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PERMANENT SEMINAR ON EFFICIENCY AND PRODUCTIVITY

THE RELATIVE IMPORTANCE OF LUCK AND TECHNICAL EFFICIENCY IN A FISHERY

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Abstract: The study of productive efficiency has not been a traditional field of research in fisheries economics. However, recent papers have dealt with testing what it is known as "the good captain hypothesis", according to which differences in catches among vessels can be explained in terms of skipper skill (efficiency). These papers introduce an interesting research issue: the distinction between luck and efficiency. In this paper we try to shed more light on this topic using a panel data set on the hake fishery in Northern Spain. In particular, we are interested in separating efficiency not only from luck but also from other time invariant variables, such as vessel characteristics, which sometimes are confounded with efficiency. In contrast to the other papers that deal with this topic, we find that luck is more important than technical efficiency in explaining catches. We argue this can be explained by the fact that other papers use data at a higher level of temporal aggregation. Over longer periods of time, skill persists while luck averages away.

Keywords: technical efficiency, fishing, panel data

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1. Introduction

In fisheries economics, the study of productive efficiency has not been a traditional field of research. However, recent papers have started to deal with this important issue (Salvanes and Steen, 1994; Kirkley *et al.*, 1995, 1998; Squires and Kirkley, 1999; Grafton *et al.*, 2000).

A common objective of some of the aforementioned papers is to test what it is known as "the good captain hypothesis", which says that differences in catches among fishing vessels are mainly due to differences in the skill of the skippers. That is, the hypothesis is that skill is more important than luck in determining the size of the catch. We can interpret differences in skill as differences in the technical efficiency of production, where the fishing boats are producing the output "fish catch" using a variety of inputs. We are then interested in the relative importance of luck versus technical efficiency in the fisheries industry.

The special characteristics of fishing as a productive activity would seem to make the effect of randomness (luck) important. Fish are a mobile resource and when the fishermen leave port they do not know with any degree of certainty where the fish will be found. Zero output is possible, and presumably more likely than in most production settings. However, all of the above studies find that technical efficiency is more important than luck (or other random factors) in explaining differences in catches. This is somewhat unexpected given the inherent randomness of the fishing process. In fact, as Kirkley *et al.* (1995) put it, "In a fishery it is surprising that technical inefficiency dominates uncontrollable random shocks".

In this paper we try to shed more light on this interesting topic using a panel data set on the hake fishery in Northern Spain. A distinguishing feature of this data set is that we have information on daily fishing trips. This avoids possible problems caused by data aggregation, and (as we will see later) the temporally disaggregated nature of our data is important in interpreting our results. Furthermore, we are interested in separating efficiency not only from luck, but also from other input and environmental variables, some of which are time invariant and therefore easily confounded with technical efficiency. This raises some methodological issues involving the difference between fixed and random effects models.

The paper is organized as follows. The next two sections review the literature on technical efficiency and previous empirical work on fishing efficiency. In section 4 we describe the fishery and our data set. Section 5 presents the models that allow us to separate technical efficiency from luck. We give our empirical results in section 6, and the final section of the paper gives our concluding remarks.

2. Technical efficiency

The literature on the measurement of productive efficiency starts with the seminal paper of Farrell (1957) and has experienced a vast growth in the last several decades. Aigner, Lovell and Schmidt (1977) introduced the notion of a stochastic frontier, allowing for the separation of pure random events (such as luck) from inefficiency. The stochastic frontier model can be written as follows:

$$y_i = f(x_i) + v_i - u_i \qquad (1)$$

where y_i is the output of firm i and x_i is the vector of inputs. The error term is composed of two terms: a one-sided (positive) error term (u_i) that represents technical inefficiency, and a symmetric error term (v_i) with zero mean which captures random events which are not under the control of the fisherman, and which we will refer to as luck. In this model the relative importance of luck and technical efficiency can be assessed comparing their respective variances: σ_u^2 and σ_v^2, and more specifically the ratio $\frac{\sigma_u^2}{\sigma_v^2}$ is a possible measure of the relative importance of skill versus luck.

With panel data, at least some of the variables will show variation both over firm (i) and time (t). We can therefore write the stochastic frontier model for panel data as:

$$y_{it} = \alpha + x_{it}\beta + v_{it} - u_{it} \qquad (2)$$

However, following Schmidt and Sickles (1984) and many subsequent papers, we will make the assumption that technical inefficiency is time invariant. In our setting, this assumption asserts that the skill of the skipper does not change over the duration of our sample (one year), whereas luck changes from day to day. With this assumption, $u_{it} = u_i$, which depends only on i and not on t, and the model becomes

$$y_{it} = \alpha + x_{it}\beta + v_{it} - u_i \qquad (3)$$

In (3), we will normally view u_i as a random variable, and then this is called a random-effects model. Alternatively, we can define the firm-specific intercept α_i as $\alpha_i = \alpha - u_i$, in which case the model can be written as

$$y_{it} = \alpha_i + x_{it}\beta + v_{it} \qquad (4)$$

When the α_i are treated as (fixed) parameters to be estimated, this will be referred to as a fixed-effects model. In this model technical efficiency is reflected in differences in the $\alpha_{i.}$

It may be worthwhile to consider what technical inefficiency would reflect in our setting. Since Farrell, it is traditional to consider technical inefficiency as the failure to properly use the best-practice technology, given the current state of knowledge. There is no limit to the number of things that could be done incorrectly, of course. A captain could fish at the wrong time of day, could set nets or lines improperly, could drop fish overboard, etc. However, these kinds of gross errors do not seem likely to be important in determining variation in output in our data. Rather, the most important decision a skipper makes is where to fish, and technical inefficiency is likely to reflect a lack of skill in choosing the correct fishing ground (given the season, weather, sea conditions, etc.).

3. Fishing efficiency. A review

Only very recently have researchers paid attention to the study of fishing efficiency in the sense of Farrell. One of the first papers to use this type of analysis is Hannesson (1983), who estimated a deterministic production frontier for the cod and saithe fishery in Norway.

Using a stochastic revenue frontier function, Salvanes and Steen (1994) were the first to study the separation between efficiency and luck in fisheries. Their objective was to test “whether the relative performance of individual boats is random or systematic”. They used panel data on the seal industry in Norway over several years to obtain time-varying efficiency scores and to test whether the series of efficiency scores were stationary.

Kirkley *et al.* (1995) estimate a stochastic frontier production function with panel data on vessels of the sea scallop fishery. As in other fishery models they include a proxy for stock size as an explanatory variable. In a follow up paper, Kirkley *et al.* (1998) use the Battese and Coelli (1995) one-stage model on the same data set to allow technical efficiency to vary systematically with dummy variables for month and vessel. Both papers conclude that technical inefficiency is more important than pure random events in explaining variation in output.

Squires and Kirkley (1999) estimate a production function comparing the fixed effects and random effects models using data on the groundfish fishery on the Pacific Coast of the United States. In the fixed effects model they cannot reject the null hypothesis that the vessel effects are equal, implying that there are no differences in technical efficiency. Furthermore, they cannot reject the null hypothesis of no correlation between the inputs and the individual effects when choosing a random effects model, but they do not report the levels of technical efficiency in this model.

Finally, Grafton *et al.* (2000) estimate a stochastic frontier production function using annual vessel-level data on the British Columbia halibut fishery. They also find that σ_u^2 is large relative to σ_v^2, so that differences in efficiency are more important than luck.

In conclusion, most of these previous papers have found that differences in technical efficiency (skill) are more important than pure randomness (luck) in explaining inter-vessel differences in catches. Interestingly, we will find evidence contrary to this result. A reasonable explanation for this difference is that we use daily data whereas previous papers used data over longer time spans. Presumably luck averages away over time, whereas skill persists.

4. The data

Our data consist of daily observations for one year (1999) for 11 vessels based in two ports located 15 miles apart in Northern Spain for one year (1999). Since vessels do not go out fishing every day the data form an unbalanced panel data set. The total number of observations is 1404. Vessels are similar in size and follow similar operational procedures. Four vessels use bottom nets while the rest use longline fishing.[1] The vessels' characteristics are summarized in Table 1.

[1] Netters lay the nets and return to port. The next day they lift the nets, harvest the fish, and lay the nets again on the same ground or on a different one. Longliners leave port earlier and cast the line with live bait, wait for several hours and lift the line before returning to port.

Table 1. Descriptive characteristics of the fishing vessels

	Mean	Coef. of Variation	Min	Max
Gross Registered Tons	21.3	0.34	16	32
Boat length (meters)	13.8	0.07	12.5	15.1
Engine power (hp)	169	0.14	128	200
Vessel age (years)	16	0.37	14	26

An important characteristic of this fishery is that fishing trips do not take longer than one day. When the vessels arrive in port, all fish are auctioned in a local market, and the quantities and prices per vessel are automatically stored in a computer, providing a very reliable measure of output. However, an important exception to this statement occurs because boats sometimes go out fishing on Saturdays, when the auction market is closed. In this case, the fish is stored and it is auctioned on the next Monday. This causes some ambiguity in the interpretation of output for Monday observations.

In this fishery there is a lot of by-catch. Even though the fishing gear is specifically designed to catch hake, other kinds of fish get caught.[2] Table 2 shows some descriptive statistics of the output.

Table 2. Descriptive characteristics of catches (kg/day)

	Mean	Coef. of Variation	Min	Max
Hake	79	0.67	0	407
By-catch	41	2.17	1	1247
Total	120	0.88	10	1247

By-catch captures account for one third of total catch. The large coefficients of variation indicate high variability in yields, especially in the case of by-catch.

[2] During the 1999 fishing season thirty other species were caught.

It is potentially of relevance that the fishery is regulated. The European Union sets quotas for hake, known as Total Admittable Catch (TAC) and when a particular fishing region reaches the TAC, the fishery is closed. However it does not appear that this regulation affects fishermen's behavior prior to the TAC being reached. Cooperative fishing arrangements to apportion the TAC do not appear to exist, perhaps because a fishing ground is accessible to many boats from many ports.[3]

We have rather limited data on inputs. We observe some characteristics of the vessels: Gross Registered Tons (GRT) is a measure of the size of the boat. PORT is a dummy variable for base port (equal to one if the base port is Lastres, and equal to zero if the base port is Ribadesella). GEAR is a dummy variable for the type of gear used (equal to one if net, and equal to zero if longline).[4] We also observed the length of the boat, but we did not use this information, since it contained little additional information once GRT is known. It is important to note that in our data all of these vessel characteristics are time invariant.

We also know the fishing ground used by most boats each day. There are some thirty different fishing grounds, so that we could use dummy variables for these as time-varying inputs. However, we do not regard the choice of fishing ground as an input in the usual sense. Furthermore, the choice of fishing ground is the main decision made by skippers and therefore it ought to be reflected in the technical efficiency measure. Therefore we decided not to account for fishing ground in our model.

We also have some measures of the fishing environment. Weather characteristics are measured with two dummy variables: w_1 equals one under "good" sea conditions and w_2 equals one under "average" sea conditions. (The omitted category is "adverse" sea conditions.) In addition, we include quarterly dummy variables for the first three quarters of the year. The quarterly dummies are expected to pick up the seasonal pattern of the fishing stock. Some papers (Kirkley *et al.*, 1995,1998; Grafton *et al.*, 2000) include a proxy for stock size. We argue that since all boats have access to the same fishing grounds, the effect of variations in stock size can be properly controlled for using dummy variables for time. We hope that dummy variables are sufficient, since our data span only one year.

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[3] Some fishing grounds are also closed during spawning season due to local regulations.

[4] All boats carry the maximal length of nets or lines allowed, so there is no further variation in this input.

That is we are trying to control for seasonal variation in the location and behavior of the fish, not for long-term changes in the stock of fish.

We also include a dummy variable for Mondays. As noted previously, some fish sold on Monday may actually have been caught on Saturday, but we do not know when this occurs. Including a Monday dummy variable is an attempt to at least partially control for this fact.

5. A model to separate luck from efficiency

It is clearly the case in our data that some skippers systematically catch larger amounts of fish. That is, some boats catch more fish on average than other boats. This is true even after controlling for inputs and environmental conditions. These differences in average catch are measures of the efficiency of production, and we presume they represent differences in the skill of the skippers. However, there is also a lot of apparently random variation in catches, both across boats and over time, which we presume represent luck. Our task is to quantify the importance of these two factors.

Our statistical model is a panel data production model of the form:

$$y_{it} = \alpha + z_i\gamma + \sum_{j=1}^{3}\lambda_j Q_{jt} + \sum_{k=1}^{2}\phi_k w_{kt} + \delta M_t + v_{it} - u_i \qquad (5)$$

Here subscript "i" indexes vessels and subscript "t" indexes time (days). Output, y, is the natural logarithm of total catch (in kg.). The vector z_i contains the three time-invariant boat characteristics: the logarithm of GRT, and the dummy variables for PORT and GEAR. The Q_{jt} are the quarterly dummies; the w_{kt} are the weather dummies; and M_t is the dummy for Monday. The random error v_{it} is assumed to have zero mean and constant variance, and to be uncorrelated over both i and t. It is intended to capture luck, and its variance, σ_v^2, is a measure of the importance of luck in determining variation in output. Finally, the random terms u_i are the individual effects, assumed to have constant mean and variance and to be uncorrelated over i. They are time-invariant, and differences across boats in the u_i are intended to capture differences in skill (or efficiency). The variance of u_i, which we denote by σ_u^2, is therefore a measure of the importance of skill

We will consider several variants of this model (fixed and random effects), depending on what is assumed about the u_i. However, it is clear that the fundamental assumption here is that the individual effects u_i are time-invariant. This corresponds to the assumption that the skill of the skipper (i.e., the efficiency of production) is time-invariant. This is in contrast to the random error v_{it} representing luck, which shows purely random variation over time. These contrasting assumptions about the intertemporal nature of skill and luck are what makes it possible to separate them statistically.

6. Estimation and results

We first consider the fixed-effects estimation of our model. In this case we simply treat the individual effects u_i as unknown parameters, about which we make no assumptions at all. This yields a model in which there are firm-specific intercepts:

$$y_{it} = \alpha_i^* + \sum_{j=1}^{3} \lambda_j Q_{jt} + \sum_{k=1}^{2} \phi_k w_{kt} + \delta M_t + v_{it} \tag{6}$$

where $\alpha_i^* = \alpha + z_i\gamma - u_i$.

In this model (that is, under the assumptions just made), it is well known that we cannot estimate the coefficients of any time-invariant variables (z_i), because these variables would be perfectly collinear with the dummy variables for the firms. Therefore, although we can measure several characteristics of the fishing vessels, we cannot include them as regressors because they are time invariant. We can estimate the firm-specific intercepts (or fixed effects) α_i^*, and an important issue is how to interpret these. Differences in the αi* include not only differences in skipper skill (u_i) but also differences in any relevant time-invariant vessel characteristics (z_i). As a result the variance of the α_i^* will be larger than the variance of the u_i and will overstate the importance of skill. On the other hand, we can estimate the variance of the v_{it}, so that we properly measure the importance of luck.

Equation (6) was estimated using the WITHIN estimator, which is the same as using least squares with dummy variables included for the firms.[5] The results are shown in Table 3.

[5] The estimations were carried out using LIMDEP v.7.0 (Greene, 1995).

Table 3. Estimates of the fixed effects model

Variable	Parameter	Coefficient	t-ratio
Vessel 1	α_1	3.92	35.4
Vessel 2	α_2	2.96	20.8
Vessel 3	α_3	3.67	30.7
Vessel 4	α_4	2.15	15.5
Vessel 5	α_5	3.20	18.2
Vessel 6	α_6	2.13	18.6
Vessel 7	α_7	2.37	14.3
Vessel 8	α_8	4.28	47.7
Vessel 9	α_9	4.14	50.6
Vessel 10	α_{10}	4.09	46.9
Vessel 11	α_{11}	3.76	44.5
Quarter 1	λ_1	0.04	0.64
Quarter 2	λ_2	0.28	3.43
Quarter 3	λ_3	0.06	0.90
Weather 1	ϕ_1	0.26	2.25
Weather 2	ϕ_2	0.22	1.93
Dummy Mondays	δ	0.49	8.02
	R^2	39%	

The coefficients of the dummy variables for good (w_1) and average (w_2) weather are positive and significant, suggesting that, *ceteris paribus*, fishermen catch more fish in good weather conditions. This is no surprise. Two of the quarterly dummy variables have coefficients that are small and statistically insignificant. However, the coefficient of the dummy variable for the second quarter is positive and significant, indicating that catches in spring are 36% higher than in the fall.[6] The significance of this dummy variable does not depend on "fall" being the omitted quarter. Fishing is just better in the spring than in the rest of the year.

Clearly the individual (vessel) effects are significantly different from zero. That is not a very interesting hypothesis to test, however. What is important is whether they are different from each other. An F-test of the restriction that there are no differences between the individual effects ($\alpha_1=\alpha_2=\ldots=\alpha_{11}$) indicates that the differences between the vessel effects are significant. The R^2, on the other hand, is 0.39, indicating that randomness is also a large component of catches.

The variance of the fixed effects is 0.61 while the error variance is 1.02. Therefore, in this model we find that skill is less important than luck in explaining differences in daily catches across vessels. This is so even though the variance of the fixed effects overstates the variance due to differences in skill (efficiency), due to the fact that the technical efficiency index (u_i) is confounded with other factors (z_i)

We now return to equation (5), which explicitly contains the vessel characteristics z_i. The issue is how to separate the individual effects (u_i) from the vessel characteristics. If the effects are not correlated with the regressors,it is well known that we can accomplish this with a random effects model. That is, now we impose the assumption that the u_i are random draws from a distribution with mean zero[7] and variance σ_u^2. We do not need to specify the form of this distribution. Then if the u_i are uncorrelated with all of the regressors and with the errors v_{it}, we estimate the model by generalized least squares (GLS). The GLS estimator is consistent and more efficient than the WITHIN (fixed-effects) estimator. More significantly, now we can include time-invariant vessel characteristics in the regression, so that our estimate of σ_u^2 reflects skill only and not the effects of z_i.

The fundamental assumption for the random effects model is that there is no correlation between the regressors and the effects. We can test this hypothesis by means of a Hausman test (Hausman, 1978) as suggested by Hausman and Taylor (1981). In our

[6] The interpretation of the coefficient of a dummy variable, say γ, when the dependent variable is in logs is (e^{γ}-1). See Suits (1981).

[7] Any non-zero but constant mean is simply absorbed by the intercept α.

case the Hausman test does not reject the null hypothesis of no correlation between the effects and the regressors. [8]

Table 4 gives the GLS estimates, as suggested by Balestra and Nerlove (1976), for this model. Note that, comparing to Table 3, we no longer have dummy variables for the various boats, but we now include the vessel characteristics Gross Registered Tons (GRT), PORT and GEAR, as described in section 4.

Table 4. Estimates of the random effects model

Variable	Param.	Coefficient	t-ratio
Constant	α	1.79	3.25
Quarter 1	λ_1	0.05	0.63
Quarter 2	λ_2	0.28	3.66
Quarter 3	λ_3	0.07	0.94
Weather 1	ϕ_1	0.26	2.22
Weather 2	ϕ_2	0.22	1.89
Monday	δ	0.49	7.51
GRT	γ_1	0.34	1.64
PORT	γ_2	1.15	4.50
GEAR	γ_3	0.12	0.51
	σ_u^2	0.073	
	σ_v^2	1.021	

As in the fixed-effects model, we find that boats catch more fish in the spring, and when the weather conditions are good. The coefficient of GRT is positive and marginally significant, indicating that larger vessels catch more fish. PORT is also quite significant, indicating that tradition or other site-specific factors play an important role. However, there is no significant difference between netters and longliners.

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[8] Previous studies (Squires and Kirkley, 1999) have also found no correlation between the individual effects and the inputs.

The most striking result is that in the random effects model the variance of the effects u_i is very small: $\sigma_u^2 = 0.073$. This compares to a value of 0.61 for the variance of the effects in the fixed-effects model. (The error variance σ_v^2 was very similar in the two models, 1.02 to two decimal places in both cases.) That is, in this model the effect of skill relative to luck is very, very small. From the point of view of this model, most of the variation in the effects in the fixed-effects model has been explained by differences in vessel characteristics, which are now included in the regression portion of the model.

This conclusion hinges on our accepting PORT as a legitimate vessel characteristic, as opposed to an indicator of skill. This is reasonable to the extent that it is exogenously determined (say, by place of family residence) and it is relevant for fundamental reasons like distance to good fishing grounds, quality of harbor, etc. On the other hand, if skippers in one port are simply more skilled than skippers in another, controlling for port will cause us to understate the effects of skill.

The last model we estimate is a stochastic frontier model of the type suggested by Pitt and Lee (1981). This model is a special case of the random effects model, in which we make the additional assumptions that the v_{it} are independently and identically distributed (iid) as $N(0,\sigma_v^2)$; the u_i are non-negative and are iid as half-normal (the absolute value of $N(0,\gamma^2)$); and the u_i and v_{it} are independent of the regressors and of each other. Estimation of this model is by maximum likelihood.[9] The results for the stochastic frontier model are given in Table 5.

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[9] An important detail is that we need to distinguish the variance of u_i, which we call σ_u^2, from γ^2, which can be thought of as the variance of the normal that is converted into u_i by taking the absolute value (or, equivalently, by truncating at zero). In the stochastic frontier literature the notation σ_u^2 is often used for what we call γ^2. The relationship between the two is that $\sigma_u^2 = \gamma^2(\pi-2)/\pi$. Since $(\pi-2)/\pi$ is about 0.36, this is not a minor distinction. What we report as σ_u^2 is our estimate of the variance of u_i, which is comparable to what we have reported for the other models in Tables 3 and 4.

Table 5. Estimates of the stochastic frontier model

Variable	Param.	Coefficient	t-ratio
Constant	α	2.80	12.94
Quarter 1	λ_1	0.065	0.78
Quarter 2	λ_2	0.33	4.19
Quarter 3	λ_3	0.10	1.29
Weather 1	ϕ_1	0.27	2.09
Weather 2	ϕ_2	0.23	1.88
Monday	δ	0.48	6.88
GRT	γ_1	0.29	4.43
PORT	γ_2	1.17	16.07
GEAR	γ_3	0.022	0.24
	σ_u^2	0.43	
	σ_v^2	0.64	

The coefficient estimates are not very different from those in Table 4 and need not be discussed separately. The stochastic frontier model has smaller standard errors for the coefficients of the time-invariant vessel characteristics. However, the most substantial difference is in the estimates of the variances of u and v. We now have $\sigma_u^2 = 0.43$ and $\sigma_v^2 = 0.64$. This is a smaller value of σ_v^2 than for either of the previous models, which is hard to explain. The value of σ_u^2 is between those reported in Tables 3 and 4 (which were widely different). The ratio of σ_u^2 to σ_v^2 is 0.67, which is quite close to the value of 0.60 from Table 3 but much larger than the value of 0.07 from Table 4. We still conclude that luck is more important than skill, but not by such a wide margin as if we had relied on the random effects model without the distributional assumption. One obvious rationalization of these results, of course, is that the random effects model is correct but the distributional assumptions are not.

While clearly there are considerable differences across models in the details of our results, our basic result is still the same. Luck is more important than skill (efficiency) in explaining catches.

7. Concluding remarks

We have estimated panel data production models using daily data for one year on 11 fishing vessels from the hake fishery in northern Spain. In the empirical application three models are estimated: fixed effects, random effects, and a stochastic frontier. The estimation shows that luck (noise) seems to be more important than skill (technical efficiency) in explaining differences in daily catches. This result differs from the findings of most of the empirical literature on fishing efficiency.

We believe that the explanation for this difference in results is that we use daily data, whereas the other papers use data at a higher level of temporal aggregation. We would suppose that the relative importance of luck is larger over shorter periods of time. Over longer periods of time, skill becomes more important, because luck is transitory but skill persists.

We can illustrate this point more explicitly in a simple stochastic frontier model:

$$y_{it} = v_{it} + u_i$$

Here i indexes firms, t indexes time, say in days, and for simplicity we have suppressed the regressors. Our measure of the relative importance of skill and luck is σ_u^2/σ_v^2. Now suppose that we aggregate over time by combining T daily observations into one aggregated (e.g. monthly) observation, where for simplicity we treat the panel as balanced. Now we would have, for the monthly observation that begins at day t,

$$y^*_{it} = v^*_{it} + u^*_i$$

where

$$y^*_{it} = \sum_{s=t}^{t+T} y_{is}, \quad v^*_{it} = \sum_{s=t}^{t+T} v_{is}, \quad u^*_i = Tu_i$$

It follows that $\mathrm{var}(u_i^*) = T^2\sigma_u^2$ and $\mathrm{var}(v_{it}^*) = T\sigma_v^2$, so that $\mathrm{var}(u_i^*)/\mathrm{var}(v_{it}^*) = T(\sigma_u^2/\sigma_v^2)$. That is, aggregating over T time periods, the importance of skill relative to luck goes up by a factor of T.

This simple illustration does not hold literally in our case, most importantly because our output is in logarithms, and so the monthly output would not be the sum of the daily outputs. However, the basic point must still be true. Skill is more important relative to luck over longer periods of time, because skill persists while luck averages away.

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