Marine Research in Bergen. As the fish stock is not directly observable, the data are rather estimates based on stock assessment models. The data from the earliest period (1900 - 1912) are estimates based on catch per fisherman. Most likely, later observations are more accurate than earlier ones. As Hannesson et al. (2010, p. 750) remark, the data are less than perfect, but they are the best available.

Since around 1857, the Lofoten fishery, which targets the spawning North-East Atlantic Cod, has been an open-access fishery. The fishery remained open-access until 1990, but certain limitations on total harvest were set already the year before. Under open-access, with a practically unobservable fish stock, the effort and stock variables can be treated as independent (Hannesson et al. 2010, p. 760, discuss endogeneity and try to instrument effort with lagged variables without improvements to the results). I analyze data from when the first stock estimates are available, 1900, to 1988, as limitations were introduced in 1989 and the fishery was no longer pure open-access. Hannesson et al. (2010) discuss the historical institutions surrounding the fishery further, give an account of the anecdotal evidence on technological change, and list a number of relevant references.

3 A State-Space Model of Technological Change

The analysis in Hannesson et al. (2010, p. 755) departs from the Cobb-Douglas production function

$$Y_t = A_t E_t^{\alpha} S_t^{\beta} \tag{1}$$

where Y_t is fish caught in period t, E_t the input effort, and S_t the stock level. A_t reflects the technology level in period t. The production function is common in fisheries economics and is inspired by the Schaefer production function, where elasticities α and β are equal to one. Hannesson et al. (2010, p. 755) envision Hicks-neutral technological change which would manifest itself in A_t rising over time (see Squires and Vestergaard 2009, footnote 8, p. 5, and p. 6). To capture an increasing technology level, they take logarithms and add time dummies d_i for $T-1$ periods of equal length. The last and residual period T has shorter length. They end up with the following equation to estimate:

$$\ln Y_t = \ln A + \alpha \ln E_t + \beta \ln S_t + d_1 + \ldots + d_{T-1} + \varepsilon_t \tag{2}$$

There is no time dummy for the last period. The technology level in any given period $i \in [1, \dots, T-1]$ is then $\ln A + d_i$; the level in the last period T is simply $\ln A$. As such, when Hannesson et al. (2010) carry out the standard t-test on the time dummies, they test whether the technology level in a given period differs from the level in period T. The test is indeed relevant, but they do not mention its interpretation. If the technology level rose over the time series and the quality of the estimates was roughly stable, t-values should be higher early in the time series; a pattern which only emerges for gill nets and hand lines. Testing whether $\ln A + d_i$ is statistically different from zero would perhaps be of more interest. The results from the time dummies specification (2) show signs of serial correlation and to deal with it they use the Prais-Winsten procedure.

A state-space model where the technology level A_t is latent can look like the following:

$$
\begin{aligned}
\ln A_{t+1} &= \ln \delta_1 + \delta_2 \ln A_t + v_t \\
\ln Y_t &= \ln A_t + \alpha \ln E_t + \beta \ln S_t + w_t
\end{aligned}
\tag{3}
$$

where A_t is unobserved and δ_1, δ_2, α, and β are parameters to be estimated. v_t and w_t are normal, independent, and identically distributed error terms with zero mean and variances σ_v^2 and σ_w^2. Technology has the law of motion $A_{t+1} = \delta_1 A_t^{\delta_2}$, which combines a linear trend model and a purely exponential model. As the model (3) is stochastic, it can capture a range of patterns in time. The unknown parameters can be estimated with maximum likelihood estimation. The first of the equations in (3) is known as the state equation; the second is known as the observation equation.

The Classical State-Space Model and the Kalman Filter

Before moving on, it may be useful to review some details about the classical state-space model and the Kalman filter . A general state-space model is written:

$$
\begin{aligned}
z_{t+1} &= F z_t + v_t \\
Y_t &= A X_t + H z_t + w_t
\end{aligned}
\tag{4}
$$

See equations (13.2.1) and (13.2.2) in Hamilton (1994, p. 377) and see surrounding discussion for the full set of assumptions. z_t is called the state vector and is unobserved in the observation equation; Y_t and X_t constitute the observations in the system. With an assumed or known initial state (z_0) and related variance (P_0), the Kalman filter yield an exact expression for the likelihood function. The Kalman filter has a recursive structure which allows the likelihood to be calculated without use of large matrices (Jones 1993, p. 78). The structure also allows sequential updating when new data arrives without having to run through the full set of observations each time. The filter estimates the state vector at time t contingent upon observations up to and including time t. In many cases, an estimate based upon all available observations is more relevant. I attain an estimate contingent on the full set of information by smoothing the filter estimate, see Hamilton (1994, pp. 394-397). Finally, equations (13.4.1) and (13.4.2) in Hamilton (1994, pp. 385-386) give the expression for the log-likelihood function $\ln L$. In principle, F, A, H, and the variances of the error terms can be treated as unknown parameters.

The Restricted Model

First, I consider a model restricted by $\delta_1 = 1$; technology is purely exponential. The state equation in (3) becomes

$$\ln A_{t+1} = \delta_2 \ln A_t + v_t \tag{5}$$

The equation is only stable when $|\delta_2| < 1$. Stability is necessary to ensure convergence of the Kalman filter (Hamilton 1994, p. 390). If the stability requirement holds, the technology level is expected to converge towards one; in the long run, gains from technological change will dry up. While the long run interpretation may be unsettling, it may on the one hand be realistic, on the other the long run interpretation does not necessarily have to interfere with a system estimated over a limited time period. Keep in mind that I do not in any sense estimate the true technology process and that the estimated process has limited, if any, out-of-sample relevance. Rather, the process suggested in the state equation should be able to capture the phenomenon and theoretical concept of interest. See Sucarrat (2010) and Hendry (1995, pp. 344-368) for a discussion that goes all the way back to Haavelmo (1944).

I expect the technology level to increase over time and thus approach one from below. If I estimate (3) directly, A_t will not necessarily be below one (compare Hannesson et al. 2010), and technological improvement cannot be a relevant interpretation. (The results in Hannesson et al. 2010 do not suffer from the interpretation problem of my model.) I remedy the problem by introducing a constant k in the observation equation:

$$\ln Y_t = \ln A_t + k + \alpha \ln E_t + \beta \ln S_t + w_t \tag{6}$$

A sensitivity analysis shows that with k sufficiently large, such that $\ln A_t$ is much smaller than zero when $\ln A_t + k$ is in the vicinity of zero, no noticeable changes in parameter estimates appear with larger k. Plots show that the same holds for the technology estimate. Table A3 in the appendix reports the results from the sensitivity analysis. Somewhat arbitrarily, I use $k = 10$. (The modification in equation (6) is equivalent to modifying equation (5) into $\ln(A_{t+1} - k) = \delta_2 \ln(A_t - k) + v_t$. When modifying equation (5), k must operate on a different scale.)

The system in (5) and (6) is a special case of the system in (4) with $z_t = \ln A_t$, $F = \delta_2$, $A = [\alpha \;\; \beta \;\; k]$, $X_t = [\ln E_t \;\; \ln S_t \;\; 1]'$, and $H = 1$ (apostrophe denotes the transpose). The method requires me to specify initial values for the expected state (the technology level; $\ln A_0 + k$) and its variance. As initial value, I use the Hannesson et al. (2010) result for the first period. The initial variance is set to one; increasing it to two or reducing it to a half makes no noticeable difference on the results. I find the maximum of the log likelihood function using the Nelder-Mead routine as implemented in Matlab's *fminsearch* function.

In effect, v_t and w_t introduce two multiplicative error terms in equation (1) while there is no mechanism to allocate variation between them. Thus, estimating both σ_v^2 and σ_w^2 can be both conceptually unsound and technically difficult. Typically, much of the variation is allocated to one term and no or little to the other. Instead, I restrict the model to:

$$\sigma_v^2 = \sigma_w^2 = \sigma^2 \qquad (7)$$

The model now mimic only one error term in equation (1); the term has mean zero and variance $\sigma_v^2 + \sigma_w^2 = 2\,\sigma^2$ (Ross 1985, p. 65). I test the additional restriction with a likelihood ratio test with one degree of freedom. The likelihood ratio test rejects the restriction (7) in the case of hand lines and Danish seine (*p*-values 0.0384 and 0.0180). Results from estimating the system without the restriction are reported in Table A1 in the Appendix. The estimates of σ_v^2 and σ_w^2 in Table A1 are relatively far apart when the likelihood ratio test rejects (7). As an alternative, I calculate the Akaike (1973) information criteria (AIC) for model selection. The information criteria lines up with the likelihood ratio test results, selecting the model with the variance restriction (7) for gill nets and long lines, but the model without the variance restriction for hand lines and Danish seine.

Although the model mimics only one error term in (1), the method nonetheless predict errors in both the state and observation equation. I test whether the errors are normally distributed with the Lilliefors (1967) test. *p*-values are reported in Table A4 in the appendix. The *p*-value for the errors in the observation equation (w_t) for hand lines is close to the conventional 5% level and could be a sign of misspecification. I also carry out a

Kolmogorov-Smirnov test to see whether the predicted errors are mean zero with variance as in (7). Table A5 in the appendix reports p-values. The p-values for errors in the observation equations (w_t) for gill nets, long lines, and hand lines are small. (On the other hand, the predicted errors from the estimations reported in Table A1 perform worse in the Kolmogorov-Smirnov test.) Thus, (7) is rejected by the likelihood ratio test for Danish seine and by the Kolmogorov-Smirnov test for the other gears. (7) implies that the variation in (1) should be equally distributed between the state and observation equation. Alternatively, one could attribute more of the variation to the observation equation. A further extension of my analysis would generalize (7). I am confident that it is possible to find the right balance of (7) such that predicted errors pass the Kolmogorov-Smirnov test because the errors pass the Lilliefors test of normality. In particular, I believe the right balance exist for the cases which pass the likelihood ratio test (gill nets and long lines). Exploratory results suggest that parameter estimates would not change substantially upon such a generalization of (7). The similarity of estimates for α and β in Tables 1 and A1 are further suggestive to that end.

Results

Table 1 lists parameter estimates for the restricted, purely exponential model (equations (5) to (7)) for the four different gear types. Standard errors are given in parenthesis. The likelihood ratio test rejects the restriction (7) for hand lines and Danish seine (the p-value is less than 0.05); for gill nets and long lines, the restriction cannot be rejected. (Notwithstanding, conclusions based upon large-sample properties like the likelihood ratio statistic may be questionable with only 30 observations in the case of Danish seine and 89 observations for the other gears.) δ_2 is estimated close to but below one for all gears but Danish seine. (The estimate is below one for all gears in the estimation without the variance restriction, see Table A1.) For all gears, the estimate is more than two standard errors away from zero.

α is estimated within two standard errors of one for gill nets and Danish seine. For long lines and hand lines, the estimates are below but more than two standard errors away from one. Finally, α is estimated more than two standard deviations away from zero for all gears. $\alpha = 1$ implies constant returns to effort. It is unclear to me whether constant returns are expected. If the fish stock arrived in Lofoten at the beginning of the season and was fished down as the season progressed, one would expect diminishing returns to effort. If, however, the stock arrived in portions or something like a flow, constant returns should at least be possible. If vessels cooperated, for example by sharing information on productive fishing grounds, even increasing returns could arise. My results from the restricted, purely exponential model suggest close to constant returns to effort for most gears.

I estimate β two standard deviations away from both zero and one for gill nets and long lines, while for Danish seine, the estimate is close to one. For hand lines, the estimate is two standard deviations away from zero but not from one. The classical Schaefer production function has $\beta = 1$ with the interpretation that the fish is distributed evenly over the fishing ground. One expects β below one for schooling fish stocks (not the case for the North-East Atlantic cod); β would also be estimated below one if the fishermen knew where to find the fish or used fish finding equipment like the echo sounder. Both possibilities are quite likely for the Lofoten fishery. Hannesson et al. (2010, p. 756) hypothesize that if too much variation is picked up by the technology parameter, β would have a downward bias. β would also have a downward bias if only a part of the stock was within reach of the fishing fleet, unless the partiality was already reflected in the data. (With $Y_t = A_t E_t^{\alpha} (cS_t)^{\beta}$, where c reflects that only a fraction of the stock is interacting with the fishery, one would estimate $Y_t = A_t c^{\beta} E_t^{\alpha} {S_t}^{\beta} = A_t^* E_t^{\alpha} {S_t}^{\beta^*}$ where $A_t^* = A_t c^{\beta}$. Since $cS_t < S_t$ and $(cS_t)^{\beta} = S_t^{\beta^*}$, β^* would underestimate β, and A_t^* would underestimate A_t since c represents a fraction.)

Hannesson et al. (2010) had problems with serial correlation. The Ljung-Box *Q*-statistic test for serial correlations, and I compute it for the realized errors in both the state and observation equation, see Table 1. For hand lines, the *p*-value of the statistic is relatively small and some serial correlation could occur. (The problem is less pronounced in the model without the variance restriction, see Table A1.) For all other gears, I find no sign of serial correlation in the error terms.

Finally, I turn to the estimated technology level. The solid curves in Figure 1 show the smoothed technology level $\ln A_t + k$ for the restricted, purely exponential model for all gears. The shaded areas show two standard errors around the estimate in both directions. The dashed curves show the technology level estimated by Hannesson et al. (2010, Table 1, regression (iii), p. 756). In comparison, the time profiles of their and my estimates are highly consistent. Also, the level of the technology level agrees to a large extent, but I have estimated a slightly higher technology level for hand lines and Danish seine. The estimated technology level depends on the estimated input elasticities α and β: For gill nets and long lines, with highly consistent level estimates, the elasticity estimates are also quite close. The estimated technology level appears noisy in the sense that it has small short-term variations around a longer-term trend. First, I expect the estimate to fluctuate within a standard deviation or two from the true level. Second, as long as the model is not perfect some exogenous variation will inadvertently end up in the technology estimate. (Indeed, the technology concept underlying the Baltagi and Griffin 1988, the Hannesson et al. 2010, and my approach derives from Solow 1957, p. 312: '*any kind of shift* in the production function.')

The Unrestricted Model

Next, I turn to the model in (3) without the restriction $\delta_1 = 1$. Without the restriction, it is not necessary to introduce an additional constant in the system like in (6). With

$$z_t = \begin{bmatrix} \ln \delta_{1,t} \\ \ln A_t \end{bmatrix}, F = \begin{bmatrix} 1 & 0 \\ 1 & \delta_2 \end{bmatrix}, v_t = \begin{bmatrix} v_{1,t} \\ v_{2,t} \end{bmatrix},$$
$$A = [\alpha \quad \beta], X_t = \begin{bmatrix} \ln E_t \\ \ln S_t \end{bmatrix}, H = [0 \quad 1] \tag{8}$$

the system is a special case of the system in (4). Technically, $\ln \delta_{1,t}$ is not treated as a parameter, but rather as a state variable and thus carries a subscript t. While $\ln \delta_{1,t}$ will have a time profile, just like the technology level, one can nevertheless think of it as a parameter of the system. Indeed, it is treated as a stochastic constant:

$$\ln \delta_{1,t+1} = \ln \delta_{1,t} + v_{1,t}$$

The error terms $v_{1,t}$ are normal, independent, and identically distributed with mean zero and variance $\sigma_{v,1}^2$. For the technology level, I use the same initial condition as in the restricted, purely exponential model: the estimated initial level from Hannesson et al. (2010). For $\ln \delta_{1,t}$, I set the initial condition equal to zero ($\delta_{1,0} = 1$). Initial variances are again set to one.

Similarly as in the restricted model, the terms $v_{1,t}$, $v_{2,t}$, and w_t introduces multiplicative error terms in equation (1) while there is no mechanism to allocate variation between them. I use the additional restriction:

$$\sigma_{v,1}^2 = \sigma_{v,2}^2 = \sigma_w^2 = \sigma^2 \tag{9}$$

(I still refer to the model as the unrestricted model, as the restriction on δ_1 is the main restriction of interest.) The additional restriction (9) is tested with a likelihood ratio test; Table 2 reports the test statistics and *p*-values (estimation results without the restriction are reported in Table A2 in the Appendix). The restriction cannot be rejected for any of the gears. The Akaike (1973) information criterion suggest the model restricted by (9) for all gears but hand line. Normality of the predicted errors is tested with the Lilliefors (1967) test; *p*-values are reported in Table A4 in the appendix. The *p*-values for $v_{1,t}$ for long lines and Danish seine are small and could be a sign of misspecification, but plots of the errors suggest rather that outliers cause problems. Finally, in Table A5, I provide *p*-values from the Kolmogorov-Smirnov test on predicted errors. As in the restricted model, *p*-values for errors in the observation equation (w_t) are low and suggest problems. Similarly as with (7), one can probably tune (9) in order to make predicted errors pass the Kolmogorov-Smirnov test.

As in Table 1, I carry out the Ljung-Box test on predicted errors; Table 2 reports both the test statistic and *p*-values. There are no signs of serial correlations in the results.

Results

Table 2 reports parameter estimates for the unrestricted model (equations (8) and (9)) for the four different gears types. Standard errors are given in parenthesis. For all gears, the likelihood ratio test cannot reject the additional restriction (9). The estimates of α and β are relatively similar to those estimated for the restricted model (Table 1). The largest differences are found for hand lines and Danish seine. If one considers intervals of two standard deviations around the estimates rather than point estimates, the intervals overlap to a large degree for all gears. The estimates for δ_2 are quite different, however. For all gears, the estimate is close to zero, only for long lines and Danish seine is the estimate more than a standard deviation away. The δ_2 estimate for Danish seine is negative. Since $\ln A_t$ also is negative for Danish seine, a negative δ_2 is consistent with an upward trend in the technology level. Setting $\delta_2 = 0$ leads to a model equivalent to the restricted model with $\delta_1 = 1$, where $\ln \delta_{1,t}$ takes the role of the term $\delta_2 \ln A_t$ in (5). As mentioned, the δ_2 estimates for the restricted, purely exponential model are close to one for all gears (see Table 1). The unrestricted model is in other words not very different from the restricted model, and the results from the two models mimic each other. I conclude that the restriction $\delta_1 = 1$ cannot be rejected.

The solid curves in Figure 2 show the smoothed technology level $\ln A_t$ for the unrestricted model for all gears. The shaded areas show two standard errors around the estimate in each direction. As in Figure 1, the dashed curves show the technology level estimated by Hannesson et al. (2010, Table 1, regression (iii), p. 756). While the overall impression is that the results are similar to those displayed in Figure 1, a few remarks are in order. The estimates contain more noise. The law of motion for the technology level in the restricted model contains one error term (see equation (5)), while for the unrestricted model, the law of motion contains two error terms. Although σ^2 is estimated at a higher level in the restricted model, it adds up to more noise in the technology level for the unrestricted model. The added noise is more pronounced in the cases where the δ_2 estimate is more than a standard deviation away from zero (long lines and Danish seine). The shaded areas in Figure 2 are slightly narrower than in Figure 1, implying smaller standard errors. The standard deviations in Table 2 are in most cases also smaller than in Table 1 and particularly so for the variance estimates: The restriction $\delta_1 = 1$ reduces precision of the estimates.

Figure 3 show the estimates of $\ln \delta_{1,t}$ for the unrestricted model for all gears. The solid curves show the smoothed estimate, while the shaded areas show two standard deviations around the estimate in both directions. With δ_2 close to zero, $\ln \delta_{1,t}$ is driving the development in $\ln A_t$ (see equation (3)). Thus, the $\ln \delta_{1,t}$ estimates in Figure 3 are similar to the $\ln A_t$ estimates in Figure 2, but the Figure 3 estimates are more smooth ($\ln \delta_{1,t}$ contains less noise than $\ln A_t$ in both Figures 1 and 2).

Table 3 shows a side-by-side comparison of estimates for input elasticities α and β from the restricted model (Table 1), the unrestricted model (Table 2), and from Hannesson et al. (2010). For gill nets and long lines, the estimates are relatively close over all specifications. For gill nets, somewhat lower α estimates are offset by somewhat higher β estimates, while the opposite occurs for long lines. Thus, the estimated technology level for gill nets and long lines agree to a large extent across all specifications. For hand lines and Danish seine, my restricted, purely exponential model estimates for α are lower and my estimates for β are higher when compared to Hannesson et al. (2010). The differences do not cancel out to the same degree as for gill nets and long lines, and I estimate a higher technology level for both hand lines and Danish seine. In the unrestricted model, I estimate both input elasticities below the estimates in Hannesson et al. (2010), and thus estimate the technology level at a significantly higher level.

The restriction $\delta_1 = 1$ does not seem to be binding. While there are some differences in the estimated technology level, the time profiles agree to a large extent, and the unrestricted model suggests the same revisions of the development of the fishery as do the restricted model. Thus, the results and their interpretation with and without the restriction do not differ very much and the unrestricted model adds little to the understanding of the importance of technological development in the Lofoten fishery.

4 Discussion

I have provided a Kalman filter approach as an alternative to the time dummy approach in Hannesson et al. (2010). The results are to some extent consistent between the methods, but they also show the limitations of the time dummy approach. The most obvious limitation is that estimates are only provided in six year aggregates. In comparison, the Kalman filter approach provides yearly estimates. The higher resolution in the estimates gives rise to an alternative view on the technological development in the fishery.

Based upon the technology time profiles, Hannesson et al. (2010, pp. 758-759, see Figure 7, p. 757, for technology time profiles) identifies four major periods in the fishery: From the beginning of the twentieth century to the end of World War II, from the end of World War II to about 1960, from the early 1960s to the early 1980s, and finally from the early 1980s to the end of the open access regime in 1988.

From my estimates in Figures 1 and 2, a different picture appears. From 1900 to circa 1920, the technology level for both gill nets and hand lines increased steadily. At around 1920, there is a clear break in the development. Motorization of the fleet took place in the years leading up to 1920, and by that time, most of the decked boats in the fishing fleet had engines. My results suggest that motorization was indeed the most important technical innovation in the pre-war period. Little improvement happened in the long line fleet, which suggests that motorization was less important for the long line technology. For the next forty years following 1920, the technology level had some ups and downs, but by the end of the 1950s, not much had happened to the technology level when compared to the 1920 level; for long lines, however, the technology level by the late 1950s was almost comparable to the technology level at the beginning of the century. From the late 1950's to around 1970, improvements occurred in all gears. The use of synthetic fibers and, for hand lines, jigging machines was probably the most important innovations in the period. The Hannesson et al. (2010) results suggest that in the early 1960s, the technology level was at the level it had been for a number of years, while in the late 1960s, the technology was at a much higher level. In comparison, my results show that the technology improvement started around

1960, or a few years later depending on the gear, and increased steadily through a number of years before leveling off in the years after 1970. Further, the change happened much faster in the long line fleet than in the rest of the fishery; synthetic fibers were probably quite important for the long line technology. In the final years, technical regress seem to occur. The regress is difficult to explain. In the Hannesson et al. (2010) analysis, the regress seems confined to the final period which covers 1984 to 1988. My results, however, suggest the regress started as early as the late 1970s. Particularly, the gill net technology seemed to have a peak around 1970 with subsequent technological regress. Total catches in the period of apparent technological regress was low, however, particularly in the 1980s, and the regress can simply be a signal that the particular production function (1) is not a very good representation of the harvesting process at low levels. Since the regress occurs in all gears, it could also suggest that some biological or environmental change was under way; all gears interact with the same biology and the same environment, after all.

To summarize, based upon the Kalman filter approach I identify four major periods of technological development in the Lofoten fishery: 1900 – 1920: Motorization lead to improvements in productivity. 1920 – 1960: Few gains from technological improvements. 1960 – 1970: Synthetic fibers and general development lead to substantial improvements. 1970 – 1988: Hard to explain technological stagnation and regress. In addition, the long line technology stands out with a different technological development than the rest of the fishery.

5 Conclusion

I have estimated production functions for the open-access cod fishery in Lofoten in a Kalman filter framework. The analysis suggests improvements to the analysis in Hannesson et al. (2010). While the estimates largely agree with the earlier analysis, I was able to produce results with a higher time resolution, and serial correlation seemed less of an issue. With the higher resolution results, year-to-year changes, which largely disappear with aggregated period estimates, become apparent. Ultimately, the new results inspire a different view on the technological development in the fishery. For example, there was a clear break in the technological development of the gill net and hand line gears around 1920. The break coincides with when motorization was completed; motors were an important development in the fishery.

My alternative empirical approach to technical change in the Lofoten fishery does not alter the main findings about productivity growth in Hannesson et al. (2010). But, if one is interested in technological development in itself, or latent variables in other contexts, I submit that the Kalman filter is a conceptually more sound approach than some of the more traditional remedies.

The Hicks-neutrality assumption, which is integral to both my and the analysis in Hannesson et al. (2010), is made more out of convenience than theoretical rigor. Non-neutral, technical change in the production function (1) amounts to input elasticities changing over time. The effort elasticity would increase over time as the same amount of effort could produce a larger harvest. The estimate of the effort elasticity does however incorporate efficiency of effort. Thus, if boats are not on the efficient frontier, the elasticity has a downward bias; if the average boat moves closer to the efficient frontier, it would manifest itself in an increasing elasticity over time. With non-neutral technical change, the stock elasticity would also be expected to increase over time, as a larger harvest could be extracted from the same stock level. However, technological change could also make the harvest outcome less dependent upon the stock level, and the stock elasticity would then decrease over time. To address non-neutral technical change nonlinear methods are necessary, while it seems apparent that the current model and data are insufficient to shed light on the issue. (With better data, both the general index and the Kalman filter approach allows for non-neutral technical change. In the present framework, it would require more observations or less correlated effort variables.) Non-neutral technical change would probably interfere with the neutral technology parameter A_t and can potentially explain the apparent technical regress which seemed to occur in the nineteen seventies and eighties. Non-neutral technical change poses challenges for future work in this line of research.

Appendix

Table A1: Results from estimating the restricted model (equations (5) – (6)) for all gears without the restriction (7) on variances.

	Gill Nets		Long Lines		Hand Lines		Danish Seine	
δ_2	0.9983	(0.0018)	0.9993	(0.0030)	0.9983	(0.0022)	0.9979	(0.0013)
α	0.9611	(0.1638)	0.4963	(0.2365)	0.7838	(0.2274)	1.0877	(0.1098)
β	0.4636	(0.1280)	0.7322	(0.1204)	0.5103	(0.2317)	0.9950	(0.1817)
σ_v^2	0.0626	(0.0141)	0.0247	(0.0115)	0.2823	(0.0432)	0.1655	(0.0535)
σ_w^2	0.0244	(0.0133)	0.0344	(0.0129)	0.0229	(0.0173)	0.0000	(0.0058)
$\ln L$	-31.0530		-12.2807		-83.0739		-17.6781	
AIC	-72.1060		-34.5614		-176.1478		-45.3562	
LB-stat (v_t)	15.2537		15.4573		29.2410		9.5694	
p-value	0.7617		0.7497		0.0831		0.9753	
LB-stat (w_t)	14.6370		15.5998		29.2934		14.5529	
p-value	0.7968		0.7411		0.0821		0.8014	
No. Obs	89		89		89		30	

Note: Standard deviations in parenthesis.

Table A2: Results from estimating the unrestricted model (equation (8)) for all gears without the restriction (9) on variances.

	Gill Nets		Long Lines		Hand Lines		Danish Seine	
δ_2	0.2897	(0.5719)	0.8100	(0.1235)	0.3061	(0.2859)	0.5372	(0.3662)
α	0.9236	(0.1728)	0.3769	(0.1316)	0.7252	(0.2356)	1.4399	(0.4466)
β	0.4532	(0.1484)	0.7321	(0.1356)	0.4405	(0.2700)	0.8527	(0.1303)
$\sigma_{v,1}^2$	0.0830	(0.1263)	0.0478	(0.0206)	0.2824	(0.2479)	0.0000	(0.1007)
$\sigma_{v,2}^2$	0.0000	(0.1325)	0.0151	(0.0157)	0.0000	(0.2543)	0.1192	(0.0800)
σ_w^2	0.0083	(0.0168)	0.0000	(0.0001)	0.0128	(0.0227)	0.0035	(0.0090)
$\ln L$	-112.9982		-94.7886		-161.9120		-46.2694	
AIC	-237.9964		-201.5772		-335.8240		-104.5388	
LB-stat ($v_{1,t}$)	12.4744		6.1193		17.1060		4.9784	
p-value	0.8988		0.9987		0.6461		0.9997	
LB-stat ($v_{2,t}$)	10.1459		14.5900		16.9761		9.1433	
p-value	0.9654		0.7994		0.6545		0.9812	
LB-stat (w_t)	10.0001		15.1653		19.5680		10.6158	
p-value	0.9682		0.7669		0.4852		0.9556	
No. Obs	89		89		89		30	

Note: Standard deviations in parenthesis.

Table A3: Parameter estimates the restricted model (equations (5) – (7)) for all gears and different values of k. The column $k = 10$ corresponds to the results reported in Table 1.

Gear	Parameter	$k = 2$	$k = 5$	$k = 10$	$k = 15$	$k = 20$
Gill nets	δ	0.9124	0.9958	0.9983	0.9990	0.9993
	α	0.8636	0.9672	0.9675	0.9672	0.9670
	β	0.3639	0.4486	0.4507	0.4511	0.4513
	σ^2	0.0450	0.0449	0.0450	0.0450	0.0450
Long lines	δ	0.9025	0.9973	0.9994	0.9997	0.9998
	α	0.4655	0.5027	0.5009	0.5002	0.4998
	β	0.7699	0.7385	0.7406	0.7410	0.7412
	σ^2	0.0290	0.0290	0.0290	0.0290	0.0290
Hand lines	δ	0.8913	0.9909	0.9971	0.9984	0.9989
	α	0.4664	0.4588	0.4731	0.4755	0.4765
	β	0.5620	0.7005	0.7022	0.7019	0.7016
	σ^2	0.1511	0.1513	0.1516	0.1516	0.1516
Danish seine	δ	0.9990	1.0001	1.0003	1.0003	1.0002
	α	1.1031	1.1114	1.1157	1.1174	1.1183
	β	0.9562	0.9546	0.9537	0.9533	0.9531
	σ^2	0.0840	0.0840	0.0840	0.0840	0.0840

Table A4: *p*-values from the Lilliefors (1967) test of the hypothesis that error terms from estimations in Tables 1 and 2 are normally distributed.

	Table 1		Table 2		
	v_t	w_t	$v_{1,t}$	$v_{2,t}$	w_t
Gill Nets	0.1126	0.0803	0.0648	0.686	0.0513
Long Lines	0.1028	0.1542	0.0133	0.2796	0.0701
Hand Lines	0.0622	0.0598	0.0958	0.1004	0.0530
Danish Seine	0.3465	0.4750	0.0084	0.1417	> 0.5

Table A5: p-values from the Kolmogorov-Smirnov test on predicted errors from estimations in Tables 1 and 2.

	Table 1		Table 2		
	v_t	w_t	$v_{1,t}$	$v_{2,t}$	w_t
Gill Nets	0.5686	0.0143	0.2147	0.3302	0.0008
Long Lines	0.5356	0.0230	0.2739	0.0474	0.0013
Hand Lines	0.3766	0.0026	0.3860	0.6940	0.0001
Danish Seine	0.8915	0.1359	0.9287	0.3346	0.0926

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Tables and Figures

Table 1: Results from estimating the restricted model (equations (5) – (7)) for all gears. The likelihood ratio statistics and p-values relate to the results in Table A1. Figure 1 shows related estimates of $\ln A_t$.

	Gill Nets		Long Lines		Hand Lines		Danish Seine	
δ_2	0.9983	(0.0024)	0.9994	(0.0027)	0.9971	(0.0042)	1.0003	(0.0063)
α	0.9675	(0.1709)	0.5009	(0.2292)	0.4731	(0.1836)	1.1157	(0.2134)
β	0.4507	(0.1336)	0.7406	(0.1204)	0.7022	(0.2355)	0.9537	(0.1476)
σ^2	0.0450	(0.0055)	0.0290	(0.0041)	0.1516	(0.0143)	0.0840	(0.0256)
$\ln L$	-31.7105		-12.4173		-85.2174		-20.4740	
AIC	-71.4210		-32.8346		-178.4348		-48.9480	
LR-stat	1.3150		0.2732		4.2870		5.5918	
p-value	0.2515		0.6012		0.0384		0.0180	
LB-stat (v_t)	14.8665		15.6840		30.6323		9.2968	
p-value	0.7840		0.7360		0.0602		0.9792	
LB-stat (w_t)	14.5871		15.8441		32.1654		10.1539	
p-value	0.7995		0.7262		0.0416		0.9653	
No. Obs	89		89		89		30	

Note: Standard deviations in parenthesis.

Table 2: Results from estimating the unrestricted model (equations (8) – (9)) for all gears. The likelihood ratio statistics and p-values relate to the results in Table A2. Figures 2 and 3 shows related estimates of $\ln A_t$ and $\ln \delta_{1,t}$.

	Gill Nets		Long Lines		Hand Lines		Danish Seine	
δ_2	0.0615	(0.1975)	0.2634	(0.1633)	0.0758	(0.1322)	-0.3427	(0.2440)
α	0.9571	(0.1723)	0.5458	(0.1474)	0.4986	(0.2178)	1.0208	(0.1011)
β	0.4306	(0.1434)	0.7279	(0.1210)	0.6297	(0.2800)	0.7988	(0.0616)
σ^2	0.0289	(0.0034)	0.0180	(0.0030)	0.0910	(0.0098)	0.0437	(0.0125)
$\ln L$	-113.9446		-95.9263		-164.0846		-47.9079	
AIC	-235.8892		-199.8526		-336.1692		-103.8158	
LR-stat	1.8928		2.2754		4.3452		3.2770	
p-value	0.3881		0.3206		0.1139		0.1943	
LB-stat ($v_{1,t}$)	13.4306		12.0648		25.5122		8.4076	
p-value	0.8582		0.9138		0.1825		0.9888	
LB-stat ($v_{2,t}$)	13.2950		14.2755		25.6454		9.4171	
p-value	0.8644		0.8163		0.1778		0.9776	
LB-stat (w_t)	13.1839		16.0888		26.6726		7.9336	
p-value	0.8694		0.7111		0.1447		0.9923	
No. Obs	89		89		89		30	

Note: Standard deviations in parenthesis.

Table 3: Comparing elasticity estimates for the restricted (Table 1) and unrestricted model (Table 2) to Hannesson et al. (2010, Table 1, regression (iii), p. 756) estimates.

	α			β		
	Re-stricted	Unre-stricted	Hannesson et al. (2010)	Re-stricted	Unre-stricted	Hannesson et al. (2010)
Gill Nets	0.9675	0.9571	1.0100	0.4507	0.4306	0.4064
Long Lines	0.5009	0.5458	0.4938	0.7406	0.7279	0.7620
Hand Lines	0.4731	0.4986	0.6844	0.7022	0.6297	0.5363
Danish Seine	1.1157	1.0208	1.2234	0.9537	0.7988	0.9015

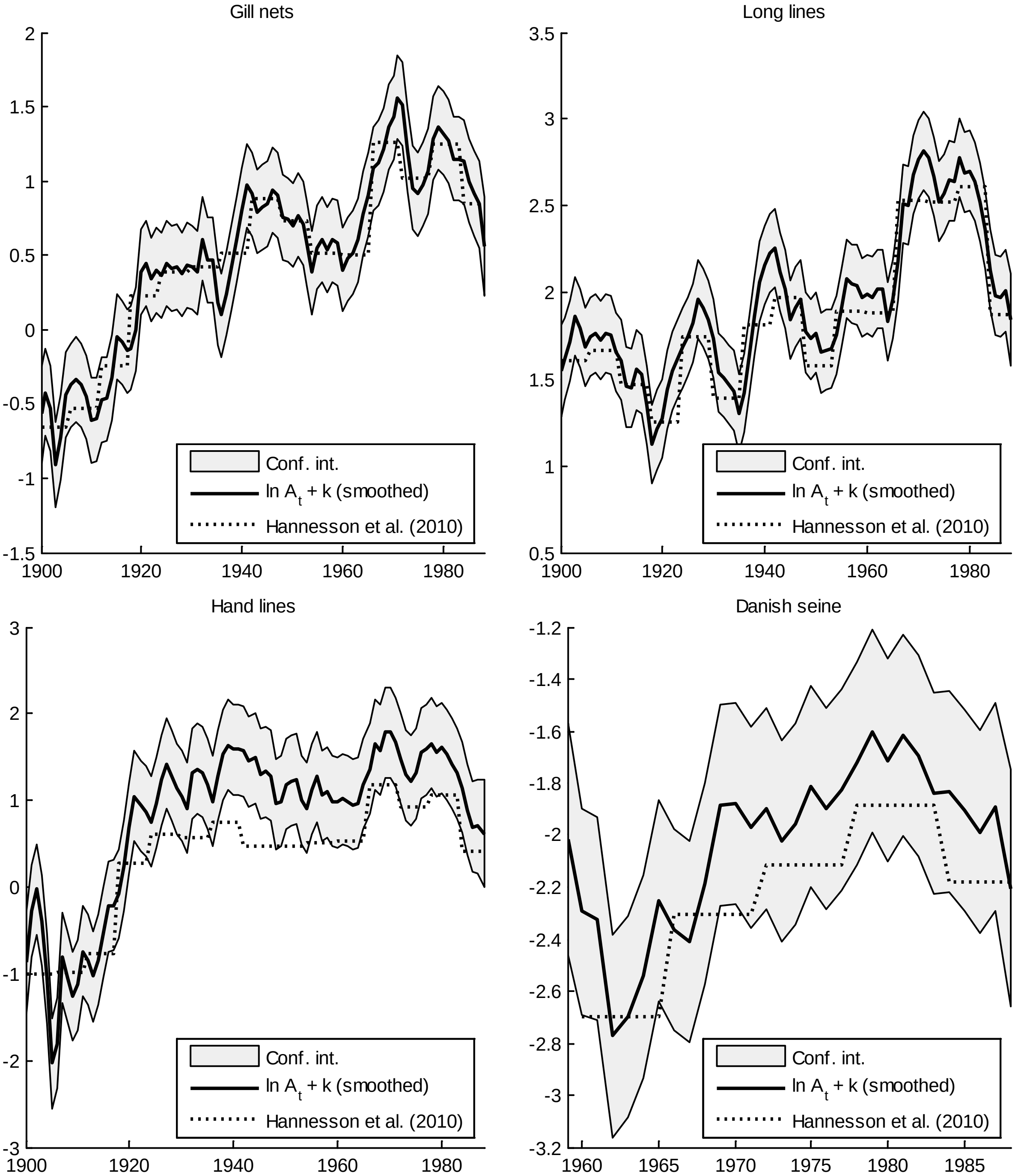

Figure 1: Smoothed estimates of $\ln A_t + k$ for the different gears in the restricted model (solid curves; the shaded areas show two standard deviations on each side of the central estimate) and the Hannesson et al. (2010, Table 1, regression (iii), p. 756) estimates of $\ln A + d_i$ (dashed curves). Parameter estimates in Table 1; the Hannesson et al. (2010) parameter estimates are listed in Table 3.

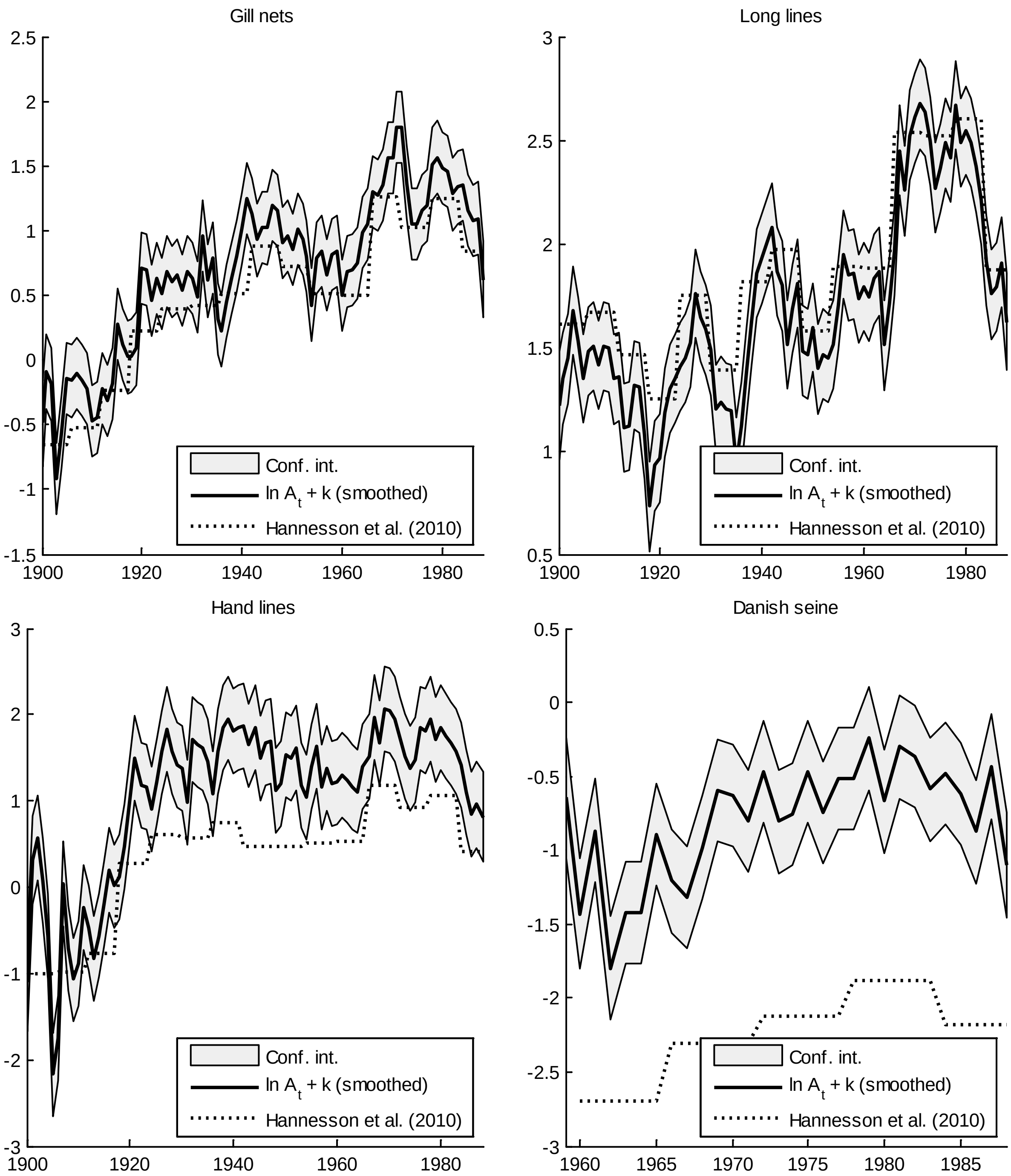

Figure 2: Smoothed estimates of $\ln A_t$ for the different gears in the unrestricted model (solid curves; the shaded areas show two standard deviations on each side of the central estimate) and the Hannesson et al. (2010, Table 1, regression (iii), p. 756) estimates of $\ln A + d_i$ (dashed curves). Parameter estimates in Table 2. The Hannesson et al. (2010) parameter estimates are listed in Table 3.

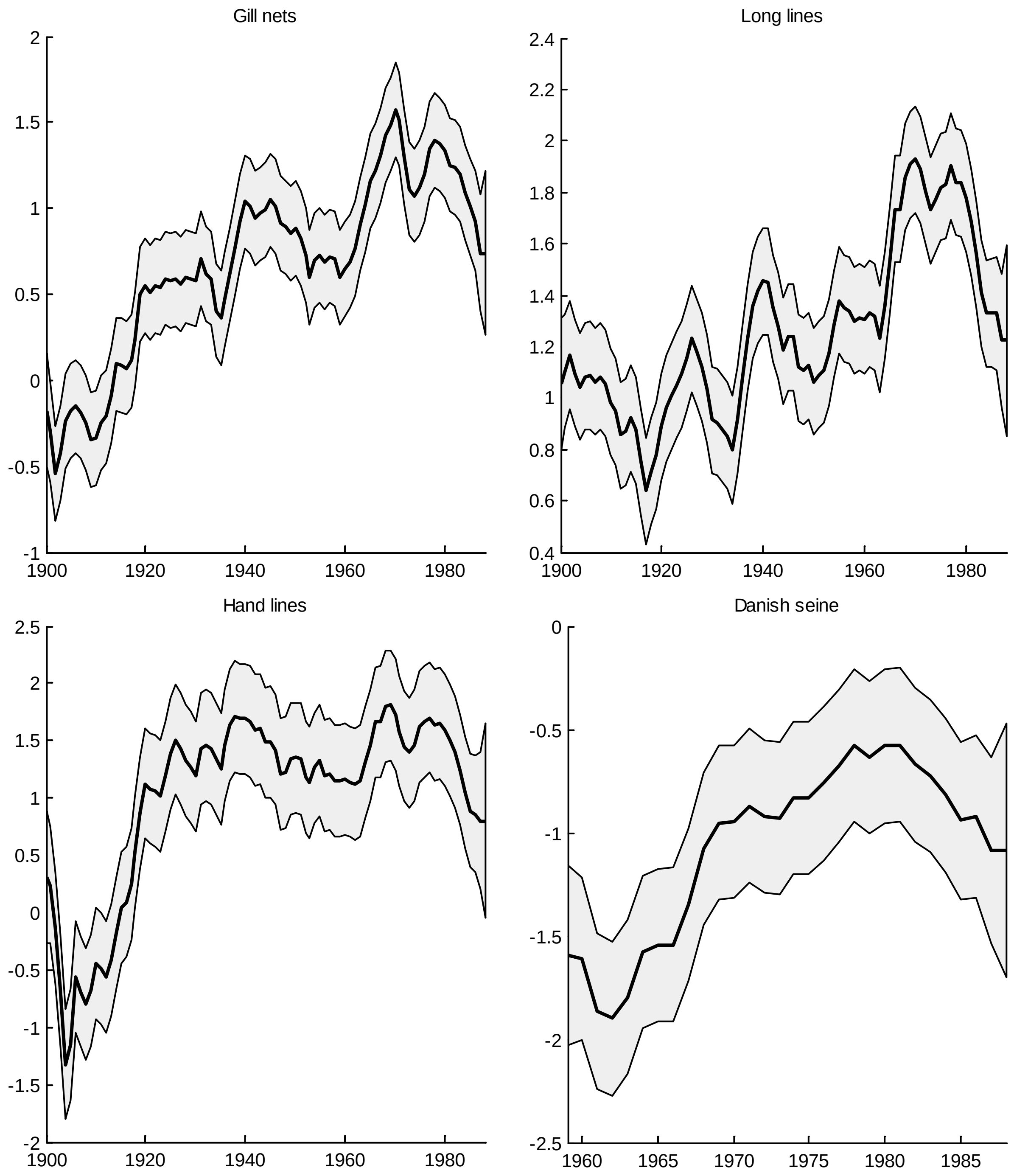

Figure 3: Smoothed estimates of $\ln \delta_{1,t}$ for the different gears, unrestricted model (solid curves; the shaded area show two standard deviations on each side of the central estimate). Parameter estimates in Table 2.