
Frequency and experiential learning in unstable markets

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ABSTRACT

Long delivery delays and long asset life times can create market conditions that are not conducive to learning. An experiment recreated market cycles of 8 to 23 years. Subjects operated in a sequence of two 40 period market trials. The hypothesis that learning is helped by higher market frequency was corroborated, yet it was found that subjects transfer poorly when market frequencies remain *unchanged* across trials. This is explained by the fact that subjects in the changed frequency condition also expect a changed environment and so adjust behavior. When subjects do not expect change in market behavior, as in the unchanged frequency condition, subjects induce negative transfer, i.e. they transfer decision timing from the past. Since the markets' external environments never remain identical, such transfer is less appropriate than structural transfer. Implications for stabilizing unstable markets and training professionals are finally laid out.

INTRODUCTION

Human decision making interact with inherent physical delays and enable market instabilities. Market characteristics, such as low product substitutability i.e. commoditization, low demand elasticity and small market entry barriers also contribute to market instability. If such instabilities are undesirable from a societal perspective, as is usually argued, why does not Adam Smith's "invisible hand" produce opportunities so as to reward enterprise profits in the short and societal utility maximization in the longer run? These questions are important to investors and politicians alike, but only recently has tools for performing experimental economic research with paid human subjects been possible with markets complex enough to address these questions (Plott, 1987).

This paper argues that inherent learning problems in markets with long delivery delays and long asset life times, due to the lack of transparent feedback relative to the dynamics of the market. The human filtering problem disable human decision makers from becoming aware of longer term dynamics. Decision makers instead pay attention to short term business cycle dynamics and incorrectly transfer decision heuristics for a short business dynamic into a setting where a different dynamic is also at work. In the following, an experiment is described to address the link between market frequency and learning. First follow a description of corporate and societal problems caused by market instabilities. Next follow some examples of unstable markets. Hypotheses related to lack of learning in such markets are defined, and a description of experimental markets and procedures follow. The findings are presented with implications for how to stabilize markets and separately, of how to use learning labs for teaching capitalists to take advantage of systematic profit opportunities.

THE UNDESIRABILITY OF MARKET INSTABILITY

The instability of economic behavior is well known, as the business cycle, capital asset cycle and economic long wave work separately and in concert to create human misery and problems of inequitable wealth distribution. As an example, after a prolonged economic boom period in the nineteen twenties, the nineteen thirties saw economic problems in the industrial world resulting in unemployment rates of more than 20 percent. Other than the direct human misery it caused, the economic problems also indirectly created a climate for aggressive and authoritarian politics that eventually resulted in another world war.



Fifty years later, one has witnessed real estate boom and bust contributing to a Savings and Loan industry collapse in the US that will cost taxpayers more than \$500 billions in the current decade. A similar development will cost Scandinavian taxpayers over \$10 billion in the next 5 years.

Apparently, this unstable economic behavior is hard to appreciate for decision makers. Investors and financiers appear to have a short historic memory. For instance, Conway and McKinley (1981) have stated:

Hindsight is 20/20, and looking back, it is easy to see what some of the major mistakes of the early Seventies were. In regard to feasibility analysis, it now appears that a common mistake was to analyze each project *independently of others*. The repercussions of 1974-76 have been so far-reaching that it is evident that the entire industry *has learned* a lesson. Among alert developers, the approach to every aspect of project planning will be more cautious.

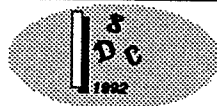
As will become apparent, Conway and McKinley were only wrong in stating that "it is evident that the entire industry has learned." Either the industry did not learn, or if it did, new entrants must have rendered impotent the learning of others. Note however that the quote is built upon the double implicit assumption that real estate instabilities are identical to business cycle instabilities, and that instabilities are caused by general economic factors outside the real estate industry. The internal dynamic of the industry is only a very partial cause of the instabilities according to these authors. Of course, if it is the general economic climate that causes market instabilities, then there is little the industry can learn other than try to outguess this general economic development. Such a view about structural factors is not conducive to inquiry and learning about market dynamics.

Companies in cyclical industries typically exacerbate the very demand instabilities they blame for causing trouble. Demand is typically *less* fluctuating than supply in paper pulp, ferro alloy, rubber, steel, real estate and shipping industries (Antun, 1982; Randers 1984a; 1984b; Torto and Wheaton 1987). One reason for instabilities is asymmetries of risk payoffs. If a Reichmann, a Trump or an Onassis invests wisely or has luck, he becomes a billionaire. In case of bankruptcy it is the man in the street, through banks, or through the private or public insurance industry, that pays the price.

Corporations still suffer in these industries, since average capacity utilization tends to be low in unstable markets. More stable markets have higher capacity utilization, since less slack resources are needed with lower production variance. Excess capacity is generally inefficient and a burden to societies through a combination of poor corporate profitability and high consumer prices.

UNSTABLE MARKETS

Several industries exhibit unstable behavior. Agricultural markets, such as grain, hog bellies and rubber typically exhibit what is termed cobweb behavior. The usual explanation of how a cobweb materializes is the farmer who, in the year of potato shortfall, achieves high profits. In the next year, he (and other farmers) therefore increases potato production so as to achieve more profits (from the higher prices). As consequence of the high production, however, supply increases and prices fall again. Farmers therefore decrease production the following season. With the lower production, prices increase again and the cycle repeats itself. Real Estate and Oil Tanker markets are similar to this idealized example, with the main difference being that the time lag from production initiation until product availability is 2-4 instead of 1/2 years. Figure 1 shows the "cobweb" generated by the price and quantity relationships.



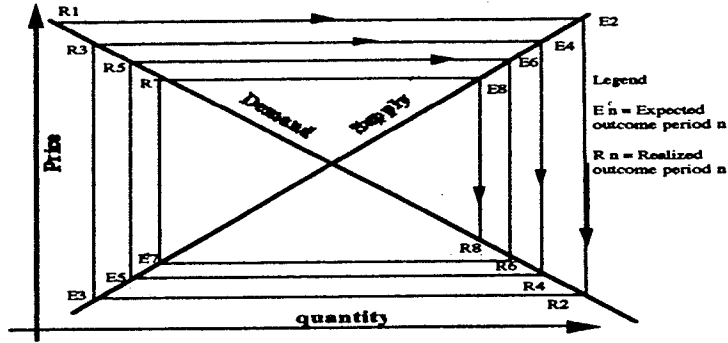


Figure 1. Cobweb created by the spiral of expected and realized prices and quantities.

Figure 2 below shows the corresponding behavior along the time axis. The length of the period in the potato example is about 1/2 to 1 year. That is the time it takes between an expectation is formed and the realization of profits or losses. One could argue that the farmers behavior in the example above is silly, and indeed the type of behavior exhibited is termed "decision myopia" (Wheaton, 1988). Any form of decision rationality will result in decision maker seeing the above picture and learning. However, the claim that people should learn becomes increasingly difficult to make as the market loses transparency through the cycle length relative to reasonable decision time horizon. Figure 3 shows cobweb quantity for a real estate market in the same time scale as the potato example. The lack of stability is less apparent.

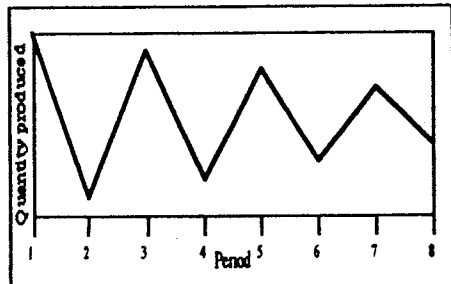


Figure 2. Cobweb as production quantity over time.

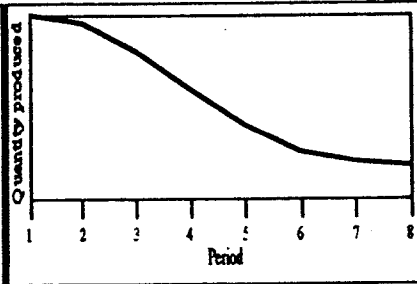


Figure 3. Longer cycle length.

Figure 4 shows a real world example of poor stability and exhibits vacancy rates for office buildings in downtown Boston.

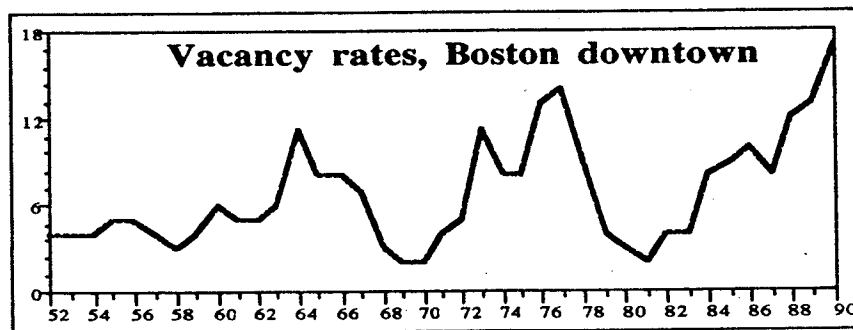


Figure 4. Vacancy rates for office buildings in downtown Boston.

The long period of instability compared to the typical decision horizon of a typical individual lead that cycles can perpetuate. Indeed, figure 4 indicate such perpetuity. The quote from Conway and McKinley (1981) above likewise suggest poor learning.

Decision makers in real estate markets will only produce learning if a historic time frame of more than 15 years is considered relevant. This appears not to be the case in unstable industries with low market frequencies, where industry wisdom usually incorporates relatively short trends. If the historic time frame is short, market instabilities of the type shown in figure 3 will not appear transparent. The transparency problem is further complicated by information overload of various frequencies. In figure 5 one can see the high frequency monthly spot rates in the oil tanker industry. Such information will likely have higher salience than the 15-25 year instabilities caused by the nature of time lags and decision making in that market as shown in figure 6. Longer term dynamics are crowded out by the short term information in the decision maker's mental model (Fuglseth, 1987).

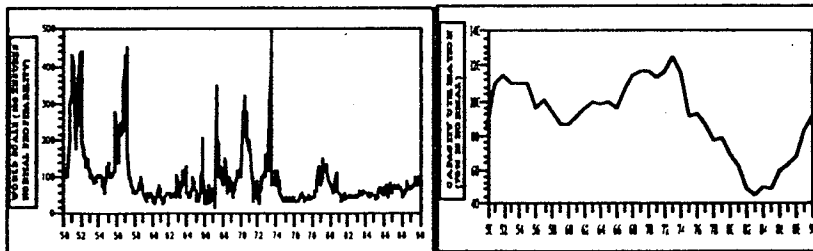


Figure 5 (left). Spot rates for transporting oil on medium sized tankers from the Arabian Gulf to the US

Figure 6 (right): Oil tanker industry capacity utilization.

Sources: Randers (1984b), Fearnleys (1983-1988) and Drewry Shipping Consultants (1990).

THE EXPERIMENT

HYPOTHESES

The arguments above give rise to two hypotheses. First, for a given learning horizon, a higher market frequency should help learning. Second, once decision makers are attuned to a certain market frequency they should not perform well if the frequency changes.

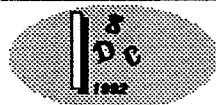
PROTOCOL

An experiment of a sequence of two forty period (year) markets was set up to test these hypotheses (as well as several others; see Bakken, 1992). The experiment used two market contexts, namely real estate and oil tankers, both represented in two frequency regimes, high and low, as shown in table 7 below. Subjects performed individually, starting with 1 % market share of assets. By shrewd investment, market share could rise substantially to about 25 %. However, most subjects went bankrupt during the first 40 period trial and average bankruptcies decreased from 1 in the first market to about 0.6 in the second.

Frequency	Completion Time constant	Average Asset Life Time	Loan Repayment Schedule	Effect of Price on Orders	→Cycle Period
High	1.5 years	15 years	15 years	^6	■ 7-11 years
Low	3.0 years	30 years	30 years	^4	■ 17-24 years

Table 7. Input parameters and output behavior in high and low frequency markets

The corresponding market behavior is shown below in figures 8 and 9. Note that the implemented design, where subjects buy and sell old assets to the market (i.e. trade) as well as constructing new assets, make the task an action feedback task. This implies that the environment changes as a consequence of subject action. However, since subject rarely achieved more than 5 % market share, market behavior was largely determined by market decision rules.



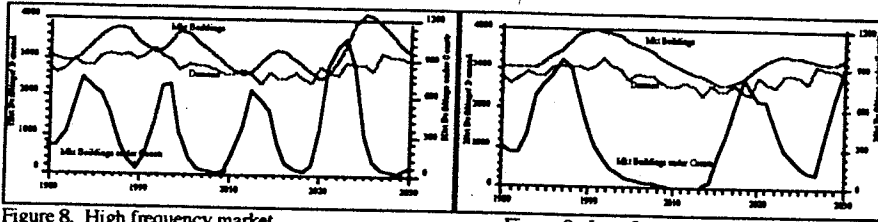


Figure 8. High frequency market

Figure 9. Low frequency market

41 subjects volunteered for the experiments by signing up after announcements in classes. Experiments took place between December 1990 and March 1991. Randomization of subjects into conditions was achieved by picking from a pre-mixed box of game disks when subjects arrived in the experimental laboratory. The students were instructed to use as much time as they wanted, but were also told that the expected length of the experiment was about 4 hours. Students were paid a combination of \$ 4 per hour and a linear bonus pay based on performance in the markets relative to a simple benchmark¹. Students were told that average bonus pay would yield an additional \$ 4 per hour, and that "previous masters have earned over \$ 100 for the four hours". The average pay was about \$31.60 for the entire four hour session. Subjects reported that they enjoyed the experimental markets.

Subjects spent about 2 1/2 hours on the first and about 1 1/2 hour on the second market in one experimental session. In addition to context and frequency being manipulated, there existed two different exogenous demand patterns. These were autocorrelated noise so as to mimic a 3 to 8 year business cycle. Thus, even subjects who experienced unchanged frequency did not experience two identical markets.

The transfer measure, T^2 is a within-subject measure indicating how well subjects do in a second trial relative to the average of both markets. All scores are adjusted for inherent market difficulty as evidenced

¹Benchmark used for payment of subjects,

$$M1_s = \sum_t \pi_{s,t} | E_{s,t} / \sum_t \pi_{b,t} | E_{b,t}$$

Where

$M1_s$ = measure 1 for subject s

$\pi_{s,t}$ = subject s ' profit for decision t

$\pi_{b,t}$ = benchmark profit for decision t

$| E_{s,t}$ = information and leverage environment available to subject s before making decision t

$| E_{b,t}$ = information and leverage environment available to benchmark before making decision t

$t = 1, 2, \dots, 40$

$s = 1, 2, \dots, n$

Benchmark used for computation of transfer measures, T :

$$M2_s = \sum_t (\pi_{s,t} | E_{s,t} \pi_{b,t} | E_{s,t}) / \sum_t \pi_{b,t} | E_{b,t}$$

Where

$M2_s$ = measure 2 for subject s

$\pi_{s,t}$ = subject s ' profit for decision t

$\pi_{b,t}$ = benchmark profit for decision t

$| E_{s,t}$ = information and leverage environment available to subject s before making decision t

$| E_{b,t}$ = information and leverage environment available to benchmark before making decision t

$t = 1, 2, \dots, 40$

$s = 1, 2, \dots, n$

$$2T_k = (M_{k,2} - M_{k,1}) / (M_{k,avg})$$

Where

T_k = Transfer score for rule k

$$M_{k,avg} = (M_{k,2} + M_{k,1}) / 2$$

by average all subjects-both trials performance in that market. The transfer measure, T, is positive as long as subjects do better in second trial than in first.

FINDINGS

The findings are shown in figure 10 through 14. The helpful effect of high initial frequency can be seen clearer in the separate frequency change/no change situations in figures 11 and 12. The effects of frequency change were opposite those expected.

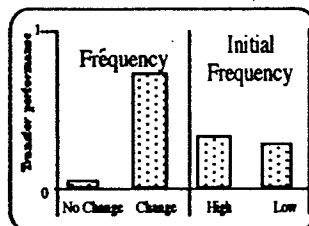


Figure 10. Effects of frequency change and initial frequency

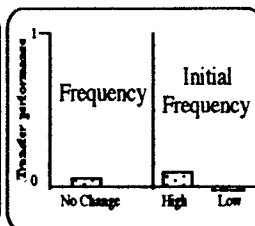


Figure 11. Effects of no frequency change

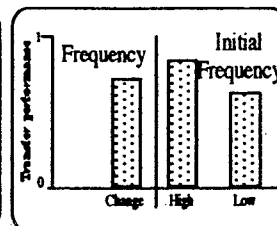


Figure 12. Effects of frequency change

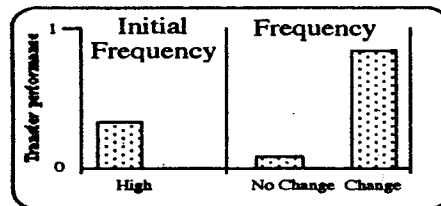


Figure 13. Effect of high initial frequency

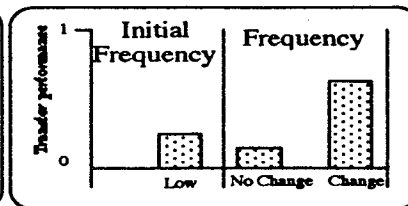


Figure 14. Effect of low initial frequency

Table 15 below shows the ANOVA table of initial frequency and frequency change. We see that both main effects are significant, but also that the interaction is not significant. Note that the ANOVA table also contains effects of context and context change (real estate and oil tankers constituted the contexts). However they are not discussed here, but in Bakken (1992).

DEPVAR: T N:39 MULTIPLE R:0.780 SQUARED MULTIPLE R: .609

ANALYSIS OF VARIANCE (2 CASES DELETED DUE TO MISSING DATA)

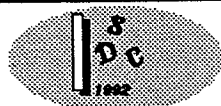
SOURCE	SUM-OF-SQUARES	DF	MEAN-SQUARE	F-RATIO	P
Frequency 1 (F1)	3.541	1	3.541	3.907	0.060*
Frequency Change (ΔF)	9.78	1	9.781	10.793	0.003***
Frequency 1*Frequency Change	0.914	1	0.914	1.009	0.326
Context 1 (C1)	2.253	1	2.253	2.486	0.129
Context Change (ΔC)	6.799	1	6.799	7.435	0.012**
Context 1 *Frequency 1	2.663	1	2.663	2.939	0.100*
Context 1 *Context Change	5.173	1	5.173	5.708	0.025**
Context 1 *Frequency Change	0.041	1	0.041	0.045	0.834
Frequency 1*Context Change	0.880	1	0.880	0.971	0.335
Context Change*Frequency Change	2.915	1	2.915	3.217	0.086*
C1*F1*ΔC	0.883	1	0.883	0.975	0.334
C1*F1*ΔF	0.105	1	0.105	0.116	0.736
C1*ΔC*ΔF	5.399	1	5.399	5.957	0.023**
F1*ΔC*ΔF	3.315	1	3.315	3.657	0.068*
C1*F1*ΔC*ΔF	4.102	1	4.102	4.524	0.044**
ERROR	20.845	23	0.906		

Table 15. ANOVA table of frequency (and context) effects

$M_{k,1}$ = Score on first trial, using measurement rule k

$M_{k,2}$ = Score on second trial, using measurement rule k

k = 1,2



DISCUSSION

The finding of a positive learning effect from a high frequency scenario was corroborated. This implies that subjects learn better in high frequency scenarios than in low frequency scenarios and may explain why low frequency phenomena, such as the 15-25 year capital asset cycle as well as the economic long wave may persist, in spite of subjects being exposed to more than one cycle.

The effect of frequency change having a positive impact on transfer performance was not expected. It appears counter-intuitive that a change in frequency should help performance. However, it must be noted that a change in frequency always was accompanied by a computer market interface including both the value of construction time and the asset depreciation factor. Subjects thus expected behavior to be different in the frequency change scenario. In the unchanged frequency scenario, behavior in the second market was still not identical to behavior in the first market. The different demand pattern rendered unprofitable an exact replication in the second market of decision timing from the first market. (As noted in figure 9, all markets started in 1989 and ended in 2029). The complacency induced by the unchanged frequency must be contrasted by the jump realized by subjects who know that they can't port decision timing across frequencies. Subjects in the changed frequency regime are induced to reflect about their own decision rules and so gain higher transfer performance.

IMPLICATIONS, LIMITATIONS AND FURTHER RESEARCH

The findings indicate that learning in high frequency markets are more likely to occur than in low frequency markets. Thus the likelihood of perpetual instabilities are higher the lower the market frequency. As an indication of this can be noted that professional subjects in a related experiment (Bakken, 1992), equated instabilities in the real estate industry with the demand instabilities that the industry is subjected to. However, as noted in the figures above, instabilities in the real estate market must necessarily be 2-5 times longer than the business cycle. This simple fact was unknown to the professionals, as were the data in figures 3, 4 and 5 that they were shown after participation in the experiment.

One must be cautious in porting the findings from the experiment back to real decision environments. However, a wealth of evidence in addition to the findings here supports the contention that learning is hard the slower the market fluctuations. Moreover, a main problem in economic policy appears to reflect the findings here of subjects not being aware that different systems have different resonant frequencies. Pure porting of decision timing, using prior cycles as patterns to recognize, without paying attention to the most important time constant and other structural factors also may prevent sound policies from being suggested. In real markets, there is no user interface stating that "now, you should be aware that the depreciation and construction lags have been modified so that market frequencies are different". On the contrary, surprisingly little attention is made to separate different modes of economic instabilities (Forrester, 1990)

Further research is needed. In particular, it must be investigated to what extent the contention that frequency change induces better behavior because subjects then know that their decision timing must also be modified. This research can be done by manipulating briefing materials with respect to how much information is given about the effect of demand patterns. Likewise, one can define demand scenarios that do not change. If the contention here, namely that subjects in the unchanged frequency environment do poorly because they fail to adjust to the present situation, then an unchanged demand scenario should induce higher performance than observed here. The failure of strategy adoption has been documented elsewhere. A recent study by Novick and Holoyak (1991) shows that transfer is impeded subjects' *inability to adapt solutions*. Subjects are able to map old solutions in a new frame, but this contextual mapping has to be adapted in each case and the poor transfer may result from poor adaption.

The findings also suggest that learning labs (Kim, 1990), where experimental markets are used to foster learning can be a way to compress market frequency so as to make learning more effective. Several programs are under way to ensure that decision makers learn from such experiences (Bakken et al, 1992).

REFERENCES

Antun, F. (1981). "Svingninger i ferrosilium-industrien: En system-dynamisk analyse. B.S thesis in Management, The Norwegian School of Management, Oslo.



Bakken, B.E., Gould-Kretzer, J.M. and Kim, D.H. (1992). "Management Flight Simulators and Organizational Learning: Some experimental evidence." *European Journal of Operational Research*. forthcoming.

Drewry Shipping Consultants, L. (1990). *Tanker Spot Rate Trends*. Shipping Statistics and Economics, # 236. June. London:

Fearnleys (1963-1988). *Fearnleys Review*. Oslo, Norway: Fearnresearch.

Fuglseth, A.M. (1989). "Beslutningsstøtte: metode for diagnose av ledes informasjons- og situasjonsoppfatninger. (Decision Support; method for diagnosing managers' information and situation experiences)." Ph D Thesis, Norwegian School of Economics and Business Administration, Bergen.

Kim, D.H. (1989). "Learning laboratories: Designing a reflective learning environment." Working paper no. D-4026, System Dynamics Group, MIT, Cambridge, MA.

Novick, L.R. and Holoyak, K.J. (1991). "Mathematical Problem Solving by Analogy." *Journal of Experimental Psychology*. 17(3): 398-415.

Plott, C.R. (1987). "Rational choice in experimental markets." In Hogarth, R.M. and Reder, M.W., ed. *Rational choice: The contrast between economics and psychology*. Chicago: Univ. of Chicago Press.

Randers, J. (1984a). "Prediction of Paper Pulp Prices: A Review Two Years After." wp 84/6, Norwegian School of Management, Oslo.

Randers, J. (1984b). "The Tanker Market." Norwegian School of Management, Oslo.

