THE LONG-TERM RELATIONSHIP BETWEEN WAGES AND KNOWLEDGE IN THE MANUFACTURING SECTOR IN PUERTO RICO

FIRST DRAFT

Diego Iribarren
CRIC & Estudios Técnicos, Inc.

JEL classification: C32, J31, O31

1 Introduction

The problem of knowledge in economic activity can be studied from at least two general broad perspectives. The first one refers to the consequences on the scope of knowledge that the modeller's point of view provides him/her. Under this standpoint the problem of knowledge refers to the modeller's limitation to understand economic activity from a distance. The second perspective is that of the modellee's knowledge, i.e. the economic agents' knowledge. Under this second stance, models of economic activity are based on the agents' limitations to understand and learn about the economic activity in which they are engaged in. Decisions, expectations, conjectures, and hypotheses all play key roles in both perspectives but in different ways.

There is a subtle but profound difference in both approaches. Both economic agents and the modeller possess more or less similar, but differentiated, abilities and limitations to know and understand economic activity. Moreover, the specific outcome of these limitations depends crucially on the surroundings that engulf the activities of which they are a part of, e.g. Belianin (2000), Iribarren (2001), Loasby (1999, 2001). In this sense, the specific forms of knowledge acquired by the modellees and the modeller may differ even though they may all observe the same economic activity during the same period of time. These differences will not only arise out of idiosyncrasies between the agents, and the modeller as well, but also from the fact that the same individual learning routines are always and everywhere context dependent, e.g. Loasby (1999, 2000), Langlois (2001), Iribarren (2001), Belianin (2000), Slembeck (1999).

This paper takes the point of view of the modellees and studies the consequences that individual knowledge bears upon wages in a technologically driven sector, such as manufacturing. Following the hypothesis that a portion of the agents' knowledge must remain invariant in order for structure to emerge, Iribarren (2001), the evolution of wages as a function of knowledge is investigated as a problem of cointegration (CI). If there is indeed a long run relationship between both of them some form of stable knowledge must generate a structured system with wages. To do so, we assume that the individual agent in each industry is representative of the individuals engaged in production in that industry. In this sense, this is a study of the long run relationship of a typical agent's knowledge with the manufacturing industry's average salary.

First, in section two, we establish the problem of knowledge in concrete terms and relate it to an econometric formulation suitable for quantitative analysis. Then, in section three the entire econometric methodology is explained in detail. That is, the use of the Kalman Filter (KF) algorithm to generate the state (unobserved) variable that drives the system and then the standard cointegration procedures. Section four presents the main empirical results and finally, in section five, we draw conclusions, particularly, on the consequences of efficiency for the puertorrican manufacturing sector.

2 The problem of knowledge

One of the traditional arguments concerning knowledge in econometrics states that if all the variables that drive a system were to be known then a completely deterministic system could be specified. Random, unanticipated shocks would disappear (since they would all be known). There would be no need for white noise processes, no need to estimate relationships and much less a need for large sample considerations. Econometrics, the argument goes, would reduce itself to difference equations theory. However, given the fact that we cannot know-it-all we are forced to conjecture and test relationships between variables, much in the popperian logic of scientific discovery (see Popper (1959)[1]).

There is a further, very important point, with respect to the modeller's ability to specify a system and the question of knowledge. As mentioned above, complete knowledge implies the absence of uncertainty, O'Driscoll and Rizzo (1984). Whence, by the same logic, unspecified variables represent undisclosed forms of knowledge for both the modeller and the agents, i.e. "unknown" knowledge. This will become a crucial issue in our methodology since there will be a trade-off between correct specifications of the system, in the first stage of estimation, and the nature of the knowledge variables, i.e. whether or not it contains a unit root (UR). This trade-off can always be manipulated depending on the characteristics that knowledge ought to possess in different models (see for example Nonaka, Toyama and Konno (2000) for an application of the question of knowledge to management). In our case, the specification was such that the KF algorithm generated a knowledge variable that was a non-stationary system. This is the reason why our system was specified in the manner it was, i.e. too many variables would have meant a knowledge variable that would have been stationary.

Knowledge is always and everywhere an entirely individual and subjective phenomenon, e.g. Metcalfe and Ramlogan (2001), Loasby (2001), Iribarren (2001). Individual agents are the ones that can "know", not the group in which they interact, nor the industry in which they trade, nor the economy of which they are of part of. Large group behaviour synthesises the interaction and interdependencies between individual behaviour irrespective of individual knowledge, intentions, desires and capabilities, Metcalfe and Ramlogan (2001), that is, Adam Smith' s invisible hand at work.

If we assume that in the manufacturing sector in Puerto Rico (PR) an individual agent faces at least two measurable variables related to manufacturing, i.e. employment (emp.) and quantities produced (q), then we can conjecture that at time t the agents learns, in this case, about employment, through some hypothetical functional relationship,

$$emp._t = f_i(q_t, z^i_t, (\text{individual knowledge})_t) \qquad [1]$$

where z^i_t represents the value of any other variables observed by agent i at time t. Each agent holds a particular functional relationship, which depends decisively on the agent's learning capabilities, information processing ability, etc. that allows him/her to

1 There are, of course, other (very strong) arguments on the need and justification of econometrics; mainly, the general practical impossibility to completely sample the universe. Whence, the need to

understand variations in the level of employment. If we further conjecture that each agent's individual knowledge evolves as

$$\text{(individual knowledge)}_t = \text{(individual knowledge)}_{t-1} + \varepsilon_t \qquad [2]$$

where (individual knowledge)$_{t-1}$ represents the agent's knowledge in the previous period and ε_t represents the current consequences of individual agent learning between periods t and t – 1 then equations [1] and [2] can fully describe the dynamics of agent understanding; in this case, of the level of employment in the manufacturing sector in PR. Equation [2] merely states that any change in the agent's knowledge is a direct consequence of that agent's individual learning process through time. Furthermore, from the modeller's point of view, the variable "individual knowledge" acts as a random variable in the system. Knowledge is indeed unobserved and bears consequences on the individual agents' actions in a way that are detectable only through variations in measurable quantities, i.e. measurable economic activity, Iribarren (2001). As will be seen shortly, equations [1] and [2] form a general basis of the KF specification. More importantly, the KF algorithm estimates the individual knowledge variable through time.

Lastly, two more issues should be considered in respect to knowledge and econometrics. The first one refers to the dependencies that are created with respect to knowledge across a pool of agents engaged in, essentially, the same economic activity. These dependencies in knowledge emerge from dependencies in learning. In other words, if agent i depends upon agent j's knowledge it must be the case that i's learning operator, e.g. routines, depend on j's learning routines and practices. In the limit, if i's learning operator is completely dominated by j's operator then i's learning routines are the same as j's routines and therefore i's knowledge is at least *logically equivalent* to j's, Iribarren (2001). These dependencies generate a non-diagonal covariance matrix when their output is measured.

---

estimate a "true" relationship between variables of interest through a finite sample.

The second point is that it can be shown that, for the underlying probability space of the random variable that channels learning, i.e. ε_t, to be a proper probability space at t, no influence from other agents must be observed at that moment. In other words, for it to be a proper probability space at t, no mutual influence amongst the agents must be exerted, Iribarren (2001). Although independence of learning is not required all throughout time it is nevertheless a necessary condition to be able to specify an econometric formulation as a random variable.

3 The estimation procedure

In order to investigate the cointegration of relevant knowledge and wages in the manufacturing sector a two-stage estimation procedure was required. First, the knowledge variable, which is unobserved, was estimated using the KF algorithm. Then, Johansen's procedure was used to investigate cointegration. Also, the Phillips Perron (PP) test was used, under all three normal specifications, to analyse the nature of the unit roots in the knowledge and wage series.

The Kalman Filter is an algorithm that estimates through sequential updating of new information. Its general form is

$$\begin{aligned} \mathbf{y}_t &= \mathbf{A}'\mathbf{x}_t + \mathbf{H}'\mathbf{s}_t + \mathbf{w}_t \\ \mathbf{s}_t &= \mathbf{F}\mathbf{s}_{t-1} + \mathbf{v}_t \end{aligned}$$

where $\mathbf{w}_t$ and $\mathbf{v}_t$ are independent vector white noise process with a standard covariance structure and $\mathbf{x}_t$ is a vector of explanatory variables. The first equation is termed the observation equation whilst the second one is called the state equation; together they are referred as the state space representation. By construction, it is assumed that $\mathbf{s}_t$ represents a (vector) unobserved variable that drives the system. The algorithm then estimates the matrices **A'**, **H'**, **F**. Also, further specification on the process, e.g. time evolving covariances and variances, could be developed for which the algorithm can estimate the covariance structure as well. All details concerning the KF algorithm could be found in Hamilton (1994), chapter 13. Finally, the conditional estimates are:

$$\hat{\mathbf{s}}_{t|t} = \hat{\mathrm{E}}\left[\mathbf{s}_t \middle| \Theta_t\right] = \hat{\mathbf{s}}_{t|t-1} + \frac{\mathrm{E}[(\mathbf{s}_t - \hat{\mathbf{s}}_{t|t-1})(\mathbf{y}_t - \hat{\mathbf{y}}_{t|t-1})']}{\mathrm{E}[(\mathbf{y}_t - \hat{\mathbf{y}}_{t|t-1})(\mathbf{y}_t - \hat{\mathbf{y}}_{t|t-1})']} \times (\mathbf{y}_t - \hat{\mathbf{y}}_{t|t-1})$$

$$\hat{\mathbf{y}}_{t|t-1} = \hat{\mathrm{E}}\left[\mathbf{y}_t \middle| \Theta_t\right] = \mathbf{A}'\mathbf{x}_t + \mathbf{H}'\hat{\mathbf{s}}_{t|t-1}$$

where $\Theta_t = \left(\mathbf{y}_t', \mathbf{y}_{t-1}', \ldots, \mathbf{y}_1', \mathbf{x}_t', \mathbf{x}_{t-1}', \ldots, \mathbf{x}_1'\right)$, i.e. the information set. Again, all details on estimation and inference can be found in Hamilton (1994), chapter 13.

In order to estimate the pertinent knowledge variable for each of the manufacturing industries we specified the state space representation as

$$\begin{aligned} mi &= \overline{c}_i + \overline{b}_i ipi_t + \overline{d}_i mi_{t-1} + k_t \\ k_t &= \alpha + \beta k_{t-1} + \varepsilon_t \end{aligned} \qquad [3]$$

where

mi = employment in industry i

ipi = US industrial production index

ki = knowledge variable pertaining to industry i

$\varepsilon_t \sim N(0,\sigma_i)$

In our specification, the KF algorithm also estimates the variance in each case. In the puertorrican case most of the manufacturing output is directly shipped to the US mainland. For this reason, we are using the US industrial production index (ipi) as a proxy for output and hence as a measure of output variation. Whence, through this specification we are making two behavioural assumptions about our representative agent, mainly:

- The agent possesses two specific forms of information to understand variation in employment in the industry. These are, a (proxy) measure of output variation, i.e. ipi, and the previous level of employment in the industry.

- The agent's novel knowledge drives his/her understanding of the observed unemployment levels.

The KF algorithm was run 15 times, once for each industry. The specification in [3] turned out to be the best in the sense that it did not show any collinearity problems nor over specification (thus generating degenerate convergence rate for the parameter estimating algorithm) as other specifications did, e.g. time varying parameters.

The application of the KF algorithm to each one of the industries thus generated 15 knowledge variables, one associated to each industry. The PP test was then used to test for UR in the knowledge variables as well as in the salary variables using the usual specifications (see the appendix for a report on these tests). Finally, cointegration was studied using Johansen's approach. To do so, we first followed Holden and Perman's (1994) suggestion to determine the correct amount of lags to be used in the cointegration test[2]. Then, the UR tests under the null hypothesis of trend and intercept were used to determine whether the data had a deterministic trend. That is, if the PP test for UR in the ki and salmi, i.e. wage in industry i, under the null of trend and intercept provided evidence of no UR then it was assumed that the data did have a deterministic trend for the CI testing purposes. In the case that only one of the pair, ki or salmi, had a UR under the null of trend and intercept in the PP test then it was assumed that the data had no deterministic trend for the CI tests. Only if the PP test showed no evidence of a UR for both the ki and salmi was it assumed that there was a deterministic trend in the data for CI testing purposes. Finally, all tests were performed using Eviews, version 4.1.

4 Main results

The data used was monthly data from January-1980 to December-2000 published by the Federal Reserve of Saint Louis (for the ipi) and the DTRH, i.e. PR Department of

---

2 Basically, this is, estimate a VAR with a "large" amount of lags and then use the maximised value of the log likelihood function (LLF) to control so that the amount of lags are reduced as long as the maximised value of the LLF remains essentially the same. The lowest number of lags that maintains more

Labour. The Marquardt algorithm is used to maximise the LLF used to estimate the parameters (see Hamilton (1994) pages 385-389 for further details). The complete identification of manufacturing industries can be found in the appendix. The results of the KF estimation of the knowledge variable are:

Industries	$\bar{c}$	$\bar{b}$	$\bar{d}$	Knowledge variable α	β
m1	-414.48 (-13.24)	-0.077 (-9.58)	0.093 (1.88)	-382.89 (-18.28)	1.86 (17.10)
m2	-240.51 (-3.50)	0.021 (1.39)	-0.217 (-4.98)	-14.83 (-4.03)	1.06 (458.69)
m3	-241.04 (-73.34)	-0.0019 (-0.304)	-0.071 (-1.18)	-15.00 (-114.68)	1.06 (819.33)
m4	-278.19 (-50.08)	-0.123 (-8.99)	0.497 (9.23)	-170.42 (-5.94)	1.56 (14.64)
m5	-375.61 (-380.33)	0.004 (1.05)	0.956 (20.94)	-296.06 (-1319.58)	1.79 (1268.33)
m6	-391.76 (-122.22)	-0.0004 (-0.141)	1.00 (92.59)	-312.70 (-2718.71)	1.80 (229.50)
m7	-392.67 (-101.37)	-0.003 (-1.68)	0.835 (26.51)	-313.74 (-10.40)	1.80 (21.30)
m8	-398.29 (-132.24)	-0.002 (-0.81)	0.846 (22.85)	-318.55 (-342.05)	1.80 (218.30)
m9	-403.76 (-94.48)	0.001 (0.552)	0.188 (7.78)	-323.01 (-396.20)	1.79 (171.40)
m10	-234.46 (-52.87)	0.014 (1.47)	-0.291 (-4.57)	-13.89 (-42.45)	1.06 (440.01)
m11	-233.80 (-64.25)	0.029 (3.07)	-0.271 (-8.69)	-13.86 (-3.22)	1.06 (57.72)
m12	-229.75 (-11.16)	-0.040 (-3.82)	.289 (5.38)	-13.17 (-8.79)	1.06 (96.47)
m13	-198.07	0.094	0.095	-1.22	1.01

or less the original maximised value of the LLF will be the optimum number of lags to be used in the CI tests (using Johansen's approach).

	(-0.025)	(2.51)	(1.46)	(-0.028)	(120.72)
m14	3.90	-0.009	-.166	.171	.988
	(.575)	(-.387)	(-3.70)	(.694)	(71.56)
m15	-239.09	-0.031	-.274	-14.70	1.06
	(-10.70)	(-3.41)	(-4.58)	(-31.43)	(295.60)

Note: the quantities in the parenthesis are the t-values.

As can be seen, the KF generated knowledge series with UR in every case with the exception of a near UR in m14. The initial values are assigned by Eviews following Koopman, Shepard and Doornik's (1998) suggestion of setting $ki_0 = 0$ and the initial covariance matrix as $P_0 = \kappa I_n$ with $\kappa = 10^6$ and then adjusting it by multiplying by the largest diagonal element of the residual covariance. This approach allows for a greater flexibility of adjustment to the initial conditions in the data.

After making sure that there was in fact evidence that the series, i.e. knowledge and wages, did in fact had a UR under at least one of the three standard specifications (see the appendix for the results) the CI tests were carried out. These were the standard log likelihood tests on the vector error correction formulation based on Granger's representation theorem. That is, tests on the rank of the Π matrix that multiplies the one-time lagged vector. The results of the cointegration of knowledge and wages in the sector were:

					Cointegrating vector		
Industries	Trace-Stat.	Max-Eig.	p	r	salmi	ki	c
m1	6.798	5.029	12	0	-	-	-
	1.769	1.769					
m2	10.433	8.780	6	0	-	-	-
	1.653	1.653					
m3	18.044	15.894	4	0	-	-	-
	2.149	2.149					
m4	19.101	19.100	6	1	1	-0.0023	-

	0.001	0.001				[0.0029]	
m5	24.899 0.0163	24.882 0.0163	8	1	1	-0.375 [0.072]	-
m6	49.406 0.500	48.906 0.500	4	1 **	1	-110.056 [18.264]	43135.92 [7156.37]
m7	11.232 0.992	10.240 0.992	8	0	-	-	-
m8	13.495 * 0.187	13.308 * 0.187	6	1	1	-0.028 [0.0047]	-
m9	30.267 0.519	29.747 0.519	9	1	1	-0.0077 [0.00074]	-
m10	34.974 12.721	22.253 12.721	12	1 **	1	-0.688 [0.978]	160.627 [190.523]
m11	32.380 11.556	20.824 11.556	12	1 **	1	0.192 [0.724]	-49.535 [171.732]
m12	9.414 3.164	6.250 3.164	12	0	-	-	-
m13	32.361 7.168	25.192 7.168	4	1	1	15.199 [7.302]	-3227.31 [1512.86]
m14	36.781 4.822	31.959 4.822	6	1	1	-5.631 [20.041]	261.964 [286.757]
m15	18.108 6.512	11.596 6.512	5	0	-	-	-

Note 1: the top values in both the Trace-Statistic and Max-Eig. columns represent the statistic under the null hypothesis of no cointegrating relationship whilst the bottom values represent the statistic under the null hypothesis of at most one cointegrating relationship.

Note 2: the number of cointegrating relationships represent evidence at both 5% and 1% levels except when noted.

Note 3: the quantities in the square brackets are the standard errors.

** : both tests statistic reported evidence for one cointegrating relationship at the 5% level but not at the 1% level.*

*** : both tests statistic reported evidence of two cointegrating relationships, one at the 5% level and one at 1% level.*

The algorithm used to maximise the LLF was once again the Marquardt algorithm. As it was mentioned before, different lags were used for the CI tests depending on the results of Holden and Perlman's suggestion (see footnote 2). These were reported in the p column above whereas r represented the number of CI relationships. Finally, as mentioned above, UR tests were used to determine the inclusion of a deterministic trend and/or a constant in the CI tests.

5 Interpretation and conclusions

Under this approach (of estimating a knowledge variable for each industry and studying its cointegration with wages) nine out of the fifteen industries showed evidence of a long run relationship. Indeed, these are:

$$
\begin{aligned}
&\text{salm4} = 0.0023 * \text{k3} \\
&\text{salm5} = 0.375 * \text{k4} \\
&\text{salm6} = -43135.92 + 110.056 * \text{k6} \\
&\text{salm8} = 0.028 * \text{k8} \\
&\text{salm9} = 0.0077 * \text{k9} \\
&\text{salm10} = -160.627 + 0.688 * \text{k10} \\
&\text{salm11} = 49.535 - 0.192 * \text{k11} \\
&\text{salm13} = 3227.31 - 15.199 * \text{k13} \\
&\text{salm14} = -261.964 + 5.631 * \text{k14}
\end{aligned}
$$

More importantly, all industries with a CI relationship except two of them, i.e. m11 and m13, showed the correct sign, i.e. positive. In other words, in all but two of the manufacturing industries there was evidence that changes in knowledge positively influenced long run changes in wages. In other words, in these industries the evidence suggests that, as expected, knowledge influenced the long run salary base.

In principle, knowledge should hold long run relationships with wages in all industries. In our case, however, the results were mixed. Amongst the industries with the correct sign, i.e. Apparel and related products, Paper products; printing and publishing, Chemical and allied products, Leather products, Wood products and furniture, Cement and stone, clay, glass and concrete products and Electronic equipment and other electric products, there were highly technologically intensive industries as well as low technology intensive industries. Amongst the industries with no CI relationship, i.e. Food, Tobacco products, Textile mill products, Petroleum and petroleum products, Industrial machinery and equipment and Miscellaneous, there were also highly technologically intensive industries as well as low intensity ones as well. One possible explanation for this diversity of results is that the PR Department of Labour publishes averaged wages of many smaller industries as if it were the salary of the bigger aggregated industry. Since technology and knowledge are not evenly distributed, rather quite the opposite, throughout the economy, it is quite possible that variations in the average salary of the industry are synchronised, i.e. do not form a stationary system, with the knowledge variable of that industry. In this case, it would be necessary to have more industry specific wage data. In any case, low technology intensive industries should not be expected to have a CI relationship. Indeed, routines and practices tend to be much more repetitive in those industries which implies a lesser need for innovation and novel knowledge. Therefore, knowledge is a lesser concern in the wage structure. There were four such cases in our results, i.e. Food, Tobacco, Textile products and Miscellaneous.

Finally, these results reinforce an old policy issue: the further development of knowledge in the population, the greater the pressure towards higher wages, particularly where knowledge does matter. The causal chain is direct: further knowledge implies greater possibilities of innovation thus improving the marginal efficiency of labour so that the propensity towards lower unit costs of production increases. If novel knowledge induces and asserts novel business and producing practices and routines there will follow a tendency towards further specialisation, i.e. further division of labour. With further specialisation there will come a smaller supply for that particular innovative-driven, knowledge-based demand. In the end, specialisation through novel knowledge will have produced a relative shortage of demand thus generating a pressure towards higher wages. In a sense, these results provide evidence on the need of further education policies, particularly, given PR's recent showing in aptitude tests in the public educational system.

References

Belianin, Alexei (2000). *Preference Reversal Revisited: Theoretical and Experimental Analysis*. Ph.D. thesis at the School of Economic Studies in the University of Manchester, U.K.

Hamilton, James (1994). *Time Series Analysis*. Princeton, New Jersey. Princeton University Press.

Iribarren, D. (2001). Knowledge and intuitions in interacting learning heterogeneous agents. PhD Thesis. University of Manchester.

Koopman, S.J., Shepard, N. and Doornik, J. (1998). Statistical algorithms for models in state spae using SsfPack 2.2. *Econometric Journal*. **1**, pp. 1-55.

Langlois, Richard (2001). Rationality in Economics. Downloaded from *http://www.sp.uconn.edu/~langlois/r700.htm*

Loasby, Brian (1999). *Knowledge, Institutions and Evolution in Economics*. The Graz Schumpeter Lectures. London, England. Routledge.

______(2000). Market Institutions and Economic Evolution. *Journal of Evolutionary Economics*. **10**, pp. 297-309.

______(2001). Cognition, Imagination and Institutions in Demand Creation. *Journal of Evolutionary Economics*. **11**, pp. 7-21.

Metcalfe, Stanley and Ramlogan, Ronald (2001). Limits to the economy of knowledge or knowledge of the economy. Mimeo for the conference on limits to knowledge by the Nexus group in Budapest.

Nonaka, Ikujiro, Toyama, Ryoko and Konno, Noboru (2000). SECI, *Ba* and Leadership: a Unified Model of Dynamic Knowledge Creation. *Long Range Planning*. **33**, pp. 5-34.

O'Driscoll, Gerald and Rizzo, Mario J. (1985). *The Economics of Time and Ignorance*. London. Routledge.

Popper, Karl (1959). *The logic of scientific discovery*. Republished by Routledge in 1998. London, England.

Slembeck, (1999). Lerning in Economics: Where Do We Stand? A Behavioral View on Learning Theory, Practice and Experiments. *Discussion Paper*. Department of Economics, University of St. Gallen.

Appendix

A. The industries

The manufacturing sector in Puerto Rico is comprised of the following industries

m1 = Food
m2 = Tobacco products
m3 = Textile mill products
m4 = Apparel and related products
m5 = Paper products; printing and publishing
m6 = Chemical and allied products
m7 = Petroleum and petroleum products
m8 = Leather products
m9 = Wood products and furniture
m10 = Cement and stone, clay, glass and concrete products
m11 = Primary metal industries and metal products
m12 = Industrial machinery and equipment and transport equipment
m13 = Electronic equipment and other electric products
m14 = Instruments and related products
m15 = Miscellaneous

Source: PR Department of Labour.

B. UR results

The UR tests were performed using the PP test under the three standard null hypotheses, i.e. constant, trend and constant and no constant, no trend. These were the t-values for each case,

		Specifications	
Industries	Constant	Trend and constant	No trend, no constant
k1	158.2029	155.0256	-0.8429
salm1	0.4004	-3.9403	7.0485
k2	-0.9790	-4.5627	-0.7334
salm2	-1.7220	-6.2924	1.4109
k3	1.3487	1.0328	-1.5004
salm3	1.9878	-1.8165	4.4406
k4	-7.1066	-7.0954	-0.1846
salm4	0.6297	-1.4435	4.5003

k5	-17.8198	-17.8178	-0.3327
salm5	-0.6403	-3.6074	3.7757
k6	-16.4902	-16.5184	-0.1122
salm6	1.1996	-3.3056	10.7367
k7	-13.69	-13.7831	0.0974
salm7	-0.1558	-2.8719	2.4190
k8	-13.7031	-13.7096	-0.4932
salm8	-0.2813	-4.1826	4.1039
k9	-11.4590	-11.7314	0.0168
salm9	0.8019	-2.9957	3.9004
k10	-1.2424	-2.1943	0.5161
salm10	1.1280	-1.6612	3.9095
k11	-2.4929	-2.2423	0.3847
salm11	0.1557	-3.1528	4.7374
k12	-1.2143	-1.1844	0.1795
salm12	-0.5515	-4.5490	2.7276
k13	-1.1950	-1.7811	-1.2143
salm13	1.5791	-0.1876	6.0190
k14	-1.5212	-2.4616	-0.0492
salm14	-0.4706	-6.1559	6.7453
k15	-2.6585	-2.8720	-0.0685
salm15	-0.8809	-5.8963	4.3494
	1% critical value: -3.4563	*1% critical value: -3.9950*	*1% critical value: -2.5742*
	5% critical value: -2.8729	*5% critical value: -3.4278*	*5% critical value: -1.9421*