DRUID

DRUID Working Paper No. 07-07

Cyclical Dynamics in Three Industries

By

Hao Tan and John A. Mathews

Danish Research Unit for Industrial Dynamics

www.druid.dk

Cyclical Dynamics in Three Industries

Hao Tan
Doctoral candidate
Macquarie Graduate School of Management
Macquarie University
Sydney, Australia, 2109
E-mail: haotan1@gmail.com or hao.tan@mq.edu.au

John A. Mathews
Professor of Management
Macquarie Graduate School of Management
Macquarie University
Sydney, Australia, 2109
E-mail: john.mathews@mq.edu.au

June 2007

Abstract:
In this paper we offer a procedure to identify the industry cycles, and apply the procedure to the industrial data of three industries, namely semiconductors, PCs and FPDs. The identified cycles enable us to conduct two comparison analyses: (1) comparing the cycles with those suggested by industry experts in the corresponding industries; (2) comparing the industry cycles across the three industries. Moreover, we examine the factors possibly contributing to the cyclical dynamics of the industries built on three lines of explanations in the literature. Our vector auto regression (VAR) models establish that the dynamics of aggregate economy and capacity are among the most significant drivers in our semiconductor industry cycle.

Key words: Industry cycle, business cycle, technology cycle, business dynamics, VAR model
Jel codes: L61, L63

ISBN 978-87-7873-236-1

Aknowledgements
This research is supported by Australian Research Council Discovery Projects Funding (DP0665528). We thank comments from participants in DRUID-DIME Academy Winter 2007 PhD Conference on an early version of the paper; and special thanks to the very helpful comments from Keld Laursen who was the discussant of the paper on the conference.

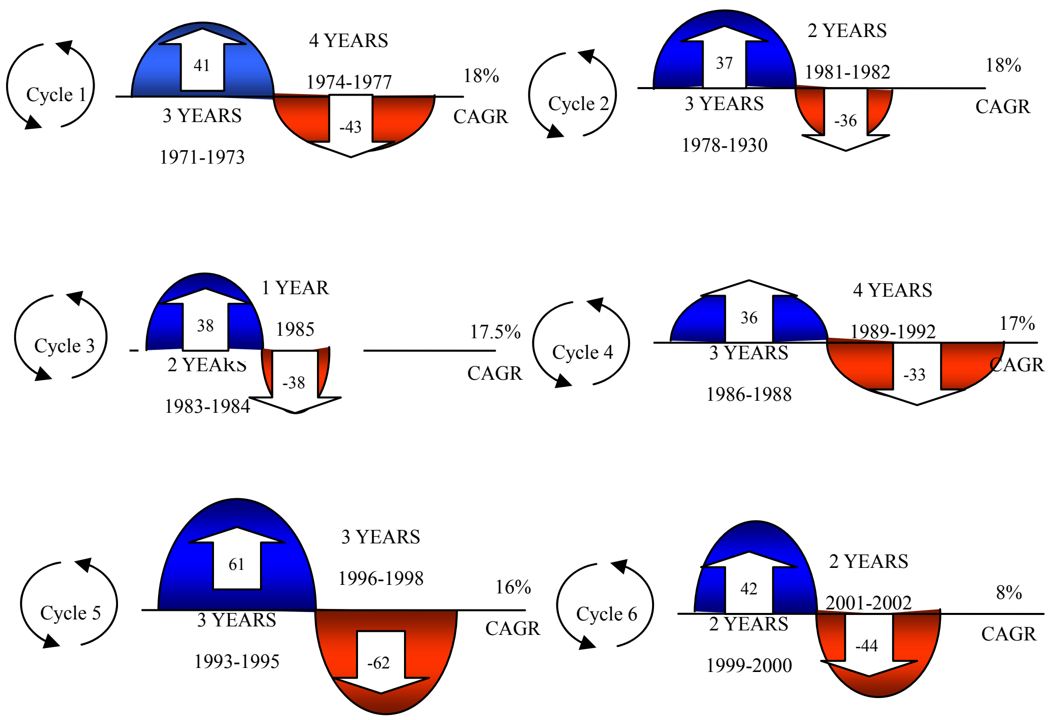
1. Introduction

The term ‘industry cycles’ frequently appears in trade journals but the phenomena have rarely been systematically examined by scholars, with some few exceptions (Liu, 2005; Mathews, 2005; Navarro, 2005). Despite applying less rigorous methods to industry data, industry experts announce the existence of industry cycles relying on their observation. Figures 1, 2 and 3 show the ‘industry cycles’ for the global semiconductor industry, the US computer industry and the global FPD industry adapted from various industrial reports. First, in the semiconductor industry, a well-known cycle (as shown in Figure 1) is given by the *IC Insights* (McClean, 2001), an industry research firm. According to IC Insights, the industry has undergone six major cycles since 1970s, triggered by various factors including worldwide recession, overcapacity and inventory burn. Second, the computer industry cycle in Figure 2 is suggested by Economic Data Resources (2000), another industry consultants firm based in the United States. The raw data available from US M3 survey, viz. the computer new orders received by manufacturing companies in the United States, are transformed twice before an approximately two-year cycle appears. The firm finds the cycle is regular and has persisted during the whole of the 1990s, featuring five peaks in 1990, 1992, 1994, 1996 and 1998. The computer industry cycle, as the firm suspected, may relate to new product introductions (technology cycle) and the capital goods replacement cycle. Third, the global flat panel display (FPD) industry is another industry with phenomenal cyclicality. *DisplaySearch*, a research firm specializing in the FPD market, defines the ‘crystal cycle’ of the industry as “the derivation of AAP [i.e. average area price] from the market-clearing price trend”. Since late 1990s three peaks are pronounced in large-sized Thin Film Transistor-Liquid Crystal Display (TFT-LCD) price (as shown in Figure 3) [1]. These peaks, as the firm believes, are the consequence of the shortage of supply, which in

[1] The segment of large-sized TFT-LCD is the core of the global FPD industry and accounts for more than sixty percent of the market value. As such we use data of the large-sized TFT-LCD market as a proxy for those of the FPDs in this manuscript.

turn relates to the pace of firms' investment. The firm predicts that the cycle may become smoother as the industry is maturing and spending is stabilizing mainly due to easier access to capital (Young, 2006).

Figure 1: Semiconductor Industry cycle suggested by *IC Insighst*

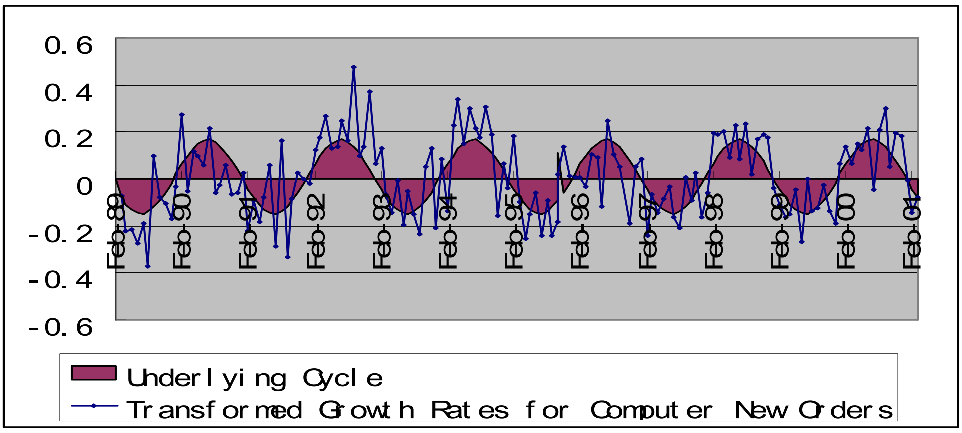


annual market growth rate during that cycle.

Number shown in arrows is total deviation from IC market CAGR during that cycle.

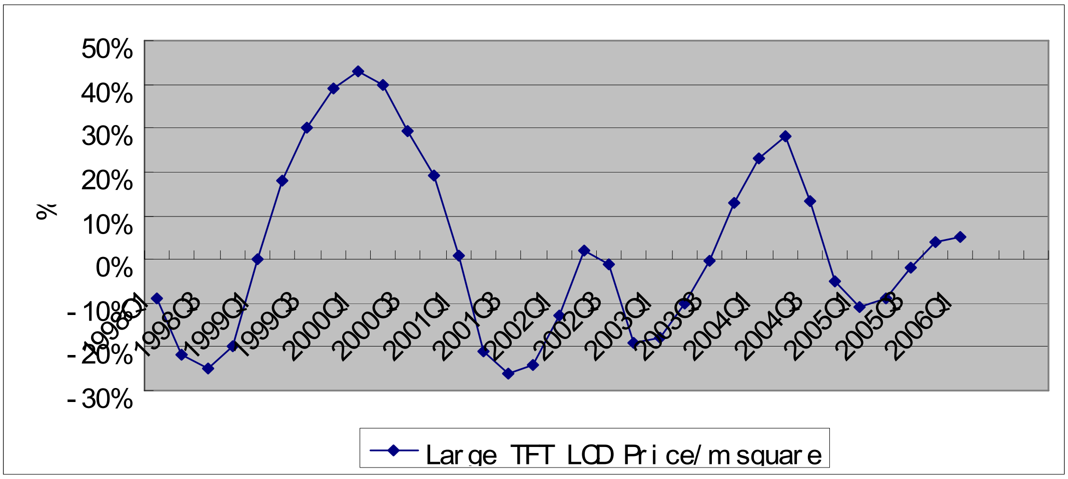
Source: IC Insights

Figure 2: Computer cycle suggested by Economic Data Resources



Source: Replicated from Figure 2-3 in Economic Data Resources (2000) with an extended period

Figure 3: Crystal cycle suggested by DisplaySearch



Source: DisplaySearch

These cycles reveal important dynamics driving the behaviors of variables such as supply, price, investment and profit in the industries. In fact, we believe the cyclical dynamics form one of important dimensions for understanding industrial dynamics, along with others such as the dynamics of firms' entry (Geroski, 1995; Gort & Klepper, 1982; Helfat & Lieberman, 2002), exit (Dune, Roberts, & Samuelson, 1988), growth (Geroski, Machin, & Walters, 1997), innovation (Dosi, 1988) and turbulence (Baldwin & Gorecki, 1994; Mansfield, 1962).

However, the term 'industry cycle' in most reports by industry experts is loosely, if at all, defined. The procedure for dating the turning points of the cycles is neither clear nor consistent. The raw industrial data are usually used without necessary preparation such as seasonal and inflation adjustment. The cyclical patterns are often brought about by taking the growth rate of the level data, a detrending method which has become increasingly unpopular in serious researches in that it may misrepresent cycle properties including frequencies and amplitudes (Baxter & King, 1999). In addition, the consultants' reports tend to provide only short-term version of the industry cycles. As a result, the cycles may be distorted by inflation, seasonal, trend and irregular factors; and are not necessarily comparable across industries. The 'stylized facts' based on these cycles are thus suspect.

More importantly, while industrial consultants make claims regarding the drivers of the cycles, the evidence is usually limited to those based on visual inspection on the co-movement of the ‘cycles’ and a range of other time series. The factors underlying those series are yet to be confirmed; and individual factors’ contribution to the cyclicality of the industries has yet to be quantitatively estimated.

In this manuscript we address these weaknesses and offer what we believe to be the first comprehensive and systematic analysis to the cyclical dynamics in the three industries that are found in the IT sector—namely semiconductors, PCs and FPDs. We define industry cycle as a cyclical pattern in the industrial shipment data [2]. Figure 4, 5 and 6 display our version of the industry cycles for the global semiconductor, PCs and FPD industries [3]. Shaded areas in the figures correspond to the upturns of the cycles; and unshaded areas to the downturns. The toughs and the peaks of the cycles are labeled with ‘T’ or ‘P’ respectively. In addition, the stylized versions of these cycles are presented in Figure 7, 8 and 9.

[2] Cyclical dynamics are usually shown in other industrial data as well such as product price, investment, and profit. However we believe that we can obtain a ‘benchmark’ of the industry cycles by focusing on shipment/sales dynamics which is perhaps the most important indicator of the ups and downs of an industry; and can further compare this benchmark with other cyclical dynamics of the industry. To define industry cycle in this way is also in line with most industry experts and piror researchers such as Liu (2005).

[3] The raw data used in this study are taken from industry associations and the leading industry research firms. The source of the worldwide semiconductor shipment data is Semiconductor Industry Association. The worldwide PCs shipment data are provided by IDC. The PC market defined by IDC consists of three major segments, i.e. standard Desktop/minitower/tower PCs, Portable computer products and x86 Servers. The worldwide large-sized TFT-LCD shipment data are complied based on reports of several leading industry consultants among which DisplaySearch is the primary source. See table for details of other data series used in this study.

Figure 4: The Semiconductor Industry Cycle

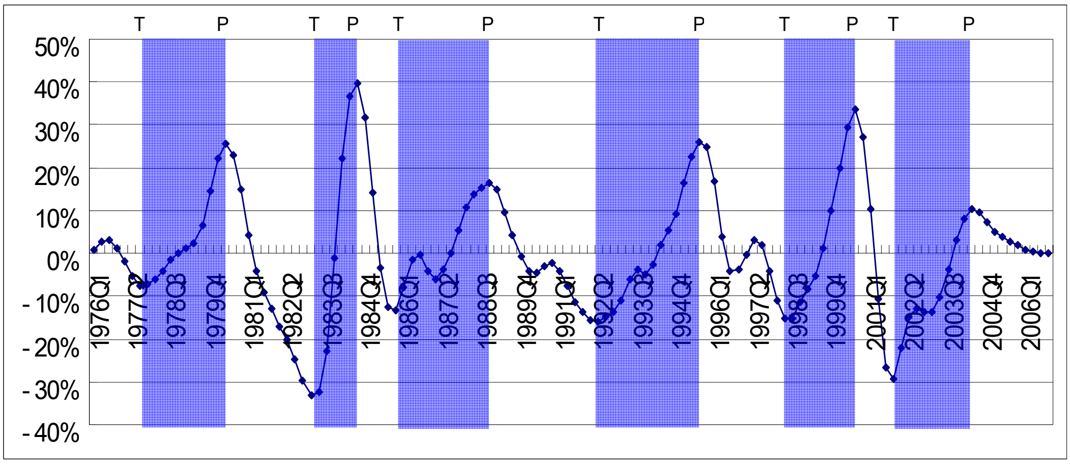


Figure 5: The PCs Industry Cycle

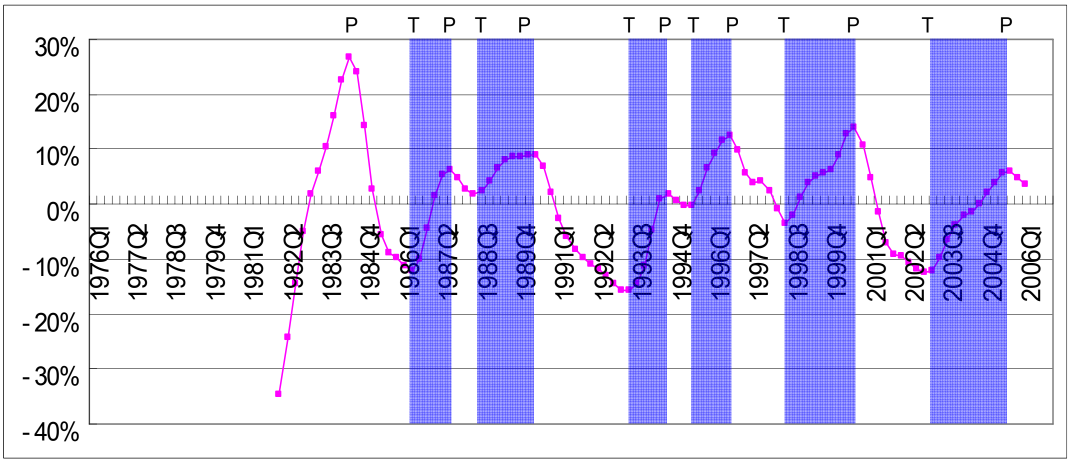
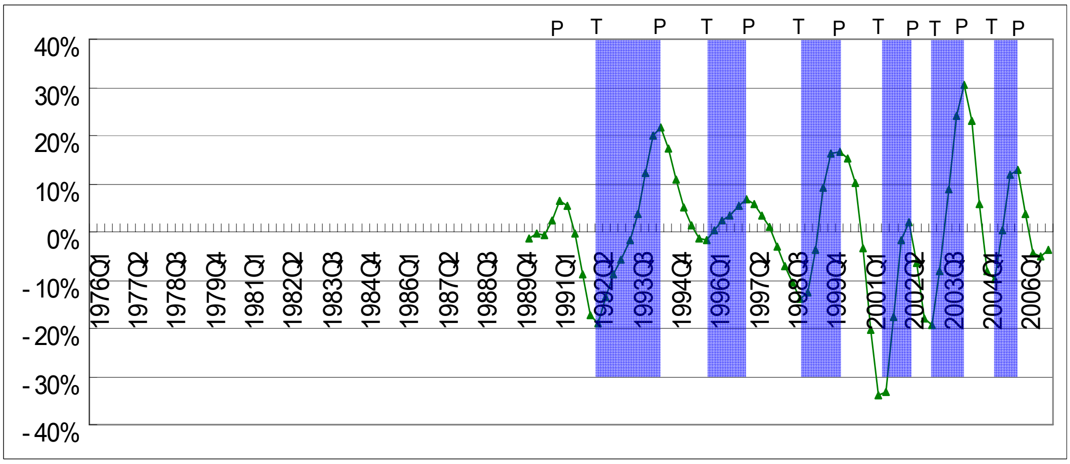


Figure 6: The FPD Industry Cycle



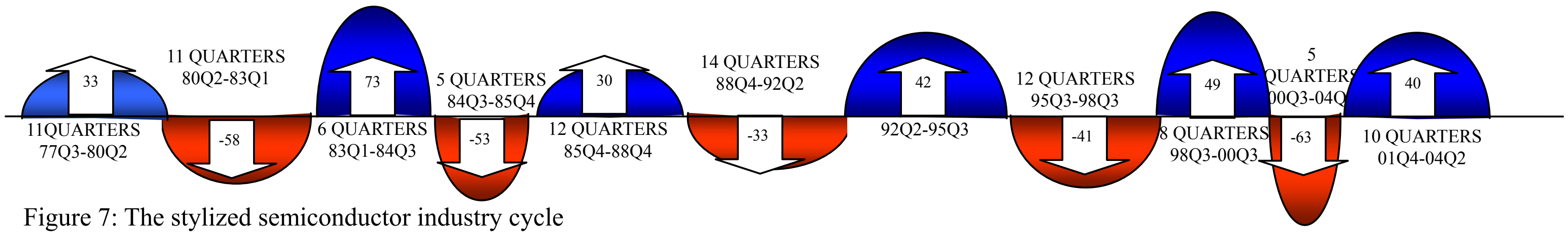


Figure 7: The stylized semiconductor industry cycle

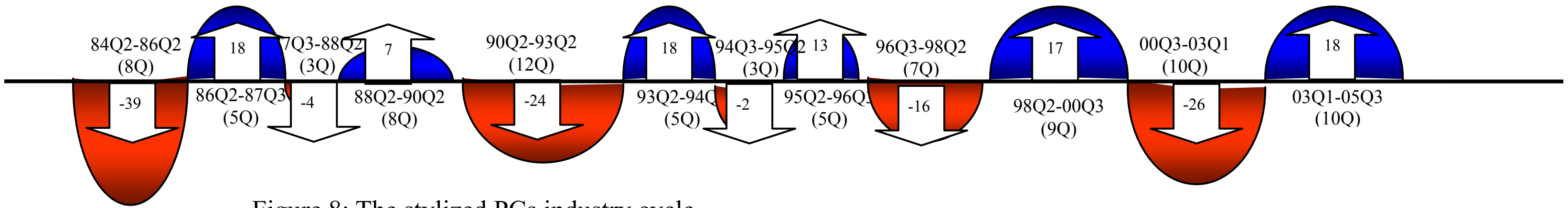


Figure 8: The stylized PCs industry cycle

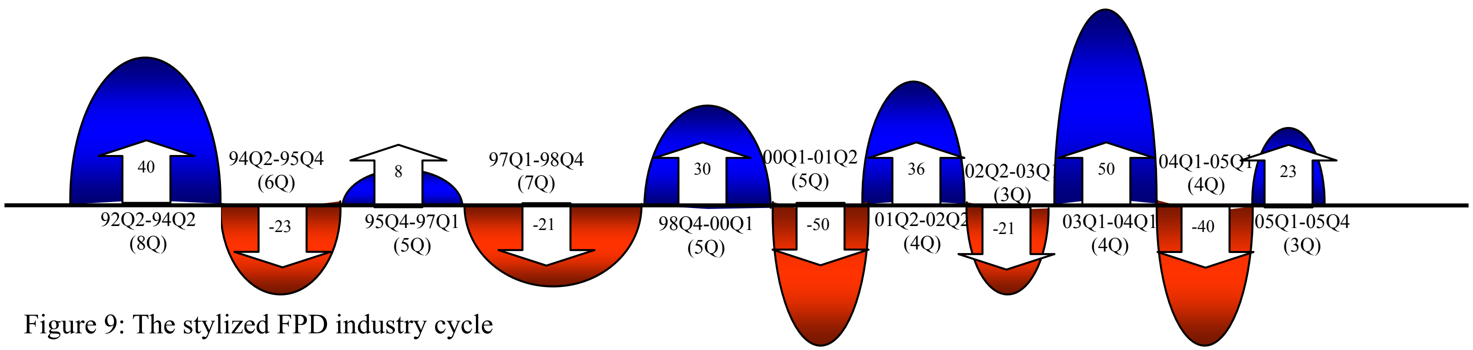


Figure 9: The stylized FPD industry cycle

The representation of those cycles is the outcome of a carefully chosen procedure which identifies the cyclical components in the industrial data in a more rigorous way. The identified cycles then enable us to conduct two comparison analyses: (1) comparing the cycles with those suggested by industry experts in the corresponding industries; (2) comparing the industry cycles across the three industries. Moreover, we examine the factors possibly contributing to the cyclical dynamics of the industries built on three lines of explanations in the literature. Our vector auto regression (VAR) models establish that the dynamics of aggregate economy and capacity are among the most significant drivers in one of our industry cycles, namely cycles for ICs [4].

The purpose of this manuscript is thus twofold. Firstly we intend to offer a more reliable procedure for identifying industry cycles; and secondly we aim at developing a framework in exploring the potential sources of the industry cycles. Overall, we hope the study can not only bring new insights for understanding the industrial cyclical dynamics in the three very important industries at the global level; but also shed lights for future industry cycle studies.

We start this manuscript with introducing a procedure in identifying the industry cycle which consists of five main steps. We apply the procedure to the industrial data of the three global industries and compare our results with those suggested by industry experts. In the section three, based on three lines of explanations for industry cycles in the literature, we examine the relationships between industry cycles and a range of dynamics, including aggregate economy, technology, price, capacity and capital investment; and use VAR models to identify the most significant factors responsible for the industry cycles. We draw some implications of the study at the end of the manuscript.

[4] At this stage we are only able to perform this analysis to the semiconductor industry cycle due to the data availability. The idea of using VARs to explore the main explanatory factors of the industry cycles is inspired by Liu (2005); but we add several elaborations in this manuscript that improve the insights obtained.

2 Identifying the industry cycles

2.1 The procedure

Our procedure for capturing the industry cycles consists of five main steps, aiming at separating the cyclical component in the industrial data series from its seasonal, irregular and trend components and also clearing out the effect of inflation [5].

(1) First, for those data series that are expressed in current US $, a deflator is used for removing the effect of inflation [6];

(2) Second, the seasonal and irregular components in the series are captured and eliminated using the Census X-12 procedure. The series are then taken in natural logarithms;

(3) Third, the remaining trend-cycle series are detrended by the Hodrick-Prescott (HP) filter which removes components with very high and very low frequencies;

(4) Fourth, the turning points are finally determined in the HP filter-generated cycles based on a set of pre-set rules;

(5) Finally, the properties of the cycles are calculated and the influences on them quantified [7].

The central element of the procedure follows the principles of a conventional time series analysis which assumes that there are four component parts underlying every time series Yt, viz. trend (Tt), cyclical (Ct), seasonal (St), and irregular (It) component. A multiplicative model of a timer series can thus be presented as follows [8].

---

[5] The procedure is inspired by Binner (2005) who uses similar procedure to identify the inflation cycles.
[6] The deflator is available from US Bureau of Labor Statistics www.bls.gov
[7] Besides the method presented in the body of the manuscript, the properties of the cycle can also be estimated using a 'parametric' approach which develops statistical models such as cosine and sine waves which fit data and select turning points with the estimated parameters. The properties of cycle resulted from our modeling using the Fourier analysis are briefly described in Appendix A for reasons of brevity.
[8] The decomposition model can take either additive form or multiplicative form. An additive model, represented as Yt = Tt+Ct+St+It, is essentially the same as the multiplicative model on taking logs to the latter.

$$Yt=Tt \times Ct \times St \times It \quad (1)$$

The seasonal and irregular components can be captured using the Census X-12 procedure, leaving trend-cycle series. The US Census X-12 is the latest variation of the Census II method developed by the US Census Bureau and is among the most widely used methods by governments and other agencies for seasonal adjustment of time series [9]. The trend-cycle decomposition, however, presents a challenge facing not only the present study but also many business cycle researchers (Baxter et al., 1999; Zarnowitz & Ozyildirim, 2002). Traditional detrending methods such as linear detrending and first-differencing (or taking growth rate form) prove less than satisfactory because trends are indeed variable; and using those methods usually skews the frequencies and amplitudes of the cycles (Baxter et al., 1999; Zarnowitz et al., 2002). Comparing twelve widely used detrending methods, Canova (1999) concludes that the Hodrick-Prescott (HP) filter (Hodrick & Prescott, 1997) [10] and the Baxter-King (BK) (or the band-pass) filter (Baxter et al., 1999) outperform others in reproducing closest cycles of the NBER benchmark. In fact, these two filters are currently most widely used detrending methods and have been built in the latest version of software packages such as Eviews. By using different approaches, the HP filter and the BK filter both extract very low and very high frequencies from time series, generating the nonlinear trend of the series. The former computes a smoothed series by minimizing the variance of the original series around the smoothed series while the latter lets cyclical components with the durations in a band 'passes through' and filters out remaining cycles (Quantitative Micro Software, 2005).

In choosing between the HP filter and the BK filter, we notice that the two methods produce very similar results when using the default parameters suggested by their creators (see Baxter et al., 1999; Canova, 1999). Given the HP filter does not require users to determine the filter 'bands', we decide to follow Binner, Bissoondeeal, & Mullineux (2005) and many others and use HP filter as our nonlinear trend-cycle decomposition filter.

---

[9] See http://www.census.gov/srd/www/x12a/ for articles concerning the X-12 method and the downloadable programs.

[10] The original draft of paper was circulated in the early 1980's.

The trend-cycle decomposition using the HP filter would generate cyclical pattern of the time series, as those displayed in Figure 4, 5 and 6 without ‘shade’. In order to determine the final turning points of the cycles we however need to set criteria to capture the major upward and downward movement and to rule out those minor ‘cycles’. Bodies including the National Bureau of Economic Research (NBER) in the United States and the Central Statistics Office (CSO) in the United Kingdom have developed reference chronologies for dating business cycle. But to our knowledge no reference chronologies are available for dating industry cycles. By primarily consulting the works by NBER (Bry & Boschan, 1971) and works on dating other economic cycles such as inflation cycles (Artis, Bladen-Hovell, Osborn, Smith, & Zhang, 1995; Binner et al., 2005), we impose the following four rules to the HP filter-generated cycles for determining the major peaks and troughs of the industry cycles. First, it is obvious that peaks should always follow trough and vice versa. Second, no phase (upturn or downturn) can be less than three quarters in duration. Third, a turning point is the most extreme value between two adjacent regimes except they are at beginning or end of the cycle. Fourth, no turning point is recognized within three quarters of the beginning or end of the series.

The key criterion we impose is the three-quarter rule for duration of phase, which is consistent with Artis et al. (1995) and Binner et al.(2005) etc.; but different from CSO (12 months) or from Bry et al. (1971) at NBER (5 months). The decision is made based on the examination to the industrial series with difference rules; and we find that the number of turns resulted from the three-quarter rule is well-balanced. Using the five-month rule would generate too many cycles. For example, the number of semiconductor cycles in our series would increase from six to ten. Using the 12-month rule on the other hand would eliminate cycles. The number of FPD cycles would drop from six to four; and more importantly, the recent cyclical movement in the industry with its contraction or expansion lasting usually thee or four quarters would be deleted.

Having identified the industry cycles for the three industries, we are thus able to calculate the durations and amplitudes of the upturns/downs of the cycles, as summarized in the table 1, 2 and 3. The duration of downturns/upturns is simply the period between a turn and its next turn [11]. The change of upturns/downturns is calculated based on value of the turns in percentage term, reflecting the deviation of the industrial data at that time from the trend [12].

Table 1: Semiconductor Industry Cycle Chronology

Type of Turns	Dates	Upturn			Downturn		
		Duration (Q)	Change (%)	Change/ Duration (%/Q)	Duration (Q)	Change (%)	Change/ Duration (%/Q)
Trough	77Q3	11	33	3			
Peak	80Q2				11	-58	-5.3
Trough	83Q1	6	73	12.2			
Peak	84Q3				5	-53	-10.6
Trough	85Q4	30	12	0.4			
Peak	88Q4				14	-33	-2.4
Trough	92Q2	13	42	3.2			
Peak	95Q3				12	-41	-3.4
Trough	98Q3	8	49	6.1			
Peak	00Q3				5	-63	-12.6
Trough	01Q4	10	40	4			
Peak	04Q2						
Average		13	41.5	4.8	9.4	-49.6	-6.8
Standard deviation		8.7	20	4.0	4.2	12.4	4.9

Table 2: PCs Industry Cycle Chronology

Type of Turns	Date	Upturn			Downturn		
		Duration (Q)	Change (%)	Change/ Duration (%/Q	Duration (Q)	Change (%)	Change/ Duration (%/Q
Peak	84Q2				8	-39	-4.9
Trough	86Q2	5	18	3.6			
Peak	87Q3				3	-4	-1.3
Trough	88Q2	8	7	0.9			
Peak	90Q2				12	-24	-2.0
Trough	93Q2	5	18	3.6			
Peak	94Q3				3	-2	-0.7
Trough	95Q2	5	13	2.6			
Peak	96Q3				7	-16	-2.3

[11] For duration of full cycles, there would be a difference between Peak to Peak cycle and Trough and Trough cycle (see Zarnowitz, V. 1992. ***Business Cycles: Theory, History, Indicators and Forecasting***. Chicago: University of Chicago Press.) However, this difference is beyond the discussion in this manuscript.

[12] IC Insight uses the term 'deviation point' to describe the amplitudes of the cycles. The deviation point of a given year is calculated as the difference of the annul growth rate and the average annual growth rate during that cycle; and the amplitude of the cycle is the sum of 'deviation points' of individual years within the cycle.

Trough	98Q2	9	17	1.9			
Peak	00Q3				10	-26	-2.6
Trough	03Q1	10	18	1.8			
Peak	05Q3						
Average		7	15.2	2.4	7.2	-18.5	-2.3
Standard deviation		2.3	4.4		3.6	14.1	1.4

Table 3: FPD Industry Cycle Chronology

Type of Turns	Date	Upturn			Downturn		
		Duration (Q)	Change (%)	Change/ Duration (%/Q	Duration (Q)	Change (%)	Change/ Duration (%/Q
Peak	91Q1				5	-25	-5.0
Trough	92Q2	8	40	5.0			
Peak	94Q2				6	-23	-3.8
Trough	95Q4	5	8	1.6			
Peak	97Q1				7	-21	-3.0
Trough	98Q4	5	30	6.0			
Peak	00Q1				5	-50	-10.0
Trough	01Q2	4	36	9.0			
Peak	02Q2				3	-21	-7.0
Trough	03Q1	4	50	12.5			
Peak	04Q1				4	-40	-10.0
Trough	05Q1	3	23	7.7			
Peak	05Q4						
Average		4.8	31.2	7	5	-30	-6.5
Standard deviation		1.7	14.6	3.7	1.4	12.1	3

2.2 Comparison analyses

We then compare our industry cycles with those suggested in consultants' reports. The comparison between the two sets of semiconductor industry cycles is shown in the figure 10.

Figure 10: Comparison between the semiconductor industry cycles suggested by IC Insights (left) and by Tan & Mathews (right)

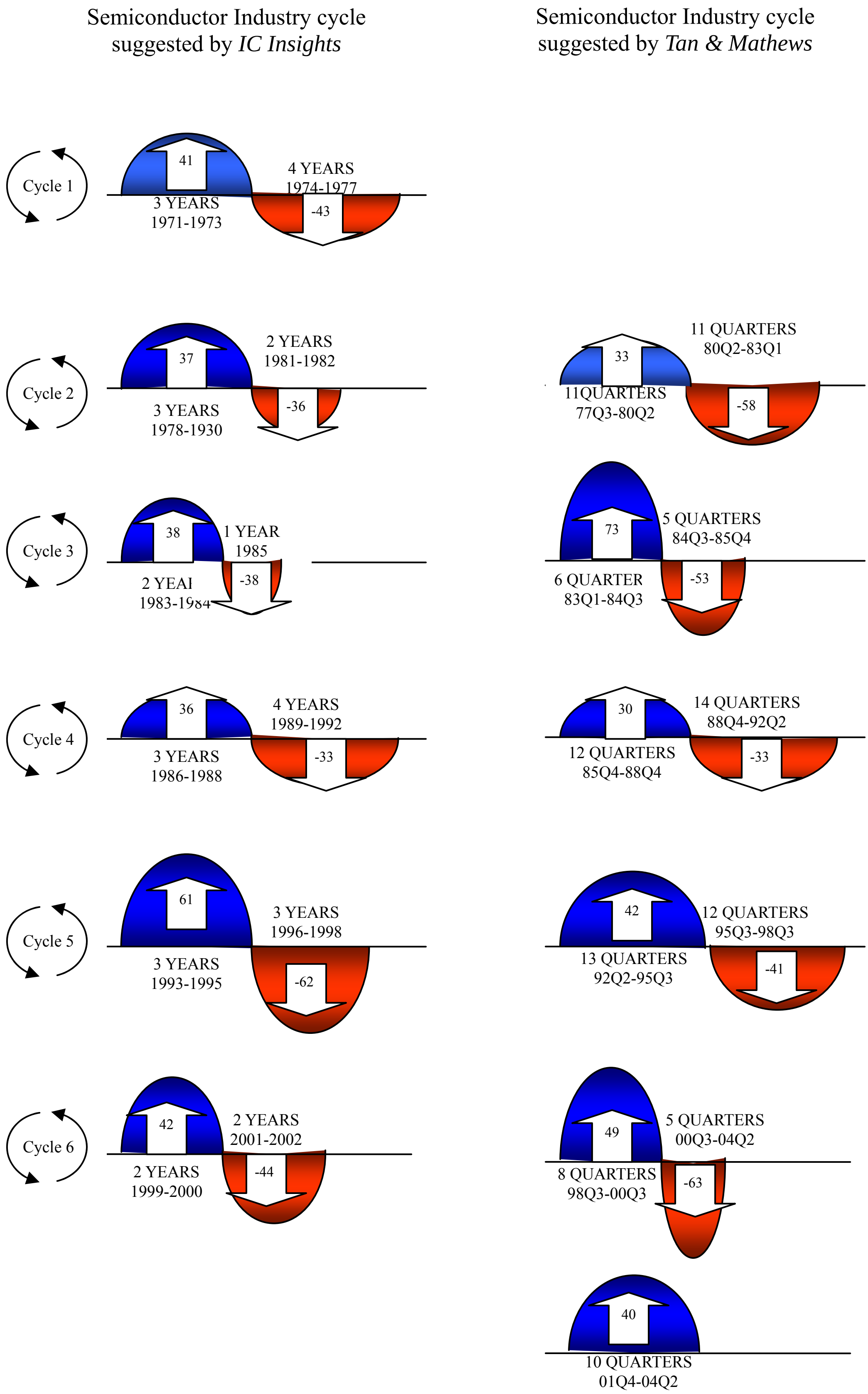


Figure 10 suggests that the two studies both identify five cycles during the period between 1977 and 2001; and the durations and amplitudes of the two sets of cycles are very consistent. However, instead of the annual data used by IC Insights, the quarterly data we use enable us to locate the turns of the industry more accurately. Moreover, our estimation establishes that the deepest downturn took place at 2000Q3-2004Q2, instead of the downturn in IC Insights's cycle between 1996 and 1998. Our largest upturn, during the period from 1983Q1 to 1984Q3, also differs from that in IC Insights which is located between 1993 and 1995. We believe the differences partly result from estimation for duration of the cycles; and partly from the methods for estimation of the industry trend.

Our PCs industry cycle largely diverges from the industry cycle that Economic Data Resource (2000) portrays for the US computer industry. Our estimation does not support that there is a regular two-year cycle in the industry. Instead, the average 'Peak-to-Peak' full cycle duration is approximately 3.55 years and the durations of individual cycles range from 2 year to 5 year. Economic Data Resource does not give its estimation of cycle amplitude. We however estimate that the average change for upturns in the PCs industry cycle is 15.2% and that for downturns is -18.5%. The statistics also suggests that upturns in the PCs industry are more 'regular' than downturns in a sense that the former has smaller standard deviation than the latter for both duration and amplitude.

For the FPD industry, the three peaks in DisplaySearch' 'crystal cycle' are all identified in our FPD industry cycle [13]. However, our FPD industry cycle does not appear to support the prediction by DisplaySearch that the industry cycle becomes smoother as the market is maturing. What we observe in the shipment data is that the industry is still displaying very strong cyclical behavior.

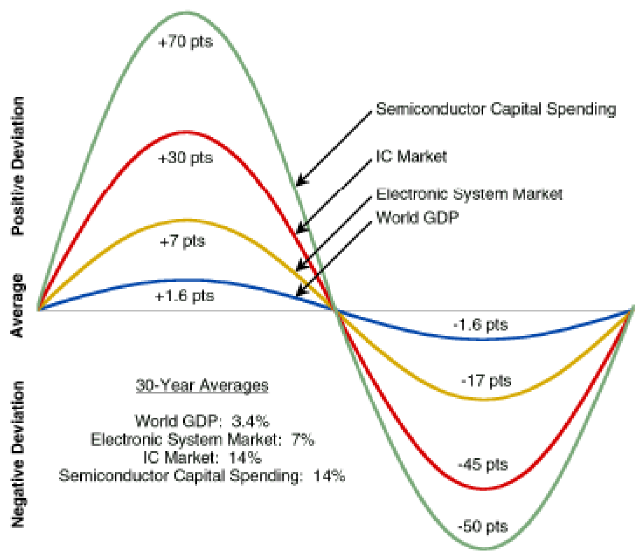
In comparing the industry cycles among the three industries, we find that the FPDs industry cycle is the most volatile one with the least average cycle duration and the largest amplitude in terms of the ratio of change to duration. The observation comes

[13] The peak at 2004Q2 in DisplaySearch's cycle is one-quarter ahead of the corresponding peak in our industry cycle.

out without much surprise given that the industry is the youngest among the three and is perhaps still at the very early stage of its life cycle. The industry reached approximately US$84.6 billion in annual revenue in 2006 from almost nothing in early 1990s, with more than 60 percent of the value contributed by large-sized TFT LCD (*DisplaySearch*). The market has witnessed stunning growth, rapidly changing technology and continually emerging applications along its development within just one and a half decades. Those features associated with a new-born industry may all contribute to the strong cyclicality of the industry.

The differences between the amplitudes of the semiconductor industry cycle and those of the PCs industry cycle can somehow be explained with the so-called *Bullwhip Effect* (Forrester, 1961; Stalk & Hout, 1990). As one of the major upstream industries of PCs, the semiconductor has much server swings than those in the PCs in terms of both the total change of upturn/downturn and the ratio of the changes to phase durations. Interestingly, the trend of 'amplification' goes back even further as it has been widely suggested by industry experts that amplitude of the semiconductor equipment cycle has much larger amplitude than that of the semiconductor cycle, as shown in Figure 11.

Figure 11 The magnifying amplitudes of cycles

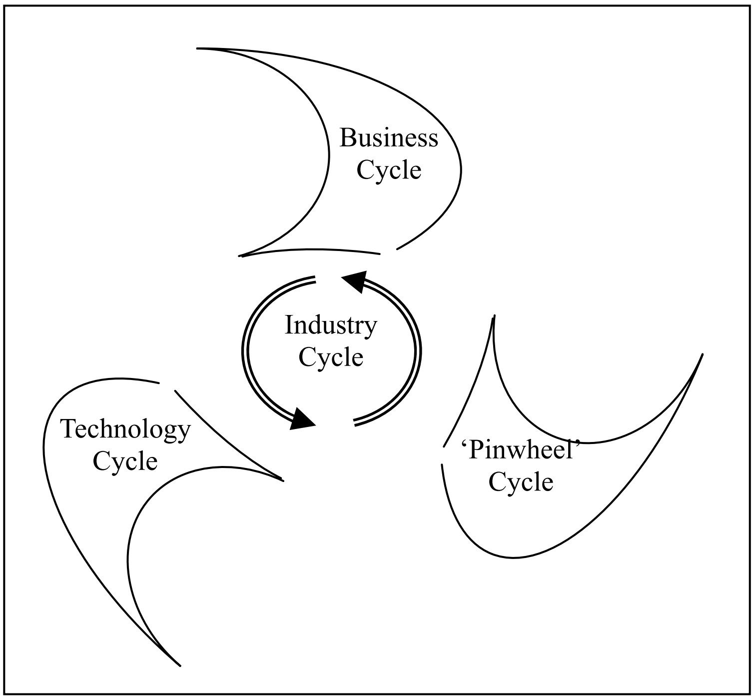


Source: IC Insights

4 Exploring the drivers of the industry cycles: A 'windmill' model

The next question we ask is 'what are the key forces contributing to the industry cycles?'. Three lines of explanations can be identified in the literature (including industrial studies), involving factors ranging from aggregate economy, pace of technological progress to time delays occurring between various business dynamics. The first explanation emphasizes the co-movement between business cycle and industry cycle (Martin, 2005; McClean, 2001). The second explanation is derived from studies on technology cycle which implies that industry cycles are likely to peak after a dominant design emerges (Anderson & Tushman, 1990; Tushman & Anderson, 1986). The third explanation considers time delays occurring in 'feedback loop' in business dynamics the fundamental reason of oscillation (Forrester, 1961; Sterman, 2000), which is well-illustrated with industry experts' 'pinwheel cycle' (displayed in Figure 16 and 17 below). Put together, we believe those three explanations can in fact form a more comprehensive framework for understanding the underlying forces of the industry cycles, as shown in a 'windmill model' in Figure 12.

Figure 12: A windmill model for understanding the drivers of industry cycles



In this section the three 'vanes' in driving the industry cycles are first examined individually; we then build all of them into vector autoregresssion models and examine their effects on the industry cycle jointly. We primarily focus the analysis on the semiconductor industry and examine evidences from the other two industries wherever the data are available.

4.1 Business cycle and industry cycle

The role of business cycle has been long explored in economics with the major contributions of the National Bureau of Economic Research (NBER) and such scholars as Schumpeter (c.f. Schumpeter, 1939) in the middle years of the 20th century. These studies established the existence of regular 'business cycles'; and explored sources of the cycles, ranging from exogenous factors such as periodicity in sun plots (W. S. Jevons, 1835- 1882) or the planet Venus (H. L. Moore, 1869- 1958), to class conflict (Marxist views), investment (the Investment School), innovation (Schumpeter, Mensch), intervention in the money supply (the Austrian School), interaction between institutional forces, infrastructure and clusters of basic innovations (Institutionalists, e.g. Freeman, Perez) [14].

There may be little doubt that business cycles do matter for individual industries' fluctuation. From one point of view, the industry cycle is mainly a product of the 'external shocks'. For example, among the six cycles observed by MacClean (2001) in the global semiconductor industry between 1970 and 2000, three are named as 'oil shock cycle' because he believes that the cycles are due to world recessions in 1975, 1982 and 1991 which were initially triggered by oil crisis. The extension of the fifth downturn in 1998 is also attributed by him to the Asian Financial Crisis. This view is shared by Martin (2005), another consultant in the industry, who however extends the observation to include events such as the booming of Taiwanese foundries, the rise of Chinese economy, the collapse of Internet bubble, Y2K and terrorism as the triggers of the recent ups or downs of the semiconductor cycle.

On the other hand, it has also been noticed that heterogeneity exists across sectors and industries when industries face common shocks of business cycle. For example, service sector generally exhibits less cyclical fluctuations than manufacturing activities, for reasons including more stable consumption due to difficulties in stocking services, less capital requirement for service activities and higher price and wage rigidities in service sector (Cuadrado-Roura & V.-Abarca, 2001). Within the sector of manufacturing, the study by Petersen & Strongin (1996) of about 300 manufacturing industries in the US finds that durable-goods industries are approximately three times more cyclical than nondurable-goods industries.

We compare our three industry cycles with the US business cycle and find evidences either supporting or against convergence of industry cycle and business cycle. The reference dates of the US business cycle established by NBER are listed in Table 4. The four recessions in the US economy between 1976 and 2006 are 1980Q1-1980Q3, 1981Q3-1982Q4, 1990Q3-1991Q1 and 2001Q1-2001Q4.

[14] See Groot, B. d., & Franses, P. H. 2005. Cycles in basic innovations: Econometric Institute Report.

Table 4 US business cycle reference dates, 1970-2006

Peak	Through
November 1973 (Q4)	March 1975 (Q1)
January 1980 (Q1)	July 1980 (Q3)
July 1981 (Q3)	November 1982 (Q4)
July 1990 (Q3)	March 1991 (Q1)
March 2001 (Q1)	November 2001 (Q4)

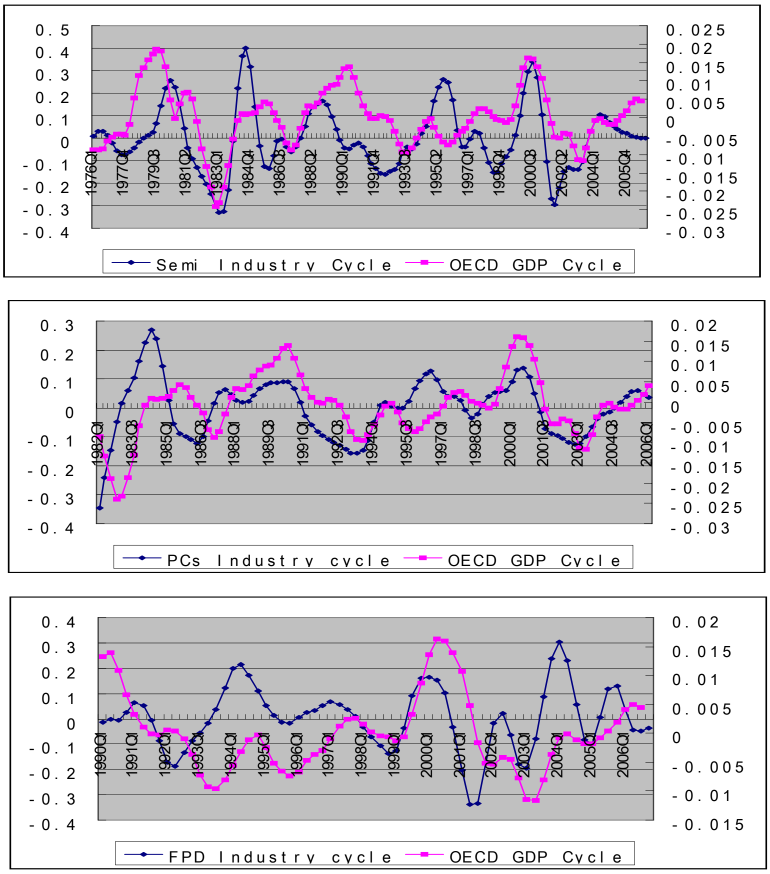
Source: NBER

The semiconductor industry turned to downturn with one quarter lag in the 1980Q1-1980Q3 recession. However, the downturn continued until 1983Q1, which also covered the next recession (1981Q3-1982Q4). It seems that the short recovery of the economy in 1981 had little influence on the downturn of the semiconductor cycle. In the 1990Q3-1991Q1 recession, again the semiconductor industry cycle moved with one quarter lag. This downturn continued until 1992Q2. By contrast, the PCs industry cycle led the business cycle with one quarter ahead; and the long downturn lasted until 1993Q2. The semiconductor and PCs industry cycles both entered into downturns in 2000Q3 during the 2001Q1-2001Q4 recession. While the FPD industry also entered into its downturn since 2000Q1, the cycle started its subsequent upturn in 2001Q2, long before the recovery of the US economy. Overall, it is suggested that the US economic cycle is less relevant to the FPD industry cycle than to the other two industries.

We then turn to the relationships between the industry cycles and the aggregate economy at the global level. The OECD 25 countries real GDP data are used as an approximation of the global output between 1976Q1 and 2006Q4 [15]. After removing the trend with the same procedure imposed on the industrial data, the fluctuations of the GDP data are portrayed and overlaid with the three industry cycles in Figure 13. Co-movement can be detected between the OECD GDP fluctuation and individual industry cycles, though the extent of consistence in term of the timing and amplitude of the turns vary. A closer analysis to the relationship between the GDP fluctuation and the semiconductor industry cycle is thus performed in section 4.4 using VAR models.

[15] In this study the WW output is proxied by the real GDP of OECD 25 countries (2000 price, GDP by expenditure) due to the data availability. Five countries that have recently joined the OECD are excluded, including the Czech Republic, Hungary, Poland and South Korea.

Figure 13: Co-movement of aggregate economy and the industry cycles



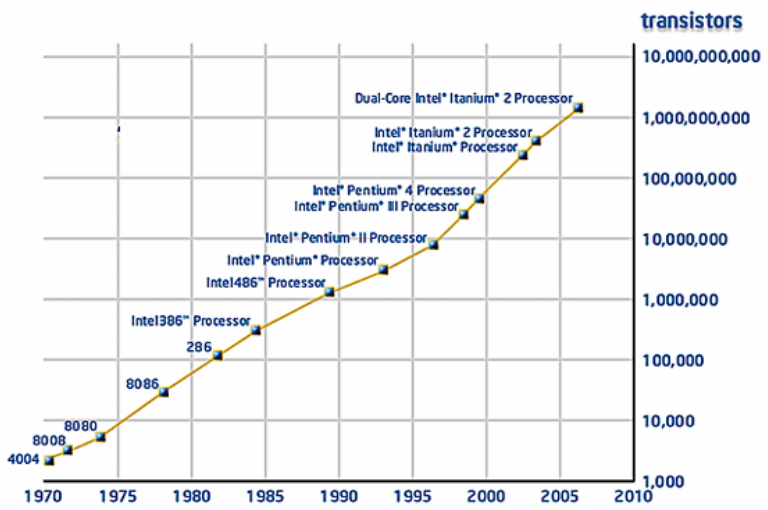
4.2 Technology cycle and industry cycle

Technological change theories argue that technological development may go through a cyclical process where continuous change and discontinuities in technological innovation take place in sequencing (Anderson et al., 1990; Ayres, 1994; Dosi, 1982). More specifically, a so-called ‘technology cycle’ or ‘product cycle’ may occur consisting of four main stages: ‘radical innovation’, ‘ferment’, ‘dominant design’ and ‘incremental change’ (Anderson et al., 1990; Tushman et al., 1986). Further, Murmann & Frenken (2006) suggests that the technology cycle can be broken down from system level into subsystem level and eventually basic component level.

Technology cycle plays important roles in changing industrial dynamics and structure; and is likely to be one of the main drivers of the industry cycles. Specifically, the occurrence of a dominant design tends to reinforce sales; and as a result, industrial cycle is likely to peak after a dominant design emerges. On the supply side, new firms will enter the market with new applications and variations built on the dominant design (Suarez & Utterback, 1995; Utterback & Suarez, 1993). On the demand side, potential customers will move forward into the market as well because the risks associated with choosing a variant which may not become the standard version of a new technology will be released after the appearance of a dominant design (Anderson et al., 1990; Tushman et al., 1986). Based on the reasoning, we would expect a substantial linkage between technology cycle and industry cycle; and look for upturns of the industry cycle at the timings when a new generation of products gradually supersedes the old and rises as dominance in the market.

As a preliminary estimation, we may relate the industry cycle to generations of technology/product resulted from technological breakthroughs in the industry. Figure 11 shows the historical development of IC technology/product. The cycle during 83Q3-85Q4 in our semiconductor industry cycle, for example, may correspond to the life cycle of Intel 286 which was produced between 1982 and 1986. The product was widely used in IBM PC compatible computers after its introduction and created massive demand, possibly triggering the upturn during 1983Q1-1984Q3 in the industry cycle. However, the subsequent downturn may be reinforced by 'holdback effects' when downstream customers were waiting for the introduction of the next generation of processor. The industry cycle started going up again just after Intel 386 was released in October of 1985. Intel 486, the successor of Intel 386, was introduced in 1989, which was in the middle of a downturn in the industry cycle. However, the next two generations of processor, Intel Pentium and Intel Pentium II that were introduced in early 1993 and middle 1997, both seem to be able to find corresponding upturns in our industry cycle.

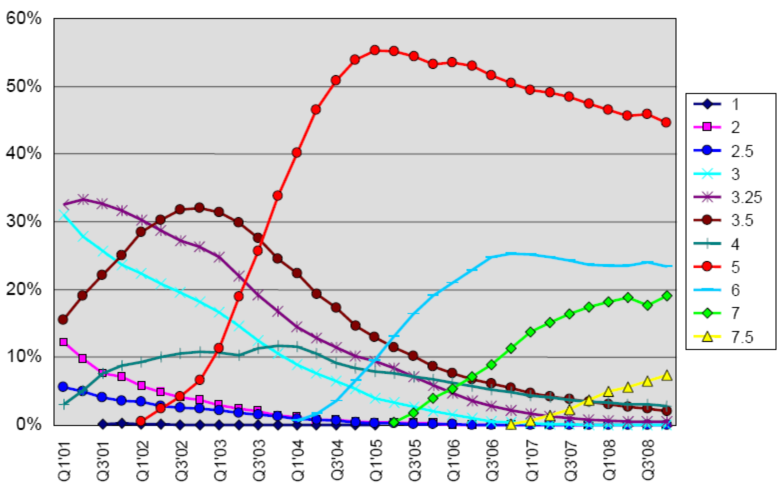
Figure 14: Historical development of IC technology/product



Source: www.intel.com

In the FPD industry, similar phenomenon can also be observed. The recent development of generations of TFT LCD is shown in Figure 15. Each of the three recent upturns in our FPD industry cycle, as we suspect, can all be related to the rise of a new generation of the product/technology, including the generation 3, 3.5 and 4 of TFT LCD.

Figure 15: TFT LCD capacity share by Generation

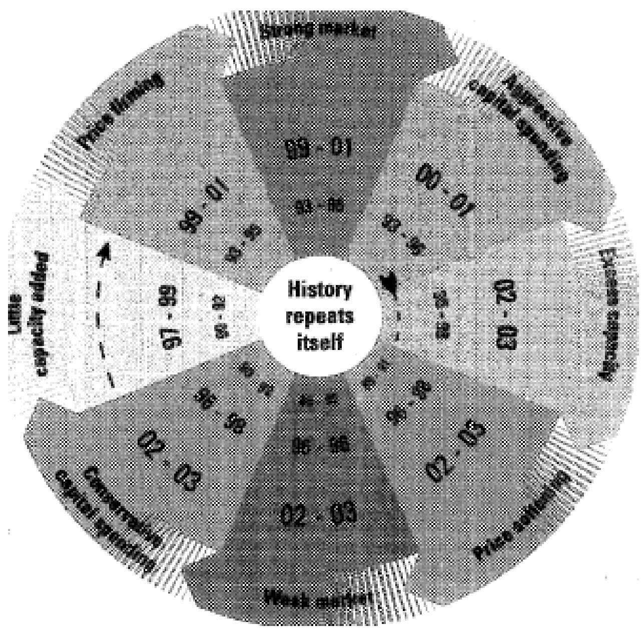


Source: DisplaySearch

4.3 'Pinwheel cycle' and industry cycle

Finally, a source for industrial cyclical dynamics may lie in interactions of market dynamics and firms' behaviors. The well-known '*Beer Distribution Game*' in supply chain management has demonstrated that cycles can arise due to significant time delays in the 'feedback loops' without any external variation (Forrester, 1961; Sterman, 2000). It takes time for dynamics of sales, price, capacity and capital investment to adjust with each other. Timely response is particularly challenging for firms in industries such as semiconductor and FPDs where large amount of capital and substantial period of time are needed for establishing those state-of-the-art fabrication plants [16]. The phenomena that business dynamics such as ales, price, capacity and capital spending move in response to one another with time delays has been termed as 'pinwheel cycle'; and the model has been applied to the IC industry (McClean, 2001) and FPD industry (Mathews, 2005), as shown in Figure 16 and Figure 17. The industry cycles essentially reflect one of the four elements in the pinwheel cycle, with the ups representing strong sales/shipments and the downs representing weak markets.

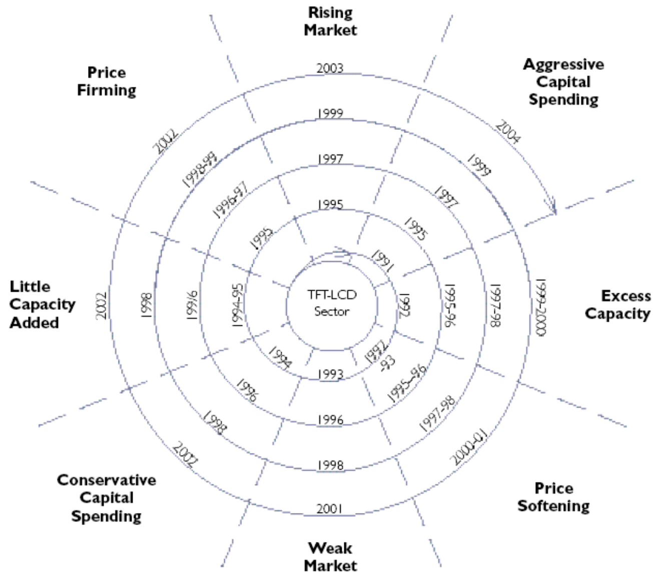
Figure 16: Pinwheel cycle for Semiconductor industry



Source: Adapted from IC Insights

[16] For example, the seventh generation of TFT-LCD fabrication plants requires an investment of between US$ 1.5 and US$2 billion per plant.

Figure 17: Pinwheel cycle for FPD industry



Source: Adapted from Mathews (2005)

In order to examine more closely the feedback loops in the industries, we conduct a leading-lagging analysis to the business dynamics shown in the pinwheel cycle. We first separate the underlying cyclical components from the long-term trends as well as short-term fluctuations in the time series with the similar procedure we use in the section three. The outcome is what we call 'price cycle' and 'capacity cycle' [17], in addition to the industry cycle we have obtained. We then estimate the 'time delays' based on the comparisons between the cycles. Figure 18 compares the industry cycle and the 'price cycle' for semiconductor; and Figure 19 compares those for PCs. Table 5 summarizes the leading-lagging relationships between the two types of cycles in both semiconductor and PCs industry [18]. The identification of corresponding turns in two cycles involves careful inspection on the patterns of the series.

[17] The primary source for generating the price cycles is the producer price indexes (PPI) in the US that available from the US Bureau of Labor Statistics. The data for estimating the semiconductor capacity expansion is available from Semiconductor Industry Association. Since the only data available for estimating semiconductor industry capital spending is in annual frequency (obtained from IC Insights), we thus do not include the variable in detailed analysis but conduct a primary estimation.
[18] More turns than those in the original industry cycle chronology are included in this analysis in order to better capture the leading-lagging relationship of two series.

Figure 18 Comparing the industry cycle and the price cycle in semiconductors

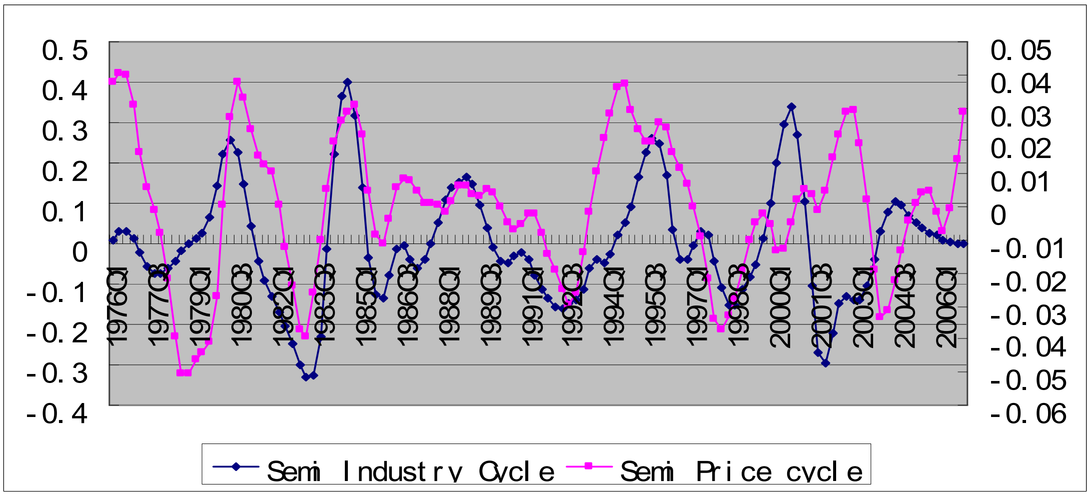


Figure 19 Comparing the industry cycle and the price cycle in semiconductors

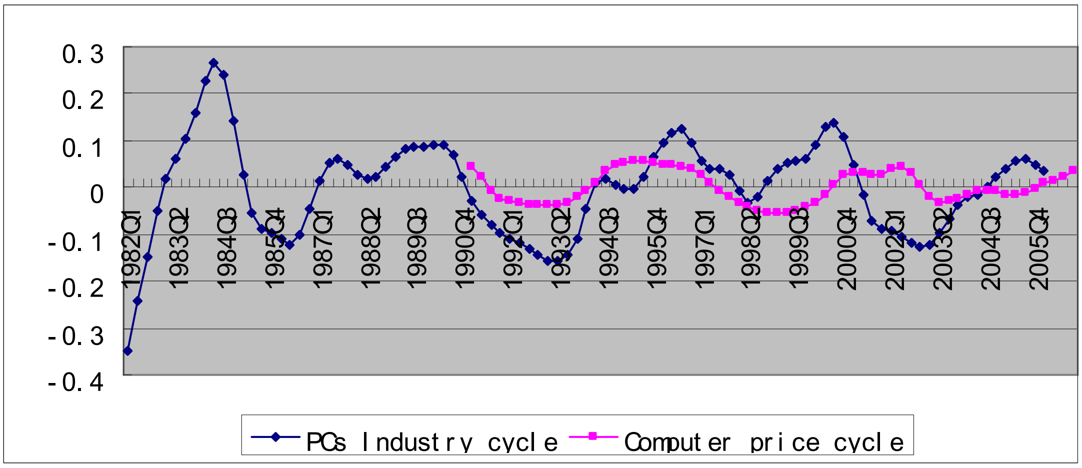


Table 5 Leading-lagging relationships between the industry cycles and the price cycles

	Semiconductor	PCs
1. The industry cycle leading the price cycle		
Number of turns	7	3
Average Leading Time (quarter)	2.7	4
Standard deviation	2.2	2.6
2. The price cycle leading the industry cycle		
Number of turns	5	2
Average Leading Time (quarter)	4.4	3
Standard deviation	2.3	0
3. The two cycles occurring at the same time		
Number of turns	4	0

For the semiconductor industry, the analysis suggests that while the two dynamics (viz. sales and price) do co-move during the period under the study, time delays can be identified between the two movements. In terms of the leading-lagging relationship, the evidences are mixed. It seems that the sales lead the price in the early time of the industry (viz. before 1990s); but the price tend to move ahead of the sales in more recent years. Similar conclusions can also apply to the PCs industry, though the co-movement between the PCs industry cycle and the PCs price cycle seems less pronounced than that in semiconductors.

Same as the ‘semiconductor price cycle’, the ‘semiconductor capacity cycle’, representing the pace of the semiconductor capacity expansion, is compared with the semiconductor industry cycle, as shown in Figure 20. The results of the leading-lagging analyses are reported in Table 6.

Figure 20 Comparing the industry cycle and the capacity cycle in semiconductors

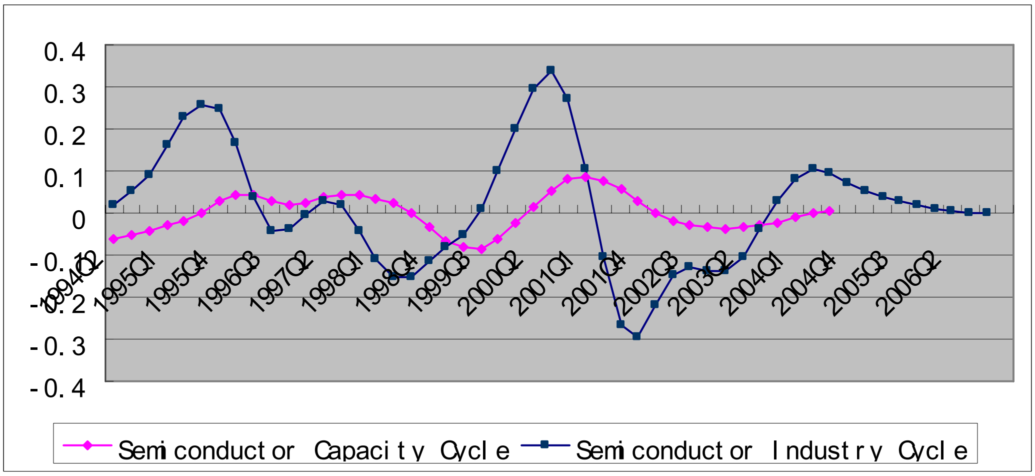


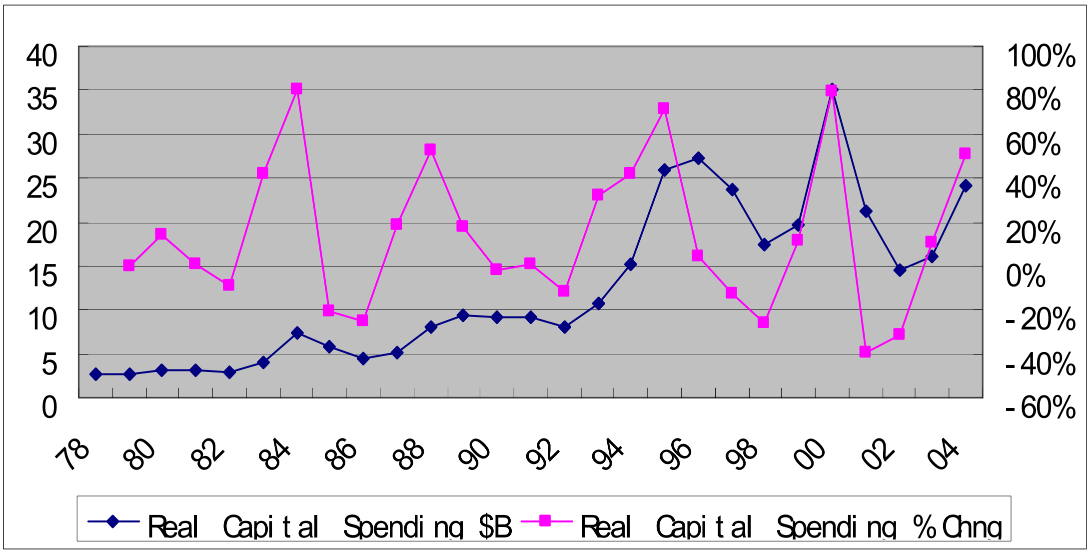
Table 6 Leading-lagging relationships between the industry cycles and the capacity cycles

	Semiconductor
1. The industry cycle leading the capacity cycle	
Number of turns	6
Average Leading Time (quarter)	2.4
Standard deviation	1.5
2. The capacity cycle leading the industry cycle	
Number of turns	0
Average Leading Time (quarter)	N/A
Standard deviation	N/A
3. The two cycles occurring at the same time	
Number of turns	0

In this shorter period of time (1994-2004), the industry cycle always leads the capacity cycle. The average leading time is approximately 2.4 quarters. However, the result shall not be hastily interpreted as the sales 'directly' lead the capacity expansion for averagely 2.4 quarters because it would have been taken much longer if firms add capacity in response to 'current' market. Rather, it would be more likely that firms' proactive capital spending based on their prediction of the future market has largely shortened the time delay between the two dynamics.

Finally, we compare the industry cycle with the pattern of capital spending in the semiconductor industry-- but in a more loose way given the capital spending data are only available in annual frequency. The capital spending in semiconductor peaks in 1984, 1988, 1995 and 2000, as shown in Figure 21. Interestingly, the semiconductor cycle also peaks and only peaks in these years (viz. 84Q3, 88Q4, 95Q3 and 00Q3) during the same period of time. If the peaks in the industry cycle are corresponding to those in capital spending, the time delays between semiconductor sales and capital spending should be less than one year, which infers a rather quick response of semiconductor firms to market conditions.

Figure 21 Semiconductor capital spending and growth



Source of primary data: IC Insights

The analyses above confirm the close linkages between the industry cycles and a range of dynamics including that of aggregate economy, technology, price, capacity and capital spending. The analyses also reveal that the relationships are complex and dynamic, often involving bi-directional feedback and interaction between the variables. To explore the sources for the industry cycles thus calls for a more sophisticated method, which we will address in the next section by using vector autoregression (VAR) models.

4.4 A more dynamic analysis

4.4.1 Data and Method

In this section, we utilize a dynamics system of VAR models to explore the drivers of the semiconductor industry cycle. The variables and data we use for this exercise are summarized in Table 7. Among the six dynamics we discuss in the previous section, the variable of 'capital spending' is dropped out in our model building because only annual data are available for that variable. In choosing the proxy variable for 'pace of technological change' in the semiconductor industry, we find those used in prior studies all seem to have drawbacks, including patenting, R&D and relative price. Many researchers use patent statistics as proxy for the level of innovation at national level (Furman, Porter, & Stern, 2002; Hu & Mathews, 2005). However, dynamics of technological change in industry level can hardly be precisely captured with the patenting rates as diffusion of patents varies. Besides, the frequency of patent data, usually in annual term, cannot satisfy the requirement of the present study. Those are also puzzling issues for using R&D data to measure technological progress. Other researchers tend to use relative price/cost as a mirror of technological progress when calculating productivity growth (Jorgenson, 2001; Oliner & Sichel, 2000). However, relative price trend may also fail to reflect pace of innovation due to factors including trade and competition (Aizcorbe, Oliner, & Sichel, 2006). On the other hand, measuring technological progress in a particular sector could be via a range of performance and cost dimensions of the key technologies across the industry (Ayres, 1994). In semiconductor industry, those dimensions include speed, computational capacity, memory storage capacity, compactness and so on, as those discussed in International Technology Roadmap for Semiconductor (2001, 2003 and 2005). Unfortunately, a 'technological progress index' does not exist covering all the dimensions and different technology categories in the industry. In this study we therefore use the 'speed of CPU' as a crude indicator for pace of technological change in the semiconductor industry.

To make data frequencies consistent, we convert the monthly data and use only quarterly data in the models. In our models the quarterly data from 1994Q3 to 2004Q2 are thus used due to the data availability for all variables. All raw data series go through the process we specify above to remove inflation effects and the seasonal, trend and irregular components of the series because our interest is in examining the relationships between the cyclical dynamics underlying the series.

Table 7 Data source for building the VAR models

Variable	Abbr.	Data	Source	Coverage	Frequency of the raw data
Semiconductor Industry Cycle	IC	Global semiconductor billing	SIA	1976-present	Monthly
Business cycle	BC	Real GDP of OECD 25 countries (2000 price, GDP by expenditure)	OECD Statistics	Mar 1960-Sep 2006	Monthly
Global Semiconductor capacity	CA	Total wafer start capacity of the integrated circuit manufacturing industry (8 inch equivalent)	SIA	1994-2004 Q3	Biannual (1994H1-1996H2)/Quarterly(1997Q1-2004Q3)
Semiconductor Price	PR	Producer price index (PPI) of semiconductor & related device	US Bureau of Labor Statistics	Jan 1967-present	Monthly
Semiconductor Technology Progress	TC	CPU speed	http://wi-fizzle.com/compsci/	1994-2005	Monthly (discrete)

These five variables are then built into a VAR system[19]. A vector autoregressive model is distinct from other traditional structural equation models in that no priori decision is needed on which variable is an endogenous variable and which an exogenous. Rather, every variable in the system is treated symmetrically as a function of the lagged values of itself and of all others. The VAR approach thus allows dynamic interaction between all variables specified in the system. While this technique has been utilized before for exploring determinants of the semiconductor cycle (Liu, 2005), our exercise makes several elaborations that we believe will

[19] In this study, an unrestricted VAR system in its reduced form is used. For detailed discussion on VARs ,see Stock, J. H., & Watson, M. W. 2001. Vector Autoregression. ***Journal of Economics Perspectives***, 15(4): 101-115. ; and Sims, C. A. 1980. Macroeconomics and reality. ***Econometrica***, 48(1): 1-48.

improve the insights. First, the factors we build into the models differ from those in Liu (2005) who chooses his variables based on frequency of factors mentioned in trade journals. While the method he uses has merit, the approach seems to lack a strong theoretical reasoning; and some of the twelve variables in his models may overlap. Second, we capture the cyclical component before we build the variables into the model. And third, we use the global data instead of the US data for all variables, which should be more appropriate because the object is the industry cycle at the global level.

Our VAR system comprising the five variables takes the form as follows.

$IC_t = \alpha_1 + a_{11}BC_{t-1} + .. + a_{1m}BC_{t-m} + b_{11}IC_{t-1} + .. + b_{1m}IC_{t-m} + c_{11}CA_{t-1} + .. + c_{1m}CA_{t-m} + d_{11}PR_{t-1} + .. + d_{1m}PR_{t-m} + e_{11}TC_{t-1} + .. + e_{1m}TC_{t-m} + u_{1t}$

$BC_t = \alpha_2 + a_{21}BC_{t-1} + .. + a_{2m}BC_{t-m} + b_{21}IC_{t-1} + .. + b_{2m}IC_{t-m} + c_{21}CA_{t-1} + .. + c_{2m}CA_{t-m} + d_{21}PR_{t-1} + .. + d_{2m}PR_{t-m} + e_{21}TC_{t-1} + .. + e_{2m}TC_{t-m} + u_{2t}$

$CA_t = \alpha_3 + a_{31}BC_{t-1} + .. + a_{3m}BC_{t-m} + b_{31}IC_{t-1} + .. + b_{3m}IC_{t-m} + c_{31}CA_{t-1} + .. + c_{3m}CA_{t-m} + d_{31}PR_{t-1} + .. + d_{3m}PR_{t-m} + e_{31}TC_{t-1} + .. + e_{3m}TC_{t-m} + u_{3t}$

$PR_t = \alpha_4 + a_{41}BC_{t-1} + .. + a_{4m}BC_{t-m} + b_{41}IC_{t-1} + .. + b_{4m}IC_{t-m} + c_{41}CA_{t-1} + .. + c_{4m}CA_{t-m} + d_{41}PR_{t-1} + .. + d_{4m}PR_{t-m} + e_{41}TC_{t-1} + .. + e_{4m}TC_{t-m} + u_{4t}$

$TC_t = \alpha_5 + a_{51}BC_{t-1} + .. + a_{5m}BC_{t-m} + b_{51}IC_{t-1} + .. + b_{5m}IC_{t-m} + c_{51}CA_{t-1} + .. + c_{5m}CA_{t-m} + d_{51}PR_{t-1} + .. + d_{5m}PR_{t-m} + e_{51}TC_{t-1} + .. + e_{5m}TC_{t-m} + u_{5t}$

where in the first equation ICt denotes the value of the industry cycle at time t; IC_{t-m} denotes the lagged value of IC at time t-m; m is the number of lags; α_i is a constant; u_{ij} represents the unobserved errors of the respective equations; a_{ij}, b_{ij}, c_{ij}, d_{ij}, and e_{ij} are the coefficients. Symbols in the other equations are similarly defined. Based on the criteria built in Eviews, including Akaike information criterion and Schwarz criterion, we choose the lag length of 5 [20].

The ‘statistical toolkit’ in VAR can then help determine the direction of relationships between the variables and estimate the relative contribution of individual factors. The most commonly used techniques include the VAR Granger causality tests, impulse

[20] For discussions on these criteria, see Lütkepohl, H. 1991. ***Introduction to Multiple Time Series Analysis***. New York: Springer-Verlag.

response and variance decomposition.

4.4.2 Results

We first examine how significant the lagged values of the variables in the VAR system in explaining variation of others. Table 8 reports the results of the VAR Granger Causality/Block Exogeneity Wald Tests for all variables. The figures in the table are the significance levels associated with joint F-tests that all five lags have no explanatory power for that particular equation in the VAR.

Table 8 Result of the VAR Pairwise Granger Tests

	Lags of variable				
Dependent variable	BC	IC	CA	PR	TC
BC		0.0000	0.0000	0.0000	0.0000
IC	0.2289		0.1271	0.0001	0.0000
CA	0.5283	0.0000		0.0000	0.0000
PR	0.1090	0.1124	0.0001		0.0000
TC	0.8047	0.0504	0.0567	0.0054	

The second column from left in the table suggests that besides the lagged values of the industry cycle itself, the lagged values of aggregate economy and of the capacity both have explanatory power for the variable of the industry cycle. In addition, the lagged value of the variable TC also helps explain variation of the industry cycle, though with the less highly significant power. On the other hand, it appears that the industry cycle has explanatory power for variables of price and technology.

The variance decomposition function and impulse response function in VAR can provide further information about the relationships between the variable of the industry cycle and the other four variables. A variance decomposition gives information about the proportions of the changes in the industry cycle series that can be attributed to other lagged variables in the VAR. Similarly, an impulse response traces the response of the industry cycle variable to a one-time shock from one of the other variables in the VAR over time.

Since the ordering of the variables is important in the variance decomposition function, we perform the variance decomposition with two orderings and consider the sensitivity of the results, a practice adopted by prior researches (Brooks & Tsolacos, 1999; Mills & Mills, 1991). We decide the first ordering, BC, IC, CA, PR and TC, based on the idea that the exogenous business cycle reinforces industry cycle. According the pinwheel cycle model, the change of sales which is represented by the industry cycle then determines the pace of capacity expansion, which triggers adjustment of the price. Finally the improvement of technology may be either speedy or stagnant depending on the level of the price. The second ordering, viz. BC, TC, IC, CA and PR, differs from the first in that the technology change follows the macro-economic condition and leads the industry cycle. Table 9 and Table 10 report the variance decomposition for the IC variable for 1-10 quarters ahead with the two ordering respectively.

Table 9 Variance decompositions for the IC variable with the first ordering

Period	BC	IC	CA	PR	TC
1	11.52001	88.47999	0.000000	0.000000	0.000000
2	9.296764	90.52828	0.003569	0.144529	0.026862
3	10.01611	85.44625	3.922005	0.352665	0.262973
4	22.07915	60.34118	16.16185	0.282168	1.135653
5	23.99728	48.15895	26.24104	0.341976	1.260757
6	29.37207	39.94030	28.67925	0.797013	1.211364
7	59.49060	22.00205	17.27629	0.486446	0.744604
8	83.88273	8.693405	6.729397	0.400232	0.294232
9	91.23426	4.658301	3.309021	0.643508	0.154906
10	90.29177	6.518313	2.357845	0.699480	0.132593
Cholesky Ordering: BC IC CA PR TC					

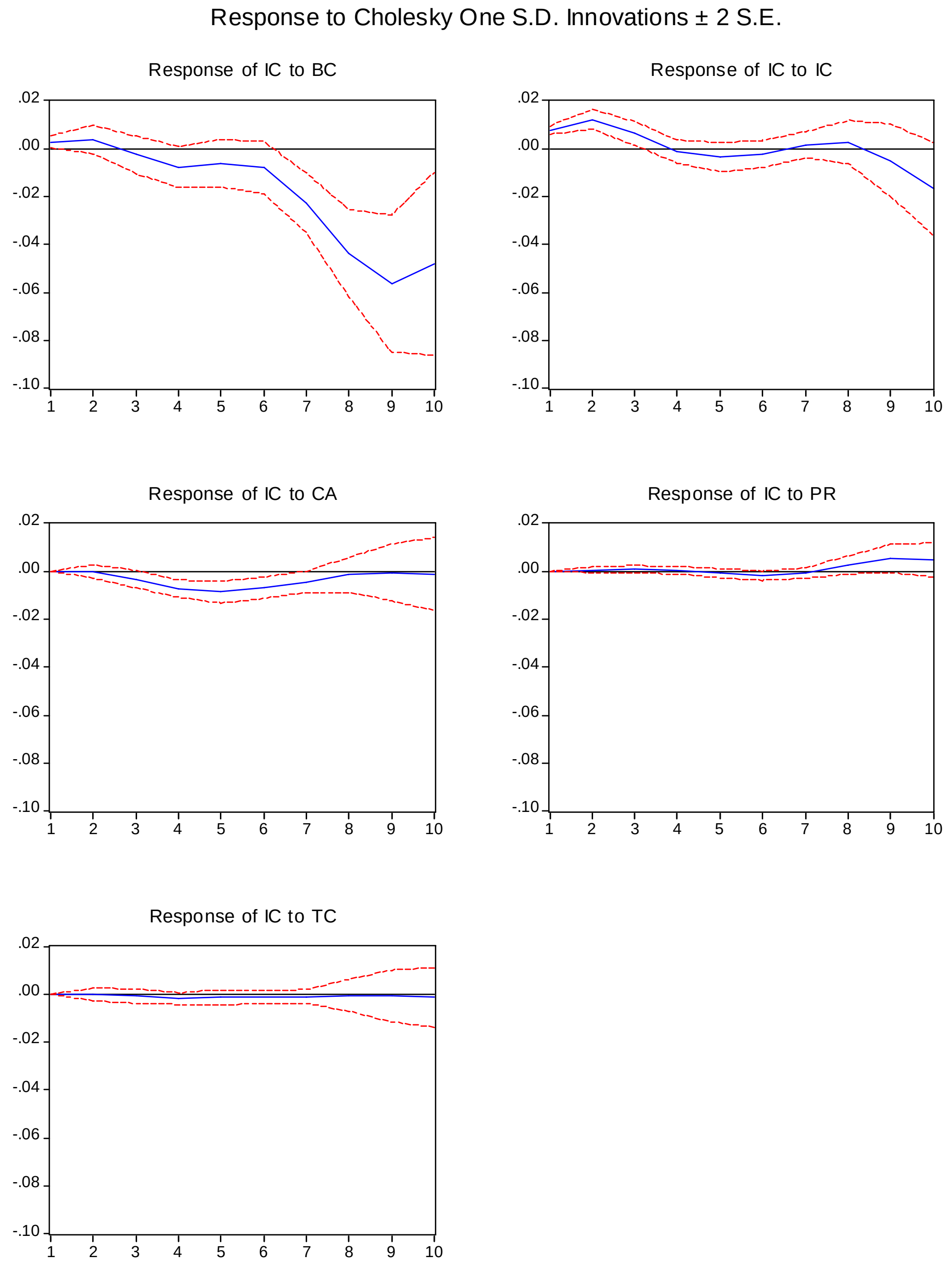
Table 10 Variance decompositions for the IC variable with the first ordering

Period	BC	IC	CA	PR	TC
1	11.52001	88.43285	0.000000	0.000000	0.047135
2	9.296764	90.42305	0.007858	0.143642	0.128686
3	10.01611	85.33309	4.152972	0.348575	0.149257
4	22.07915	60.27102	17.18507	0.276770	0.187990
5	23.99728	48.10093	27.41133	0.341145	0.149319
6	29.37207	39.88998	29.80846	0.800733	0.128762
7	59.49060	21.97337	17.97218	0.489403	0.074443
8	83.88273	8.681400	7.003913	0.400801	0.031153
9	91.23426	4.654872	3.446652	0.642800	0.021411
10	90.29177	6.524922	2.462465	0.697910	0.022934
Cholesky Ordering: BC TC IC CA PR					

Both the results of the analyses with two orderings show that most of the forecast error variances are explained by industry cycle itself during the first several periods. However, the importance of the aggregate economy appears after seven quarters and eventually becomes the major source of the industry cycle. In addition, the variable of the capacity explains approximately 30% of the variance of the industry cycle in the six-quarter ahead forecast.

Finally, the middle curves in Figure 22 trace the impulse response of IC to unit shocks in each of the other five variables in the VAR; and the upper and lower lines indicate two standard error bounds. In line with the result of the variance decomposition, the shock from the BC has most significant impact on the IC after the first several periods. CA only has significant impact on IC during a particular period of time. The response of IC to shock from CA initially increases until approximately 5-period ahead and then die down afterwards. Increasing shock TC and PR have no significant impact on IC during most periods of time.

Figure 22



5. Implications of the research

Identifying industry cycles and exploring their potential drivers brings important implications to both policy and strategic management. One of us has demonstrated that firms' entry behavior can be better understood through the lens of industry cycle in a prior research (Mathews, 2005). With the definitive industry cycle identified and the new evidences regarding the firms' entry, we are thus able to examine the notion more closely.

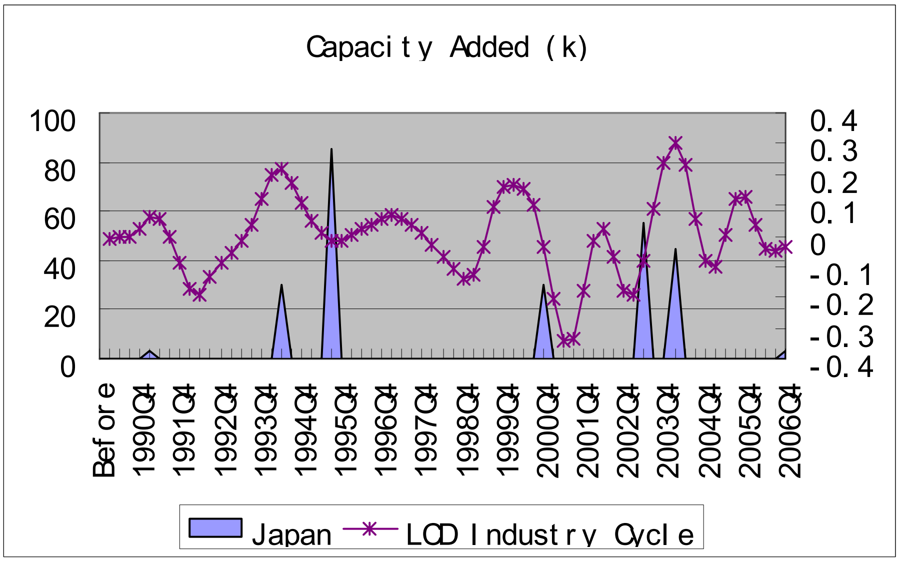
Figures 23-26 show how the major firms entered the FPD industry against the industry cycle by using the historical data of the commencement dates and designed capacity of the production lines of major large-sized TFT-LCD manufacturers [21]. These firms, as listed in Table 11, apparently have all enjoyed significant success since they entered the market.

Table 11 Major TFT-LCD manufacturers by location, 2005

Japan	Korea	Taiwan	US	China
Sharp	Samsung LG Philips Display Sony-Samsung LCD	AU Optronics Chi Mei HannStar Quanta Display Chunghwa	None	Beijing Orient Electronics SVA-NEC

Source: Hart (2007)

Figure 23 Entry of Japanese LCD company



[21] The source of the primary data is http://cn.fpdisplay.com/

Figure 24: Entry of Korean LCD companies

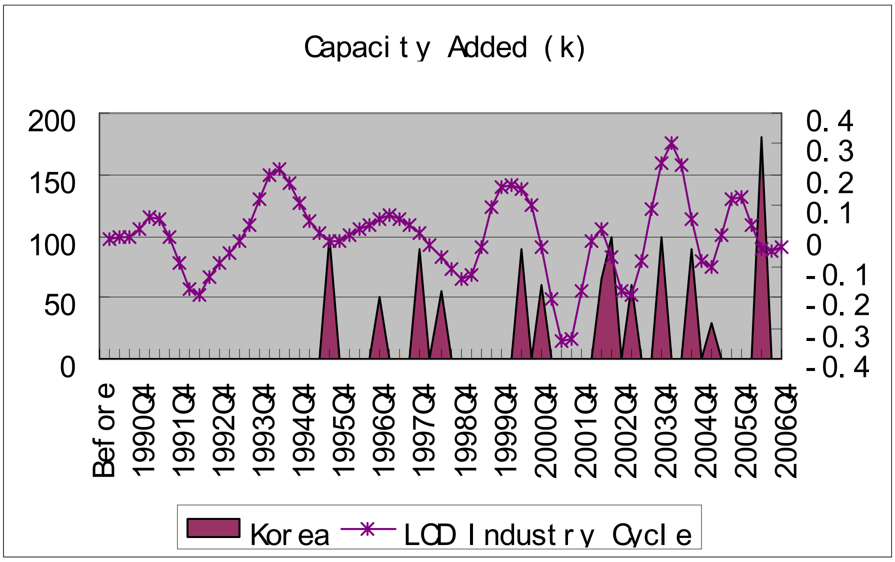


Figure 25: Entry of LCD companies in Taiwan, China

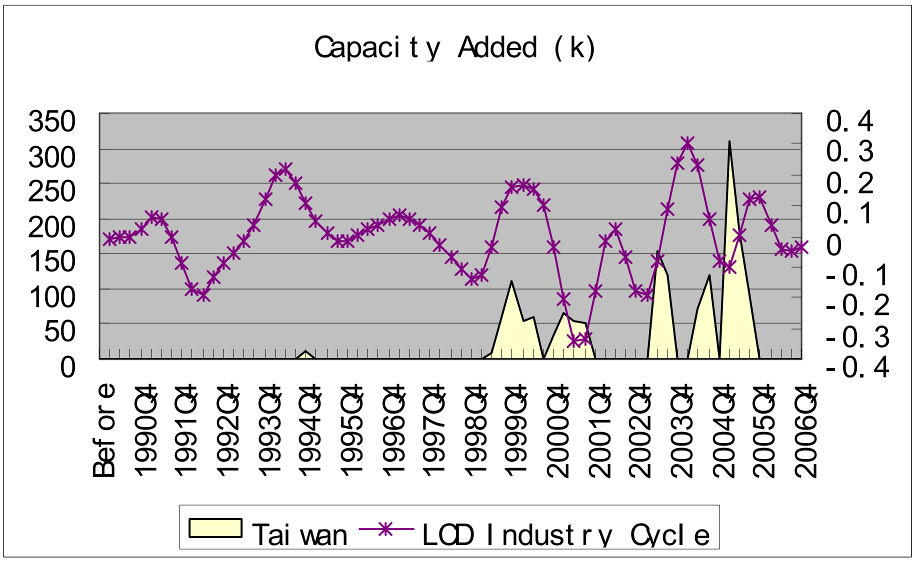
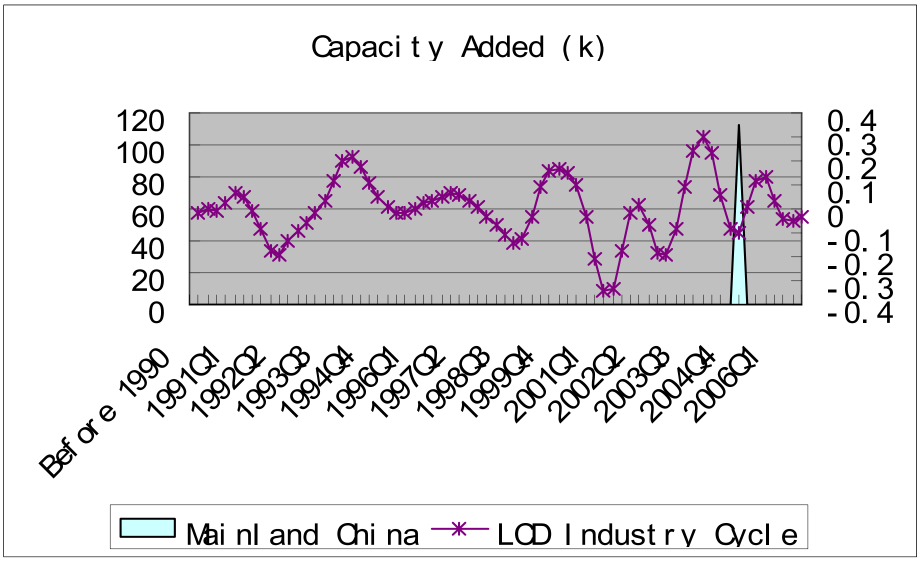


Figure 26: Entry of LCD companies in mainland, China



Although the scale of newly added production capabilities by country varies, a feature shared by the firms is that that the majority of production lines was set up in the downturns of the industry cycle; and was put into production at the troughs, or shortly after the troughs, in the industry cycle. The Japanese firm, notably Sharp, added its large-sized LCD production capacity mainly in the 1994-95 and the 2000 downturns of the industry cycle; and recently in the 2004 downturn. The capacity added by Korean manufacturers has been relatively evenly distributed over time; but as we can detect, the amount of capacity that were added in downturns is much larger than that in upturns. Several periods that witness intensive capacity expansion by the major Korean companies include 1994-95, 1997-98, 2000, 2002 and 2006, all identified as downturn in our FPD industry cycle. By far the Taiwanese firms added most capacity among the companies under study. Again, the timings for the Taiwanese firms to put the production lines into production have been largely around troughs of the cycle, including 2001Q3, 2003Q1 and 2005Q1. Finally, the latest players of the industry, two large-sized LCD manufactures from mainland China, both put into their lines into production at the end of the 2004 downturn.

The entry behavior of the firms is very much in line with that discussed in Mathews (2005). We believe that rather than a coincidence, it is more likely to result from intentional strategizing by these successful firms. Endeavoring to absorbing resources in downturn, these firms thus have been able to put their capacity into the place just before the industry was ready for the next upswing.

Appendix A An alternative approach for calculating properties of the cycles

Two sorts of approaches can be potentially employed for identifying the frequencies and amplitudes of the cycles, under the category of either non-parametric methods or parametric methods (Harding & Pagan, 2005). A non-parametric method relies on a set of preset rules to determine turning points, inspect the durations between the turns and subsequently calculate the average. This method has a long tradition back to the original study on business cycles by Burns and Mitchell, and has been 'standardized' by later NBER researchers Bry & Boschan (1971). Recent applications of the NBER dating algorithm can be found in Layton (1997), King & Plosser (1994) and Binner et al. (2005).

A parametric method however develops statistical models which fit data and estimates the characters of the cycles based on the parameters of the models. For example, any time series consisting of cyclical components can be modeled by adding together sine waves with appropriate frequency, amplitude and phase. The simplest form of periodic data can be taken as follows

$$Xt = \mu + R \cos 2\pi(ft + \varphi) + et \qquad (2)$$

where Xt is the value at time t, ft is the frequency at time t, R is the amplitude and φrepresents the phase, μ represents the origin and scale, and et is the residual at time t.

The Equation (2) may be rewritten to a linear form as follows

$$Xt = \mu + A \cos 2\pi ft + B \sin 2\pi ft + et \qquad (3)$$

where A = Rcos2π$\varphi$and B = - Rsin2πφ

In the so-called Fourier analysis (Bloomfield, 2000), the frequencies of cycles can be first estimated through the 'Fourier transform' which translates data in 'Time Domain' to those in 'Frequency Domain', as illustrated in Figure A1 where the 'peak' at 0.25 and Figure A2 where the 'peak' at 0.1875 can be chosen as the frequencies of the semiconductor industry cycle and the PCs industry cycle respectively [22];

Figure A1

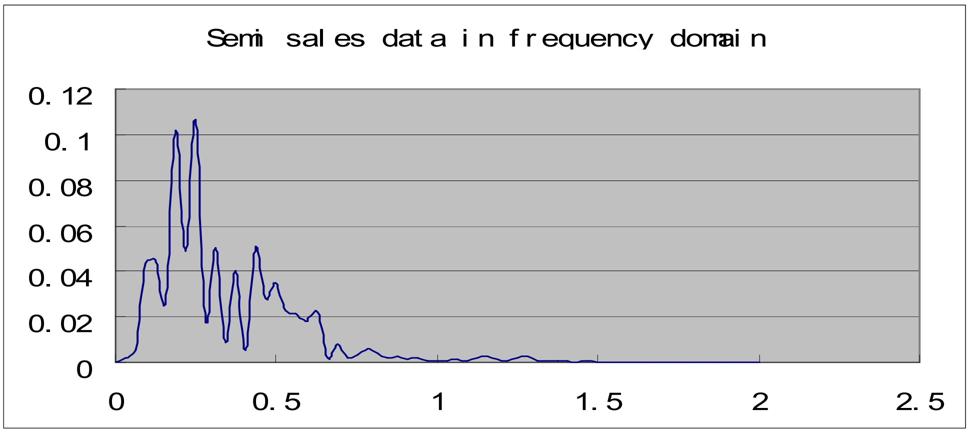
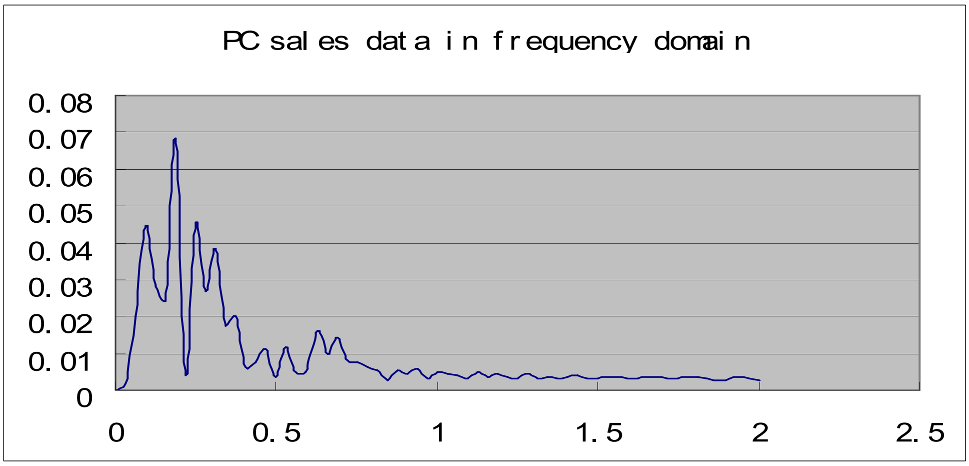


Figure A2



The amplitude R and phase φ can then be estimated given

R = square root (A square + B square) (4)

[22] Following Binner, J. M., Bissoondeeal, R. K., & Mullineux, A. W. 2005. A composite leading indicator of the inflation cycle for the Euro area. ***Applied Economics***, 37: 1257-1266. and Binner, J. M., & Wattam, S. I. 2003. A new composite leading indicator of inflation for the UK: A Kalman filter approach. ***Global Business & Economics Review***, 5(2): 242-264. , we only chose the principal cyclical components for the model. However the models can be modified to include multiple cyclical components.

and

$$\tan 2\pi\varphi = -B/A \tag{5}$$

In comparing between the two methods, we find both have merits and meanwhile drawbacks. We find the cycle properties resulted from the non-parametric method are sensitive with the pre-set rules. However, while the Fourier transformation is ideal for searching for the frequencies, the turning points determined in the model usually move away from those in the reality. Moreover, the models usually underestimate the amplitudes of the cycles because the models do not present real values of the peaks/troughs. The properties of the three industry cycles including average cycle duration and average cycle amplitude result from the Fourier analysis are reported in Table A1.

Table A1 Properties of the industry cycles by using Fourier analysis

Parameters	Semi industry cycle	PCs industry cycle	FPD industry cycle
Average Duration (year)	4	5.33	3.2
Average Amplitude (%)	10.69	9.0	8.63

References

Aizcorbe, A., Oliner, S. D., & Sichel, D. E. 2006. Shifting Trends in Semiconductor Prices and the Pace of Technological Progress, ***Federal Reserve Board Finance and Economics Discussion Series Working Paper***: 1-44.

Anderson, P., & Tushman, M. L. 1990. Technological discontinuities and dominant designs: A cyclical model of technological change. ***Administrative Science Quarterly***, 35: 604-633.

Artis, M. J., Bladen-Hovell, R. C., Osborn, D. R., Smith, G., & Zhang, W. 1995. Predicting turning points in the UK inflation cycle. ***The Economic Journal***, 105(September): 1145-1164.

Ayres, R. U. 1994. Toward a non-linear dynamics of technological progress. ***Journal of Economic Behavior and Organization***, 24: 35-69.

Baldwin, J. R., & Gorecki, P. K. 1994. Concentration and Mobility Statistics in Canada's Manufacturing Sector. ***Journal of Industrial Economics***, 42(1): 93-103.

Baxter, M., & King, R. G. 1999. Measuring business cycles" Approximate band-pass filters for economic seris. ***Review of Economics and Statistics***, 81(4): 575-593.

Binner, J. M., Bissoondeeal, R. K., & Mullineux, A. W. 2005. A composite leading indicator of the inflation cycle for the Euro area. ***Applied Economics***, 37: 1257-1266.

Binner, J. M., & Wattam, S. I. 2003. A new composite leading indicator of inflation for the UK: A Kalman filter approach. ***Global Business & Economics Review***, 5(2): 242-264.

Bloomfield, P. 2000. ***Fourier Analysis of Time Series*** (2nd ed.). New York: John Wiley & Sons.

Brooks, C., & Tsolacos, S. 1999. The impact of economic and financial factors on UK property performance. ***Journal of Property Research***, 16(2): 139-152.

Bry, G., & Boschan, C. 1971. ***Cyclical Analysis of Time Series: Selected Procedures and Computer Programs***. New York: National Bureau of Economic Research.

Canova, F. 1999. Does detrending matter for the determination of the reference cycle and the selection of turning points? ***The Economic Journal***, 109: 126-150.

Cuadrado-Roura, J. R., & V.-Abarca, A. O. 2001. Business Cycle and Service Industries: General Trend and the Spanish Case. ***Service Industries Journal***, 21(1): 103-122.

Dosi, G. 1982. Technological paradigms and technological trajectories. ***Research Policy***, 11: 147-162.

Dosi, G. 1988. Sources, procedures and microeconomic effects of innovation. ***Journal of Economic Literature***, 26(3): 1120-1171.

Dune, T., Roberts, M. J., & Samuelson, L. 1988. Patterns of firm entry and exit in U.S. manufacturing industries. ***Rand Journal of Economics***, 19(4): 495-515.

Economic Data Resources LLC. 2000. The Computer Industry Cycle and Computer Orders in 2000. Colorado, USA: Economic Data Resources LLC.

Forrester, J. W. 1961. ***Industrial Dynamics***. USA: MIT Press.

Furman, J. L., Porter, M. E., & Stern, S. 2002. The determinants of national innovative capacity. ***Research Policy***, 31: 899-933.

Geroski, P. A. 1995. What do we know about entry. ***International Journal of Industrial Organization***, 13: 421-440.

Geroski, P. A., Machin, S., & Walters, C. 1997. Corporate growth and profitability. ***Journal of Industrial Economics***, 45(2): 171-190.

Gort, M., & Klepper, S. 1982. Time paths in the diffusion of product innovations. ***The Economic Journal***, 92(September): 630-653.

Groot, B. d., & Franses, P. H. 2005. Cycles in basic innovations: Econometric Institute Report.

Harding, D., & Pagan, A. 2005. A suggested framework for classifying the modes of cycle research. ***Journal of Applied Econometrics***, 20: 151-159.

Helfat, C. E., & Lieberman, M. B. 2002. The birth of capabilities: Market entry and the importance of pre-history. ***Industrial and Corporate Change***, 11(4): 725-760.

Hodrick, R. J., & Prescott, E. C. 1997. Postwar U.S Business Cycles: An Empirical Investigation. ***Journal of Money, Credit, and Banking***, 29(1): 1-16.

Hu, M.-C., & Mathews, J. A. 2005. National Innovative Capacity in East Asia. ***Research Policy***, 34: 1322-1349.

International Technology Roadmap for Semiconductors. 2001, 2003 and 2005: US

Semiconductor Industry Association and similar associations in Europe Japan Korea and Taiwan, available at www.itrs.net.

Jorgenson, D. W. 2001. Information Technology and the U.S. Economy. ***American Economic Review***, 91(1): 1-32.

King, R. G., & Plosser, C. I. 1994. Real business cycles and the test of the adelmans. ***Journal of Monetary Economics***, 33: 405-438.

Lütkepohl, H. 1991. ***Introduction to Multiple Time Series Analysis***. New York: Springer-Verlag.

Layton, A. P. 1997. A new approach to dating and predicting Australian business cycle phase changes. ***Applied Economics***, 29: 861-868.

Liu, W.-H. 2005. Determinants of the semiconductor industry cycles. ***Journal of Policy Modeling***, 27: 853-866.

Mansfield, E. 1962. Entry, Gibrat's Law, Innovation and the Growth of Firms. ***American Economic Review***, 52(5): 1023-1051.

Martin, R. 2005. Product Management through the Ups and Downs of a Cyclical Industry: Industry Conference Presentation: Asyst Technologies, Inc.

Mathews, J. A. 2005. Strategy and the Crystal Cycle. ***California Management Review***, 47(2): 6-32.

McClean, B. 2001. 2001 IC industry at the crossroads. ***Semiconductor International***, 24(1): 73-75.

Mills, T. C., & Mills, A. G. 1991. The internal transmission of bond market movements. ***Bulletin of Economic Research***, 43(3): 273-281.

Murmann, J. P., & Frenken, K. 2006. Toward a systematic framework for research on dominant designs, technological innovation, and industrial change. ***Research Policy***, 35: 925-952.

Navarro, P. 2005. The well-timed strategy: Managing the business cycle. ***California Management Review***, 48(1): 71-91.

Oliner, S. D., & Sichel, D. E. 2000. The Resurgence of Growth in the Late 1990s: Is Information Technology the Story. ***Journal of Economic Perspective***, 14(4): 3-22.

Petersen, B., & Strongin, S. 1996. Why are some industries more cyclical than others? ***Journal of Business & Economic Statistics***, 14(2): 189-198.

Quantitative Micro Software. 2005. ***EViews 5.1 User's Guide***. CA, USA: Quantitative Micro Software, LLC.

Schumpeter, J. A. 1939. ***Business Cycles: A theoretical, historical and Statistical Analysis of the Capitalist Process***. New York: McGraw-Hill Book Company.

Sims, C. A. 1980. Macroeconomics and reality. ***Econometrica***, 48(1): 1-48.

Stalk, G., Jr. , & Hout, T. M. 1990. ***Competing Against Time***. USA: The Free Press.

Sterman, J. D. 2000. ***Business Dynamics***. Boston: McGraw-Hill.

Stock, J. H., & Watson, M. W. 2001. Vector Autoregression. ***Journal of Economics Perspectives***, 15(4): 101-115.

Suarez, F. F., & Utterback, J. M. 1995. Dominant designs and the survival of firms. ***Strategic Management Journal***, 16(6): 415-430.

Tushman, M. L., & Anderson, P. 1986. Technological discontinuities and organizational environments. ***Administrative Science Quarterly***, 31(3): 439-465.

Utterback, J. M., & Suarez, F. F. 1993. Innovation, competition, and industry structure. ***Research Policy***, 22(1): 1-21.

Young, R. 2006. Flat Panel Display Market Outlook: From Cyclicality to Maturity: Presentation, Displaysearch.

Zarnowitz, V. 1992. ***Business Cycles: Theory, History, Indicators and Forecasting***. Chicago: University of Chicago Press.

Zarnowitz, V., & Ozyildirim, A. 2002. Time series decomposition and measurement of business cycles, trend and growth cycles, ***NBER Working Paper 8736***. Cambridge, MA: National Bureau of Economic Research.