New Product Entry Success: an Examination of Variable, Dimensional and Model Evolution

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DECLARATION

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ABSTRACT

This thesis examines the evolution of antecedents, dimensions and initial screening models which discriminate between new product success and failure. It advances on previous empirical new product success/failure comparative studies by developing a discrete simulation procedure in which participating new product managers supply judgements retrospectively on new product strategies and orientations for two distinct time periods in the new product program: (1) the initial screening stage and (2) a period approximately 1 year after market entry. Unique linear regression functions are derived for each event and offer different, but complimentary, temporally appropriate sets of determining factors. Model predictive accuracy ascends over time and conditional process moderators alter success factors at both time periods. Whilst the work validates and synthesises much from the new product development literature, is exposes probable measurement timing error when single retrospective models assess success dimension rank at the initial screen.

Six of seven hypotheses are accepted and demonstrate that:

1. Many antecedents of success and measures of objective attainment are perceived by NPD (new product development) managers to differ significantly over time.
2. Reactive strategy, NPD multigenerational history and a superior product are the most important dimensions of success through one year post launch.
3. Current linear screening models constructed using retrospective methods produce average prescriptive dimensions which exhibit measurement timing error when used at the initial screen.
4. Success dimensions evolve from somewhat deterministic to more stochastic over time with model forecasting accuracy rising as launch approaches based on better data availability.
5. Product market PiLC (the life expectancy of an introduction before modification is necessary calculated in years and months) and its order of entry and level of innovation alter aggregate success model accuracy and dimension rank.
6. Proper initial dimensional alignment and intra-process realignment based on changing environments is critical to a successful project through one year post launch.

The work cautions practitioners not to wait for better models to be developed but immediately: (1) benchmark reasons for their current product market success, failure and kill historical "batting average"; (2) enhance and/or replace contributing/offending processes and systems based on these history lessons; (3) choose or reject aggregate or conditional success/failure models based on team forecasting ability; (4) concentrate on the selected model's time specific dimensions of success and (5) provide/reserve adequate resources to adapt strategically over time to both internal and external antecedent changes in the NPD environment.

Finally, it recommends new research into temporal, conditional and strategic trade-offs in internal and external antecedents/dimensions of success. Best results should come from using both linear and curvilinear methods to validate more complex yet statistically elegant NPD simulations.

Chapter One - Introduction

1.1 Background

New product development (NPD) is defined as the overall process of strategy, organisation, concept generation, product and marketing plan creation and evaluation, and commercialisation of a new product (Crawford 1994). Booz Allen and Hamilton (1982) suggest that the process carries great risk, with Cooper revealing that 46% of the resources American firms devote to new products are spent on failures or cancellations (Cooper 1985a). Given early documented failure rates of 36.2% (Crawford 1979) and recent anecdotal estimates as high as 80-90% (Semon 1996), an improved understanding of the process is desirable.

Failure rates can be reduced by more proficiently conducting up-front pre-development NPD activities (Cooper and Kleinschmidt 1987b). Benefit measurement screening models such as NewProd (1979b, 1981, 1985, 1992), if used at the initial screen (see Figure 1-1), should help (Cooper 1985a). But despite field scholarship, up-front processes remain ineffective (Cooper and de Brentani 1984) and account for only 7.1% of NPD process expenditures (Cooper and Kleinschmidt 1988). Regrettably, new product success rates have not improved significantly in the last twenty years (Wind and Mahajan 1988).

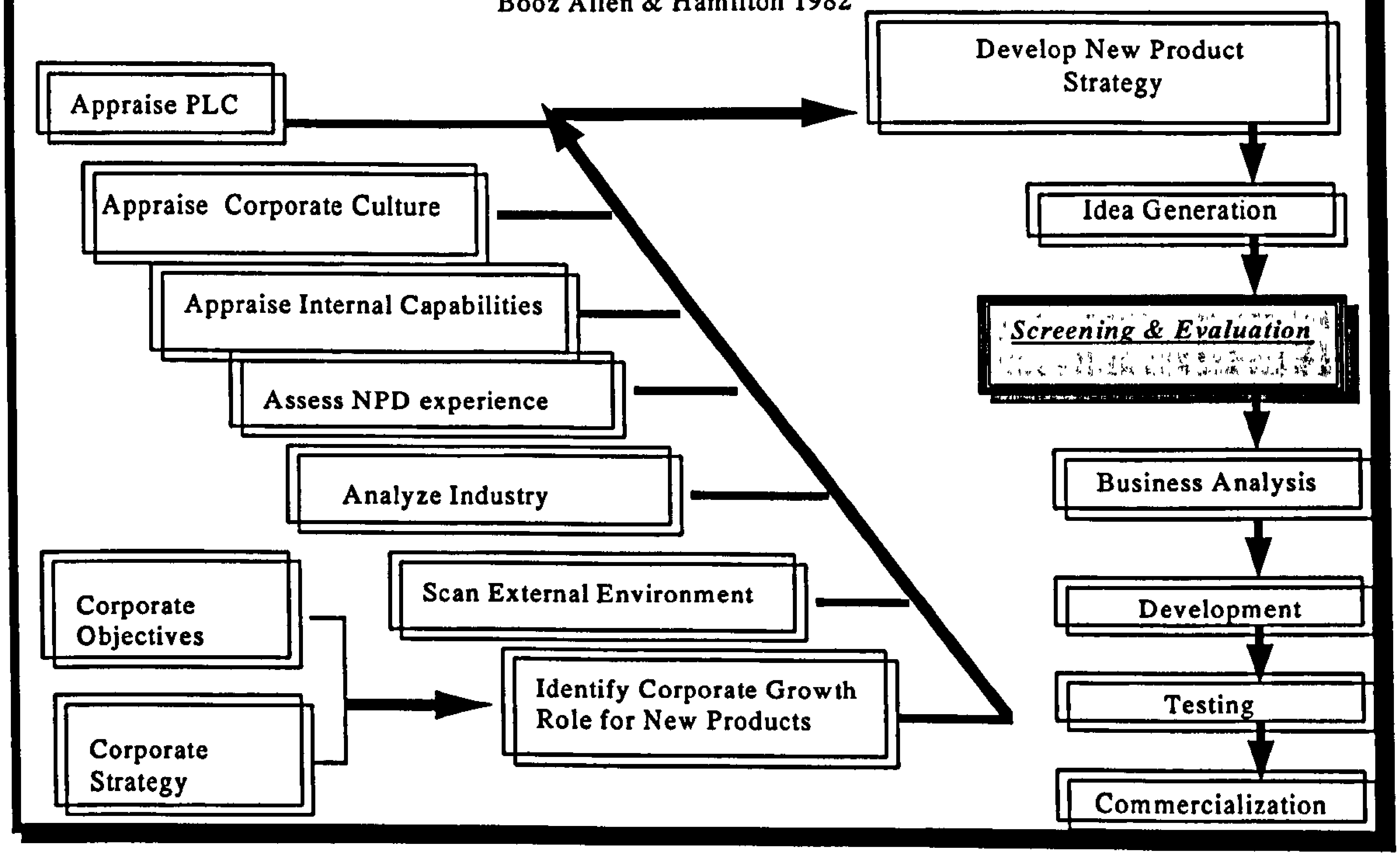
1.1.1 The problem with current screening models

Ideally, screening models should: (1) be a tentative commitment in a sequential process; (2) have a reasonable balance of rejection and acceptance errors; (3) use uncertain information allowing for an absence of financial data; (4) allow multiple objectives and evaluation criteria and (5) be realistic and easy to use. However, this prototype does not exit (Cooper 1985a).

later studies X

The most important efforts to deliver this ideal emanate from the NewProd Project (Cooper 1979b, 1981) and the Stanford Innovation Project (Maidique and Zirger 1984; Zirger and Maidique 1990). Their linear screening models exhibit some differences in methodology, construction, dimension selection and dimension order. But they have notable common dimensions of success to recommend them to practitioners. Unfortunately, despite their claims of 73%-84% and 88% accuracy respectively, NPD up-front activities still go under-funded, weakly performed (Cooper and Kleinschmidt 1987b) and models under-utilised (Cooper and de Brentani 1984; Cooper and Kleinschmidt 1988). The simplest explanation for avoidance of early NPD activities is that it is more direct and quicker to allow an experienced manager to predict the actual NPD outcome straightaway (Insinga 1986). This is credible in an age when the three year interval between the development of a new technology and its obsolescence, as in the 150MHz Pentium Pro chip, has shrunk to three months (PC Week 1995). A more complex explanation involves the inappropriateness of using time invariant deterministic linear optimisation models requiring early, expensive, speculative information to solve what is really a long-term stochastic problem.

Figure 1-1: Strategic Approach to New Product Planning:
Booz Allen & Hamilton 1982



Deterministic designs are inappropriate where time is a critical factor (Burns and Austin 1985). At the initial screen, the only certain project level dimension which will remain unchanged over the life of the process is past NPD product market history. All else is probabilistic and subject to changing environments ranging from stable to volatile (Kotler 1994). Single use deterministic optimisation models such as NewProd and Stanford, whilst acceptable for average prescriptive guidance, are unsuited for dynamic probabilistic environments where both the data available (Albala 1975; Cooper 1985a) and the criteria for success (Hultink and Robben 1995; Ronkainen 1985) are time variant. With NewProd recommending dynamic environment avoidance (Cooper 1979b, 1981), this may be seen by today's practitioner as a severe model limitation.

Evaluating new products is really a system not an act with the evaluation system evolving as the product evolves (Crawford 1986). NewProd and Stanford are not evolving evaluation systems since they do not "gradually develop, especially from a simple to a more complex form"[1]. Rather, both are "monomorphic" and "do not change form during development"[2]. This static character prevents them from properly representing the internal and external antecedent change which occurs naturally (Albala 1975).

Practitioners in today's dynamic environments may understand implicitly, the incongruity of using the same model in different environments (Albala 1975) and for changing sets of go/no-go/continue criteria (Hart 1993; Hultink and Robben 1995; Ronkainen 1985). Their under-utilisation may be the manifestation of what has been noted by scholars, that models: (1) fail to account for internal and external efforts; (2) lack interdisciplinary perspective; (3) are inflexible; (4) fail to reduce development time; (5) perform poorly under dynamic market conditions; (6) lack sufficient accuracy (Wind and Mahajan 1988); (7) have suspect construct validity and temporal stability (Montoya-Weiss and Calantone 1994) and (8) suffer from survivor bias (Kerin, Varadarajan and Peterson 1992; Mitchell 1991).

1.1.2 One solution

Deterministic models optimising one linear objective function are appropriate only if variables remain constant over time (Burns and Austin 1985). NewProd and Stanford are typical of such models. They offer a single static prescription to solve multiple, dynamic problems. A multiple model (Albala 1975) system (Crawford 1986) employing discrete simulation is one possible solution. This technique would be quite conservative in its use of seminal methods for individual model construction. Yet it would still be consistent with proposals for new 3rd generation fluid, fuzzy, focused and flexible model characteristics (Cooper 1994b).

Multiple mini models make more sense than one big test (Crawford 1986) and better represent the *go⇒no-go⇒continue* NPD decision. As the building blocks of a simulation, smaller, time sensitive conditional models would move the decision and project along faster. Those meeting *fuzzy* initial screening conditions would be given a *conditional go* to speed up the process subject to tasks being completed and environmental antecedents being favourable at specified times in the future (Cooper 1994b). Each would still represent tentative commitments in a sequential process

[1] The concise Oxford Dictionary (1990).
[2] Ibid.

(Cooper 1985a). But unlike NewProd or Stanford, their temporal, conditional nature would optimise early versus late information requirements since they would be constructed from temporally appropriate dimensions. As such they would be more realistic, easier to use and have a lower expected cost of information. Because each would evolve over time with the product, they would accept the initial screen for what Crawford suggests it is - an estimate of what will be possible later in a changing environment with the advantage then of information yet to surface (Crawford 1986). Furthermore, a system of models would provide the option to change the plan and simulate a new result along the way whilst allowing multiple performance criteria (Ronkainen 1985) thought important to proper dimensional assessment (Cooper and Kleinschmidt 1987a; Hart 1993; Hultink and Robben 1995).

A continuous simulation solution replicating internal and external system dynamics at infinite points in time would permit the most robust response to static model criticisms. However, before a system requiring sets of differential equations could be deemed appropriate, a simpler discrete simulation using traditional model construction methods should demonstrate significant change over time. This conservative procedure would extend seminal methods incrementally. Yet it would measure dynamic change over time as requested (Wind and Mahajan 1988).

Successful demonstration of a discrete simulation technique capturing model and dimensional variation over time is important to field advancement because it would:

1. support Albala's (1975) contention that single deterministic models used early, lead to eventual contradiction. This would give impetus to empirical tests of more complex NPD CPM/PERT network paradigms (Grossman and Gupta 1974; Hart and Baker 1994; Lilien and Kotler 1983; Urban and Hauser 1980; Wasson 1978).
2. deliver on requests to demonstrate dimensional temporal stability and improved construct validity (Montoya-Weiss and Calantone 1994) by minimising problems associated with perceived measurement timing error (Cooper 1992; Crawford 1979) and survivor bias (Kerin, Varadarajan and Peterson 1992; Mitchell 1991).
3. make models more relative (Lilien 1975) by integrating and relating requested heterogeneous inter-disciplinary antecedents (Wind and Mahajan 1988) with more homogeneous established factors of success.
4. support Cooper's (1994b) proposal for 3rd generation "fuzzy gate" schemes by demonstrating model situational and conditional differences vis-à-vis product life cycle (PLC), order of entry and level of innovation.
5. shed light on deterministic versus stochastic NPD model development issues by investigating the importance to success of past product market NPD history versus future strategic activity.

Better understanding, requested synthesis (Montoya-Weiss and Calantone 1994) and accelerated product development, key to a new product's success (Cooper 1995), may result. Higher model utilisation and rising success rates might also.

1.2 Objectives

This research responds to scholarly criticism and practitioner under-utilisation of current initial screening models. It attempts to demonstrate that better models are possible in consideration of temporal, strategic and conditional process phenomena. A more refined understanding of NPD models and dynamic processes is sought by examining perceived antecedent, factor and linear regression model differences over time. Important new knowledge should result from accomplishing the following research objectives:

1. use well accepted, conservative seminal methods to simulate the beginning and end of the NPD process by benchmarking perceived variables, factors and linear regression success models at the initial screen and one year post launch.
2. evaluate seminal model temporal and construct validity at these extreme points, concurrent with the reduction of perceived measurement timing error and survivor bias.
3. determine the relationship of heterogeneous inter-disciplinary antecedents on previously demonstrated homogeneous dimensions of success.
4. appraise the moderating influence of product life cycle and order of entry/level of innovation on aggregate models.
5. investigate deterministic influences of past product market NPD history as it relates to the stochastic influences of reactive strategic alignment.

Accomplishing these objectives should enrich academic understanding of NPD model and process dynamics, whilst providing a more realistic foundation for NPD decision making under changing conditions.

1.3 Research rationale

Early assessment of the dimensions of success and outcome prediction based on dimension achievement is axiomatic to accomplishing NPD objectives (Booz, Allen and Hamilton 1982). Despite calls for better understanding (Cooper 1975; Crawford 1977; Hatch 1957, Hopkins and Bailey 1971; Mahajan and Wind 1992; Montoya-Weiss and Calantone 1994; NICB 1964; Wind and Mahajan 1988) the NPD process remains speculative (Cooper and Kleinschmidt 1987b, 1990) and the initial screen the most poorly performed NPD activity (Cooper and Kleinschmidt 1986). Research into initial screening model improvement and better early process understanding is both important and timely.

Though models exemplified by NewProd (Cooper 1979b, 1981) and Stanford (Maidique and Zirger 1984, Zirger and Maidique 1990) are reasonably accurate, they recommend sweeping, prescriptive, temporally insensitive success factors. Validity and reliability challenges by scholars (Mahajan and Wind 1992; Montoya-Weiss and Calantone 1994) parallel practitioner requests for improvement in model accuracy, length of implementation time and the ability to capture market complexity (Wind and Mahajan 1988; Mahajan and Wind 1992). Established findings lack inter-disciplinary data integration (Wind and Mahajan 1988), field research efforts are disjointed and success factor relative importance inconclusive (Montoya-Weiss and Calantone 1994).

Clearly, no model meets all requirements (Calantone, Vickery and Droge 1995; Cooper 1985a, 1994b; O'Connor 1994) - and this work does not pretend to do so. However, this work is important because:

1. simulation may better represent the NPD process than the current static approach. Empirical justification of the technique as a valid representation of NPD dynamic phenomena should be pursued.
2. the temporal stability of established success dimensions has been challenged. Finding established dimensions of success as more appropriate to early or later activities would validate and synthesise their temporal order and importance in the process.
3. the consequences of requested heterogeneous inter-disciplinary data integration on established homogeneous models needs to be studied.
4. the effects of conditional phenomena such as PLC and order of entry on initial screening model validity and accuracy needs investigation. Better understanding could lead to probabilistic "fuzzy" cycle shortening procedures.
5. the balance between deterministic consequence of past product market NPD history and the probabilistic effects of strategic reactive alignment has not been examined. Exploratory research to determine the effect of feedback, learning and realignment on NPD success is appropriate.

1.3.1 Discrete simulation methods

Current models exemplified by NewProd and Stanford fail to adequately account for post screening dynamics and market complexities (Mahajan and Wind 1992). Their limited acceptance (de Brentani 1983, 1986) may be due to their simple, deterministic approach. They are static, only maximise simple linear predictive functions and yield inflexible "what's best" solutions for probabilistic "what if" environments. Though still valuable, these methods need to be extended to meet today's dynamic requirements.

Using seminal methods to construct a simulation at two discrete points in time is conservative, extends field methods incrementally, captures perceived internal and external process change over time and makes sense. The approach delivers empirical support to long recommended NPD CPM/PERT network paradigms (Grossman and Gupta 1974; Hart and Baker 1994; Lilien and Kotler 1983; Urban and Hauser 1980; Wasson 1978) practised in the field today as 2nd generation stage-gate (Cooper 1990a; Cooper and Kleinschmidt 1991) systems. Demonstrating a simple discrete simulation solution using traditional linear regression methods would establish baseline beginning and ending NPD process norms. It is through benchmarking and analyses of these that process improvement emanates (Griffin 1993) and by which concurrent/parallel processing efforts to reduce "slack[3]" (Meredith 1992) and NPD cycle time (Cooper 1994b, 1995) should be measured.

1.3.2 Temporal validation

The validity and reliability of NPD models has been challenged (Mahajan and Wind 1992). This has been followed by calls for established antecedents and dimensions of success to be tested for temporal stability (Montoya-Weiss and Calantone 1994) and difference as a function of changing performance measurement criteria (Hart 1993; Hultink and Robben 1995). Because it is at the initial screen that most projects are killed (Cooper 1981; McGuire 1973), differences in the quality, availability and cost of early versus late information is critical. If information differs significantly over time, then models constructed from that information should also differ (Hultink and Robben 1995) along with the model's expected value to the team.

Uncertainty and mistakes at the initial screen stem from the fact that little reliable information is available regarding the proposed product's market, costs and investment required (Cooper and de Brentani 1984; Cooper and Kleinschmidt 1987b, 1990). NewProd claims to capture early antecedents of success using long term retrospective cross-sectional techniques. However, measurement of early perception many years after launch is problematic since it can be affected by memory loss, subjective interpretation by operational function, survivour/post hoc bias towards early successful products and failure to account for "kill" characteristics and/or early failures (Cooper 1992; Crawford 1979; Kerin, Varadarajan and Peterson 1992; Mitchell 1991).

[3] the delay in activities off the critical path (Meredith 1992).

Static methods as used by NewProd only produce one prescriptive model based on average dimensions measured imprecisely after launch. Even worse, these then are not recommended for use in dynamic markets (Cooper 1979b, 1981). Rather than one static model, multiple time specific models are more realistic because they could use information apropos to dynamic environments, circumstances (Albala 1975; Crawford 1986), development criteria (Ronkainen 1985) and long versus short term performance criteria (Hultink and Robben 1995). Components of success can vary dramatically by time (Hultink and Robben 1995) and based on different performance criteria such as "financial" versus "market impact" (Cooper and Kleinschmidt 1987a). Work which does not recognise temporal change in the way one measures new product success may produce dimensions of limited value (Hultink and Robben 1995). This work attempts to correct for measurement timing error caused by imprecise performance benchmark dates and survivour bias inherent in seminal models. The result should be a refinement of the sweeping, average dimensions they endorse.

1.3.3 Inter-disciplinary evaluation

Re-examination of the NewProd and Stanford homogeneous findings, in light of heterogeneous integrated antecedents from adjunct fields, satisfies requests for better inter-disciplinary perspective (Wind and Mahajan 1988). NewProd validations suffer from limited size, different country contexts and changing data sets (Cooper 1992). Stanford (Zirger and Maidique 1990) has received no published external validation.

The four most frequently utilised factors, proficiency of technological activities, proficiency of market-related activities, product advantage and protocol, not surprisingly, are typically identified as the primary discriminators between success and failure (Montoya-Weiss and Calantone 1994). This work validates these as they relate to others thought under-represented (the environment, financial/business factors, strategy, speed to market and company resources) and to some which have not had statistics reported consistently (market competitiveness and market potential; Montoya-Weiss and Calantone 1994). Though models containing these "extra dimensions" may not be the most parsimonious or internally consistent, they may relate better to other branches of the literature, actual management practices and practitioner beliefs (Lilien 1975). Furthermore, this work hopes to broaden the discussion beyond the important, but now repetitive conclusion, that successful firms must develop a "superior product" based on "technical knowledge and skills" and "market it aggressively" to "target customer wants and needs" (Montoya-Weiss and

Calantone 1994). This should encourage NPD research by scholars in adjunct fields and higher model use by practitioners.

1.3.4 Conditions moderating success dimensions

Cooper (1979b, 1980b, 1981) and Cooper and Kleinschmidt (1993) generally relegate external conditions to a moderating status without investigating their ultimate impact. However, because all new products are not the same (Hultink and Robben 1995; Cooper and Kleinschmidt 1991) or even measured using the same criteria (Cooper and Kleinschmidt 1987a; Hart 1993; Hultink and Robben 1995; Maidique and Zirger 1985), there may be no simple set of success/failure factors that govern NPD outcome. Rather, sets of conditions (Rubenstein, Chakrabarti, O'Keefe, Soulder and Young 1976) such as PLC, order of entry and innovativeness may moderate (Cooper 1979b, 1981; Kleinschmidt and Cooper 1991, 1993) final outcome. Seminal NPD model development work diminishing the importance of the product life cycle (Buzzell 1966, Catry and Chevalier 1974; Cox 1967; Doyle 1976; Kotler 1994; Luck 1972; Michael 1977; Polli and Cook 1969, Rink and Swan 1979; Staudt et al. 1976; Tellis and Crawford 1981), order of entry (Ansoff and Stewart 1967; Booz, Allen and Hamilton 1982; Hopkins and Bailey 1971; Lambkin 1988; Lilien and Yoon 1990; Robinson and Fornell 1985; Robinson, Fornell and Sullivan 1992; Urban, Carter, Gaskin and Mucha 1986) and the level of product innovativeness (Booz, Allen and Hamilton 1982; Kleinschmidt and Cooper 1991) is illogical. Furthermore, if PLC, order of entry and level of innovativeness are important concepts to practitioners, their absence from initial screening models may contribute to under-utilisation (Lilien 1975). A more precise operationalisation of select moderating conditions of success, in conjunction with normal NPD timing constraints, is needed to determine their true potential in conditional "fuzzy gate" cycle shortening schemes for new 3rd generation processes (Cooper 1994b).

1.3.5 History versus strategy

Strategic planning based on historical experience (Boston Consulting Group 1972; Booz, Allen and Hamilton 1982) and environmental alignment/realignment is important to success (Abell and Hammond 1979; Ansoff 1965; Ansoff and Stewart 1967; Booz, Allen and Hamilton 1982; Calantone and di Benedetto 1988; Hopkins and Bailey 1971; Lambkin and Day 1989; Mahajan and Wind 1992; Maidique and Zirger 1984; Porter 1980, 1985; Thorelli and Burnett 1981; Wind and Mahajan 1988). The process is a fundamentally dynamic one, proceeding as a form of learning (Mintzberg 1994; Slater and Narver 1995). Current models fail to measure the impact of the team's ability to react strategically over time based on newly learned information and application of resources.

Multiple model simulation featuring dimensional evolutionary feedback would allow initial strategy based on history to be compared with new intra-process learning based on reality. Demonstrating a real time intra-process strategic alignment system incorporating the history⇒learning⇒alignment⇒realignment relationship would allow the analyses of the worth of deterministic versus stochastic methods.

1.4 Hypotheses

Hypotheses in the alternate form have been developed and tested subsequently. They are designed to explore the differences between perceived antecedents and dimensions of success at both the initial screen (T_0) and one year post launch (T_1). The first set of hypotheses, H_1a through H_1d, pertain to the differences managers perceive over time in: (1) individual antecedent variables (H_1a); (2) normalised factors constructed from these variables (H_1b); (3) factors significant to success (H_1c) and (4) the predictive accuracy of the linear models constructed (H_1d). In all cases, accepting the null form of the hypotheses indicates no statistically significant difference is perceived over time in variables, normalised factors, significant factors and/or accuracy. The alternate form of each follows:

1.4.1 Hypothesis H_1a: Antecedent evolution

Many variables relating to a new product's success are dynamic and perceived to evolve over the life of the NPD process.

1.4.2 Hypothesis H_1b: Normalised factor evolution

The factors constructed from screening variables are dynamic with respect to their construction, percent of variance, order and magnitude. They evolve over time from the initial screen to the end of the first year of market entry.

1.4.3 Hypothesis H_1c: Linear regression model evolution

Factors significant to a new product's successful introduction are dynamic. As more information becomes known to the team over time, these significant factors evolve from an inadequate, incomplete, uncertain condition at the initial screen, to a more adequate, more complete, more certain condition at the end of the first year of market entry. They change in their order and magnitude.

1.4.4 Hypothesis H_1d: Forecasting accuracy evolution

As the factors contributing to a new product's success evolve, the resulting new product screening model's predictive proficiency evolves also.

The second set of hypotheses examines the differences in model construction at each time period as the aggregate model and success dimensions are affected by product life cycle (H_2), order of entry/innovation level (H_3) and strategic reactive capability

(H_4). Accepting the null form of H_2 and H_3 would indicate no difference is observed in success dimensions by PiLC and order/innovation. Accepting the null form of H_4 indicates that there is no difference in success/failure outcome by virtue of ability to adjust strategically. The alternate form of each follows:

1.4.5 Hypothesis H_2: P_iLC conditions

Factors significant in contributing to a new product's successful introduction vary as a function of the length of the product's introductory life cycle (PiLC) - the life expectancy of the product before modification is necessary.

1.4.6 Hypothesis H_3: Order/innovation conditions

Factors significant in contributing to a new product's successful introduction vary as a function of its order of entry and relative level of innovativeness.

1.4.7 Hypothesis H_4: Strategy as dynamic link

Firms which develop precise initial strategies but react flexibly to deal with deficiencies in early assumptions of internal and external environments, are more successful than those that do not.

1.5 Conclusion

Current initial screening models exemplified by NewProd and Stanford are adequate for describing an unchanging, average new product development process and predicting an idea's ultimate success. However, because they are born of single, long term retrospective methods they fail to describe adequately, true initial screening dimensions and the dynamic NPD post screening strategic activity leading to short term success or failure. Because of their inability to reflect these phenomena, NewProd actually recommends avoiding projects targeted at dynamic markets (Cooper 1979b, 1981). Inability to recommend and guide participation in dynamic opportunities is a severe limitation as shorter PLCs become more common. This dates current models as primitive and may be a reason for their limited appeal.

This Thesis assesses dynamic intra-process phenomena by measuring the perceived temporal stability of antecedents, dimensions and models over time when: (1) heterogeneous but important interdisciplinary variables are integrated with established data sets; (2) precise beginning and ending variable recollection dates are used in lieu of imprecise long-term averages; (3) models are constrained by the moderating influences of product life cycle, order of entry and level of innovation and (4) team learning and strategic reaction align internal and external environments over time. This assessment is important because if variables, dimensions and models are perceived to change over time and by moderating condition, then applying deterministic model dimensions in stochastic environments is inappropriate. If significant evolutionary, conditional and strategic influence is demonstrated, managers would be more confident in their use of resulting dynamic initial screening and post screening models alternatives.

1.6 Chapter outline

Chapter two presents a review of the scholarly literature relevant to the development of each hypothesis. Justification is made for old and new variables and dimensions to be examined. The grounds for choosing selected seminal works, as the basis of comparison to this work, is presented also. Chapter three employs Churchill's (1991) six step sequence as a foundation for the research design and describes the procedures used to examine all hypotheses. Survey logistics and statistical procedures to test the null hypotheses are described in detail. Chapter four describes the findings from testing H_1a through H_1d and their relationship to seminal work. The same is true for Chapter five, with explanations of the findings for H_2, H_3 and H_4. Finally, Chapter six summarises all findings and draws conclusions germane to scholars and practitioners. It suggests weaknesses of this work, whilst making recommendations for correction. Finally, it envisions a combination of linear and curvilinear methods, used within a PERT framework, to advance field knowledge of the dynamic NPD process.

Chapter Two - Literature review and hypotheses development

2.1 Introduction

Chapter two reviews the NPD literature drawing attention to success/failure factors governing the NPD process. Works resulting in linear success/failure forecasting models are featured. These are the best basis of comparison to this work because they are comprehensive, incorporate much of earlier findings and forecast success based on the application of recommended third and fourth level methods of dimensionality and interpretation (Montoya-Weiss and Calantone 1994). Seven hypotheses were developed based on gaps apparent in that linear forecasting branch of the literature. In addition to validating previous work, they posit the evolutionary (hypotheses H_1a through H_1d), conditional (hypotheses H_2, H_3) and strategic nature (hypotheses H_4) of established and new to the field variables, dimensions and linear models.

2.2 Factors associated with NPD success

There is considerable qualitative and quantitative research on conducive environments and factors driving new product performance. Booz, Allen and Hamilton (1982) suggest that the companies utilising specific "best practices" are most likely to succeed in developing new products. These best practices have multi-disciplinary, multi-functional roots (Cooper 1976) requiring an eclectic analysis and articulation.

Montoya-Weiss and Calantone (1994) recently attempted to bring syntheses to the field by applying meta-analysis techniques (see Wolf 1986; APPENDIX B) to works which: (1) studied a dependent variable measuring the performance of a new product project or programme and (2) identified one or more explanatory factors as determinants of new product performance (see Table 2-1). Cardinal to this effort were the works of Cooper and Kleinschmidt (1987b), Maidique and Zirger (1984), Rothwell, Freeman, Jervis, Robertson and Townsend (1974) and Utterback, Allen, Hollomon and Sirbu (1976). Eighteen drivers of performance classified as strategic, development process, marketing environment and organisational were found to dominate the literature. These came from the fields of marketing, organisational behaviour, engineering and operations management.

Table 2-1: Multi-disciplinary literature associated with new product performance[4]

Reference	*Scope*	*Success/ Failure*	*Function*
1. Balachandra, R. Critical signs for making go/no go decisions in new product development. *Journal of Product Innovation Management* 2(2):92-100 (1948).	Project	Success Failure	R&D, Mgmt.
2. Brockhoff, Klaus and Chakrabarti, Alok K. R&D/Marketing linkage and innovation strategy: some West German experience. *IEEE Transactions on Engineering Management* EM-35(3):167-174 (1988).	Programme	Success Failure	Mkt. R&D
3. Bronnenberg, J.J.A.M. and van Engelen, M.L. A Dutch test with the NewProd model. *R&D Management* 18(4):321-332 (1988).	Project	Success Failure	Varied
4. Calantone, Roger J. and Cooper, Robert G. A discriminant model for identifying scenarios of industrial new product failure *Journal of the Academy of Marketing Science* 7(3):163-183 (1979).	Project	Failure	
5. Calantone, Roger J. and di Benedetto, C. Anthony. An integrative model of the new product development process: an empirical validation. *Journal of Product Innovation Management* 5(3):201-215 (1988).	Project	Success Failure	Mgmt.
6. Calantone, Roger J. and di Benedetto, C. Anthony. Canonical correlation analysis of unobserved relationships in the new product process. *R&D Management* 20(1):3-23 (1990).	Project	Success Failure	
11. Cooper, Robert G. Why new industrial products fail. *Industrial Marketing Management* 4(6):315-326 (1975).	Project	Failure	
12. Cooper, Robert G. Identifying new product success: Project NewProd. *Industrial Marketing Management* 8(2):124-135 (1979).	Project	Success Failure	Varied
13. Cooper, Robert G. The dimensions of industrial new product success and failure. *Journal of Marketing* 43(3):93-103 (1979).	Project	Success Failure	Varied
14. Cooper, Robert G. How to identify potential new product winners. *Research Management* 23:10-19 (1980).	Project	Success Failure	Varied
15. Cooper, Robert G. Project NewProd: factors in new product success. *European Journal of Marketing* 14(5/6):277-291 (1980).	Project	Success Failure	Varied
16. Cooper, Robert G. New product success in industrial firms. *Industrial Marketing Management* 11(3):215-223 (1982).	Project	Success Failure	Varied
17. Cooper, Robert G. New product strategies: what distinguishes the top performers? *Journal of Product Innovation Management* 2(3):151-164 (1985).	Project	Success	Mgmt.
18. Cooper, Robert G. How new product strategies impact on performance. *Journal of Product Innovation Management* 1(1):5-18 (1984).	Project	Success	Mgmt.
19. Cooper, Robert G. Predevelopment activities determine new product success. *Industrial Marketing Management* 17(3):237-247 (1988).	Project	Success Failure	Mgmt.
20. Cooper, Robert G. New products: what distinguishes the winners? *Research & Technology Management* 33(6):27-31 (1990).	Project	Success Failure	Mgmt.
21. Cooper, Robert G. and Kleinschmidt, Elko J. An investigation into the new product process: steps, deficiencies and impact. *Journal of Product Innovation Management* 3(2):71-85 (1986).	Project	Success Failure	Varied
22. Cooper, Robert G. and Kleinschmidt, Elko J. New products: what separates winners from losers. *Journal of Product Innovation Management* 4(3):169-184 (1987).	Project	Success Failure	Mgmt.
23. Cooper, Robert G. and Kleinschmidt, Elko J. Success factors in product innovation. *Industrial Marketing Management* 16(3);215-223 (1987).	Project	Success Failure	Mgmt.
24. Cooper, Robert G. and de Brentani, Ulrike. New industrial financial services: what distinguishes the winners. *Journal of Product Innovation Management* 8(1):75-90 (1991).	Project	Success Failure	Mgmt.
26. De Brentani, Ulrike and Droge, Cornelia. Determinants of the new product screening decision. A structural model analysis. *International Journal of Research in Marketing* 5(2):91-106 (1988).	Project	Success Failure	Mgmt.
27. Dillon, William R., Calantone, Roger and Worthing, Parker. The new product problem: an approach for investigating product failures. *Management Science* 25(12):1184-1196 (1979).	Project	Success Failure	Mgmt.
29. Dwyer, Larry and Mellor, Robert. Organisational environment, new product process activities and project outcomes. *Journal of Product Innovation Management* 8(1):39-48 (1991).	Project	Success Failure	R&D, Mkt.
30. Dwyer, Larry and Mellor, Robert. New product process activities and project outcomes. *R&D Management* 21(1):31-42 (1991).	Project	Success Failure	Mgmt.
31. Edgett, Scott, Shipley, David and Forbes, Giles. Japanese and British companies compared: contributing factors to success and failure in NPD. *Journal of Product Innovation Management* 9(1):3-10 (1992).	Programme 5 yrs.	Success Failure	
32. Edgett, Scott, Shipley, David and Forbes, Giles. Japanese and British Companies Compared: Contributing Factors to Success and Failure in NPD. In:	Programme 5 yrs.	Success Failure	

[4] Montoya-Weiss and Calantone (1994).

1990 PDMA Proceedings (1990).			
34. Germunden, H.G., Heydebreck, P. and Herden, R. Technological interweavement: a means of achieving innovation success. *R&D Management* 22(4):359-3766 (1992).	Programme	Success Failure	
35. Gerrstenfeld, Arthur. A study of successful projects, unsuccessful projects and projects in process in West Germany. *IEEE Transactions on Engineering Management* EM-23(3):116-123 (1976).	Project	Success Failure	R&D
38. Hise, Richard T., O'Neal, Larry, Parasuraman, A. and McNeal, James U. Marketing/R&D interaction in new product development: implications for new product success rates. *Journal of Product Innovation Management* 7(3):142-144 (1990).	Project	Success Failure	Mkt.
39. Hopkins, David S. New-Product winners and losers. *Research Management* 24(3):12-17 (1981).	Programme	Success Failure	
41. Johne, Frederick A. How experienced product innovators organise. *Journal of Product Innovation Management* 4(4):210-223 (1984).	Project & Programme	Success Failure	Varied
43. Kleinschmidt. E.J. and Cooper, R.G. The impact of product innovativeness on performance. *Journal of Product Innovation Management* 8(4):240-251 (1991).	Project	Success Failure	Mgmt.
45. Larson, Erik W. and Gobeli, David H. Organising for product development projects. *Journal of Product Innovation Management* 5(4):180-190 (1988).	Project	Success	Varied
46. Lilien, G.L. and Yoon, Eunsang. Determinants of new industrial product performance: a strategic re-examination of the empirical literature. *IEEE Transactions on Engineering Management* EM- 36(1):3-10 (1989).	Project	Success	Mgmt.
47. Maidique, Modesto A. and Zirger, Billie Jo. A study of success and failure in product innovation: the case of the US electronics industry. *IEEE Transactions on Engineering Management* EM-31(4):192-203 (1984).	Project	Success Failure	Varied
48. Pinto, Jeffrey K. and Slevin, Dennis P. Critical factors in successful project implementation. *IEEE Transactions on Engineering Management* EM-34(1):22-27 (1987).	Project	Success	Students
49. Pinto, Mary Beth and Pinto, Jeffrey K. Project team communication and cross-functional co-operation in new programme development. *Journal of Product Innovation Management* 7(4):200-212 (1990).	Project	Success	
53. Rothwell, Roy, Freeman. C., Norsley, A., Jervis, V.T.P., Robertson, A.B. and Townsend, J. SAPPHO updated-Project SAPPHO phase II. *Research Policy* 3(3):258-291 (1974).	Project	Success Failure	
54. Sanchez, Angel Martinez and Elola, Luis Navarro. Product innovation management in Spain. *Journal of Product Innovation Management 8(1):49-56 (1991).*	Programme	Success	Mgmt., R&D
56. Sherman, J. Daniel and Olsen, Eugene A. Stages in the project life cycle in R&D organisations and the differential effects of organisational culture on performance. In: *1992 National DSI Conference.*	Project		R&D
57. Song, X. Michael and Parry, mark E. The dimensions of industrial new product success and failure in the People's Republic of China. In: *1992 PDMA Proceedings*, L.P. Feldman, T.P. Hustad and A.L. Page (eds.). 1992, pp. 30-41.	Programme	Success Failure	Mkt., R&D
58. Song, X. Michael and Parry, Mark E. The R&D-Marketing interface in Japanese high-technology firms. *Journal of Product Innovation Management* 9(2):91-112 (1992).	Project	Success Failure	
60. Souder, William E. Managing relations between R&D and marketing in new product development projects. *Journal of Product Innovation Management* 5(1):6-19 (1988).	Project	Success Failure	Mkt., R&D
61. Souder, William E. and Chakrabarti, Alok K. The R&D Marketing interface: results from an empirical study of innovation projects. *IEEE Transactions on Engineering Management* EM-25(4):88-93 (1978).	Project	Success Failure	Varied
63. Storey, Chris, Edgett, Scott, Easingwood, Chris and Kleinschmidt, E. Factors affecting the successful launch of new financial services. In: *1992 PDMA Proceedings*, L.P. Feldman, T.P. Hustad and A.L. Page (eds.). Product Development and Management Association, 1992. pp. 42-53.	Project	Success Failure	
64. Szakasits, Georges D. The adoption of the SAPPHO method in the Hungarian electronics industry. *Research Policy* 3(1):18-28 (1974).	Project	Success Failure	R&D Mkt.
65. Teubal, Morris, Arnon, Naftali and Trachtenberg, Manuel. Performance in innovation in the Israeli electronics industry: a case study of biomedical electronics instrumentation. *Research Policy* 5(4):354-379 (1976).	Project	Success Failure	Mgmt.
66. Thamhain, Hans J. Managing technologically innovative team efforts toward new product success. *Journal of Product Innovation Management* 7(1):5-18 (1990).	Programme	Success Failure	Varied
67. Utterback, James M., Allen, Thomas J., Hollomon, J. Herbert and Sirbu, Marvin A. The process of innovation in five industries in Europe and Japan. *IEEE Transactions on Engineering Management* EM-23(1):3-9 (1976).	Project	Success Failure	Varied
68. von Hippel, Eric. Successful industrial products from customer ideas. *Journal of Marketing* 42(1):39-49 (1978).	Project	Success Failure	Varied
69. Voss, Christopher A. Determinants of success in the development of applications software. *Journal of Product Innovation Management* 2(2):122-129 (1985).	Project	Success Failure	Varied

71. Yoon, Eunsang and Lilien, Gary L. New industrial product performance: the effects of market characteristics and strategy. *Journal of Product Innovation Management* 3(3):134-144 (1985).	Project	Success	Mgmt.

The eighteen significant dimensions were categorised as follows:

- *Strategic factors* - product advantage, technological synergy, company resources, strategy and marketing synergy.
- *Development process factors* - proficiency of technical activities, proficiency of marketing activities, protocol, top management support/skill, proficiency of pre-development activities, speed to market, financial/business analysis and costs.
- *Marketing environment factors* - market potential, market competitiveness and environment.
- *Organisational factors* - internal/external relations and organisational conditions.

The literature's most studied factors were: (1) proficiency of technological activities (included in 69.2% of all research analysed); (2) proficiency of market related activities (61.5%); (3) product advantage (61.5%) and (4) protocol (46.2%). The least studied were : (1) the environment; (2) financial/business analysis; (3) costs; (4) strategy; (5) speed to market and (6) company resources. Though they were not able to define the order of factor importance due to diverse designs, methods and publication bias, they argue that it is not surprising the top four factors studied are typically identified as the primary determinants of success. This suggests field effort has been somewhat self-fulfilling.

To properly isolate the diverse factors affecting new product success, combinations of multi-disciplinary, multi-functional inputs must be considered (Cooper and Kleinschmidt 1986; Wind and Mahajan 1988). The gap formed by the narrow homogeneous focus and factor under-study provides the opportunity for validating the most studied factors, whilst simultaneously examining the integration effects of the less studied factors. This should broaden the discussion beyond the indisputable, but now somewhat redundant conclusion, that successful firms must market a superior product aggressively to target customer wants and needs (Montoya-Weiss and Calantone 1994).

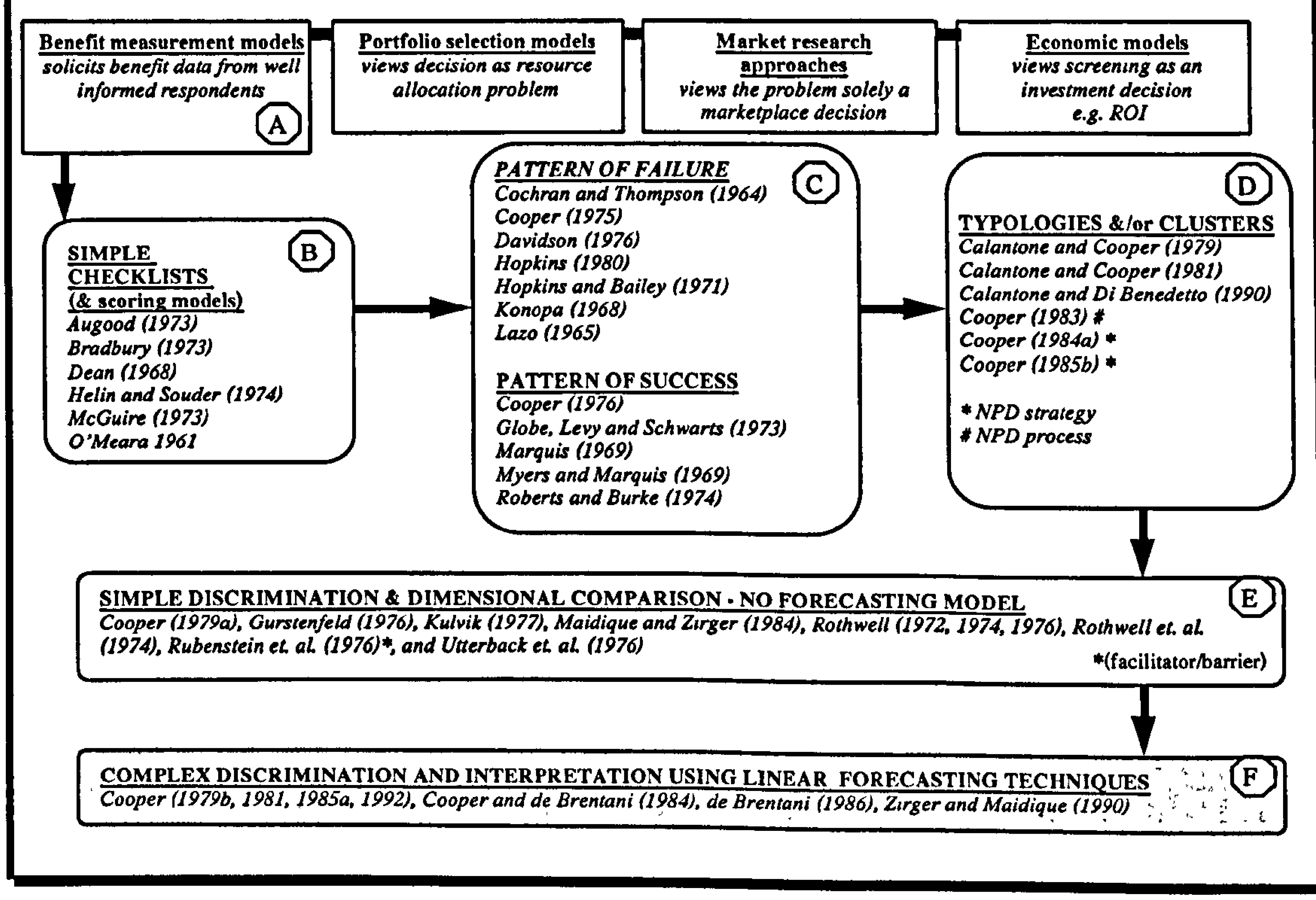
2.3 Maturation of the literature and linear forecasting methodology

The eclectic nature of the literature suggests that success/failure can be explained and/or predicted by antecedent variables from numerous disciplines. Unfortunately, most of the work remains exploratory (Cooper and Kleinschmidt 1987b), lacks an organised synthesis and has not evolved in an orderly fashion. However, some maturation of focus and method in management and marketing is apparent, as exemplified by the field's most notable NPD initial screening forecasting models -

NewProd (Cooper 1979b, 1981) and Stanford (Maidique and Zirger 1984; Zirger and Maidique 1990).

The NewProd Project is the most comprehensive work to date (Montoya-Weiss and Calantone 1994) and is the best basis of comparison for the current work's accuracy and validity. It has been replicated (see Table 2-3) and refined over time (Cooper 1985a, 1992) but it is actually founded in elementary benefit measurement forecasting

Figure 2-1: Maturation of significant NPD product, strategy and process literature & methodology



models. In their simplest form these models integrate benefit data from well-informed respondents (Cooper 1985a; see Figure 2-1, panel A). Their earliest NPD manifestations were subjective checklists and scoring models (see Figure 2-1, panel B). Their latest manifestations are exemplified by the NewProd linear regression model and Stanford discriminant analysis model (see Figure 2-1, panel F).

2.3.1 Checklists

Checklists (see Figure 2-1, panel B) and scoring models range from simple to complex. They attempt to separate winners from losers but exhibit significant problems (Simon and Freimar 1970), especially in interpretation and application. Though, in their simplest form they are attractive and convincing, there are hazards in determining what is an acceptable pattern of success. Their qualitative nature makes it possible, unconsciously or deliberately, to favour some projects over others (Augood 1973). In their most complex form they become unwieldy as they are superimposed over budgeting restrictions, resource allocations, project variations and scheduling problems. Representative of the work in this area are Augood (1973), Bradbury, Gallagher and Suckling (1973), Dean (1968), Helin and Souder (1974), McGuire (1973) and O'Meara 1961.

2.3.2 Patterns of failure or success

Both failure and success patterns have been studied, typically on the assumption that they were models to avoid or emulate. Their main weakness is that they are unilateral and do not compare success against failure.

2.3.2.1 Failure patterns

Representative of research into patterns of failure (see Figure 2-1, panel C) are Cochran and Thompson (1964), Cooper (1975), Davidson (1976), Hopkins (1980), Hopkins and Bailey (1971), Konopa (1968) and Lazo (1965). Hopkins and Bailey (1971) are typical and find a definite pattern to new industrial product failure based on inadequate market analysis, product technical problems, lack of effective marketing effort, higher than expected costs, competitive strength or reaction, poor timing and technical/production problems. Many of these reasons for failure were validated later by Hopkins (1980). He found poor marketing research, technical problems in design or production, improper timing of market introduction and failure to support the introduction with ample selling effort related to failure. Similarly, Cooper (1975) found a low level of sales was the most important general reason for failure. The specific causes of low sales levels included firmly entrenched competitors, overestimating the number of potential users, high price, technical difficulties with the product and misdirected marketing efforts. Finally, both Cochran and Thompson (1964) and Lazo (1965) found similarly, that the overwhelming causes of failure were marketing, not technical problems. These were exemplified by inadequate market analysis, product deficiencies, higher costs than anticipated, poor timing, competition, insufficient market effort, inadequate sales force and weakness in distribution.

2.3.2.2 Success patterns

Representative of success pattern case method research are Cooper (1976), Globe, Levy and Schwartz (1973), Marquis (1969), Myers and Marquis (1969) and Roberts and Burke (1974). This genre sought to infer future patterns of success from past patterns of success. Globe, Levy and Schwartz (1973) are typical finding early recognition of need and adequate funding important to the successful innovation process. External factors such as economic, political and social factors were least important with formal market analysis far down the list.

Cooper (1976) looked at the success process for three model products at Dupont, Northern Electric and Pratt and Whitney. He linked success to a stage-wise process of sequential, multi-disciplinary, multi-functional yet integrated activities supported by technical and market research. Incremental commitment was key, with relatively minor expenditures on initial stages compared to major financial investment required of later stages. Each GO stage meant to "go only to the next stage" with constant re-evaluation providing timely bail-outs. This laid the groundwork for current stage-gate processes (Cooper 1990a; Cooper and Kleinschmidt 1991).

Another good example of success case methodology is the work of Myers and Marquis (1969). They suggested that optimising technology push and market pull factors was important. Success, they argued, was based on the process of potential demand recognition and technical feasibility leading to idea formulation, problem solving, information gathering and solution utilisation.

2.3.3 Success/failure typologies and clusters

These designs focus on the project, the process or the strategy typology or cluster and are more statistically sophisticated than simple unilateral comparison (see Figure 2-1, panel D). They measure dimensionality. Representative works include Calantone and Cooper (1979, 1981), Calantone and Di Benedetto (1990) and Cooper (1983, 1984a, 1984b, 1985b). All flow from Hopkins and Baileys' (1971) and Cooper's (1975) determination that a definite pattern of project failure does exist and that marketing-related functions are the key to understanding patterns.

Calantone and Cooper (1977) indicated that most new product failures can be manifest by a limited number of scenarios. They devised, for the first time, a conceptual framework and failure classification scheme using discriminant analysis, ANOVA and Duncan's Multiple Range Test. They concluded that marketing-related functions were a root cause of failure and that the same mistakes are made over and over again (Calantone and Cooper 1979). Six failure scenarios included "the better mousetrap no one wanted", "the me-too product meeting a competitive brick wall", "the competitive one upsmanship", "the environmentally ignorant", "the technical dog" and "the price crunch". Seven variables emerged as important determinants discriminating between types of product failure. These were a lack of R&D, marketing research, selling and promotion resources, poor preliminary market assessment, poor in-house prototype testing, market newness to the firm and product newness to the market.

Subsequently, Calantone and Cooper (1981) developed new product success/failure scenario based on factor analysis and cluster analysis techniques. There, the largest single scenario representing 15.38% of the sample, was "old but simple money saver" with the most successful scenario being the "synergistic, close to home, product". Other significant scenario included "the better mousetrap with no marketing", "innovative mousetrap, not better", "close to home, me too", "innovative high tech", "me-too product with no technical/product synergy", "synergistic product that was new to the firm" and "innovative superior product with no synergy".

With respect to process and programme strategy typologies, Cooper is most representative (1983, 1984a, 1984b, 1985b). In the first of these works Cooper determined that the concept of an "average NPD process" is misleading. In fact each process has its own distinct set of activities and emphases, is not sequential and has activities which overlap or are undertaken in parallel. Seven clusters representing types of new product development processes were uncovered. The most successful was the "balanced complete" and the least successful of all was the "design dominated process". The remaining processes isolated were the "market oriented process", the "front-end dominated process", the "minimum process", the "launch with prototype process" and the "prototype dominated process".

In the second and third work Cooper looked at the firm's total programme strategy, not its individual project strategy. The elements of the overall programme strategy were reduced to nineteen factors and then to five clusters types. Similar to the process findings, the best overall programme strategy was "balanced and focused". Others included "technology driven", "technology deficient" and "low budget, conservative". "High budget, diverse" tied with "technology deficient" for the worst performing programme strategy.

2.3.4 Simple discrimination and dimensional comparison - *no forecasting models*

The premise underlying these works was that only through a direct comparison of successes and failures could the variables that discriminate between them be identified (see Figure 2-1, panel E). Works which attempted to discriminate in this way include Gerstenfeld (1976), Kulvik (1977), Maidique and Zirger (1984), Rothwell (1974, 1976), Rothwell et. al. (1974) and Rubenstein et. al (1976).

Particularly representative of this design were SAPPHO (Rothwell 1972), Utterback, Allen, Hollomon and Sirbu (1976) and Cooper (1979a).

Using a comparative analysis of forty-three paired innovations, SAPPHO was the first to identify, in this way, measures which differentiate success from failure. Each pair were market competitors, with one a commercial success and the other a commercial failure. Prior to Rothwell's analysis of one hundred and twenty-two variables, unilateral studies of either success or failure dominated the literature. Rothwell determined that successful innovators have a better understanding of users' needs, they pay more attention to marketing and publicity, use greater sales and customer educational efforts, make better use of outside technology, foster better internal and external communications, use senior management as product champions and are more efficient. SAPPHO laid the methodological groundwork for future forecasting works.

Similarly, Utterback, Allen, Hollomon and Sirbu (1976) found the most striking difference between successes and failures was the degree to which successes had no initial difficulty in marketing. Other competitive and market related factors were found significant including having a great or moderate advantage over competing approaches or products. Important also were projects demonstrating a recognised need before a solution was found, a product intended for a particular situation or user specification, a project initiated by the firm's top management and situations where project planning was more highly structured.

Cooper's NewProd Project (1979a) was paramount in the maturation of field focus and method. This work founded the conceptual framework for the NewProd discriminant analysis (1979b) and linear regression forecasting (1981) models. These are the most important predictive/prescriptive work in the field to date and they laid the groundwork for more complex forecasting models and methods. The variables/activities found significant to success included:

- proficiently executing the launch.
- having a new product that more clearly meets customers' needs than do competitors products.
- having a higher quality new product than competitors in terms of tighter specifications, greater durability and reliability.
- undertaking a good prototype test of the product with the customer.
- having the sales force and/or distribution effort well targeted.
- undertaking a proficient test market or trial sell.
- proficiently starting up full-scale production.
- knowing customers' price sensitivities.
- executing product development well.

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- proficiently starting up full-scale production.
- knowing customers' price sensitivities.
- executing product development well.

- understanding buyer behaviour and the customers purchase decision.
- having a product that permits the customer to reduce his costs.
- having a good company product fit in terms of sales force and/or distribution.
- having a good company-product fit in terms of marketing research skills and needs.
- doing a good job on idea screening.
- understanding customers' needs, wants and specifications for the product.

2.3.5 Complex discrimination and interpretation - *linear forecasting models*

Complex discrimination and interpretation using linear forecasting techniques represent the most accomplished work today (see Figure 2-1, panel F). The original NewProd model (1979b) and the latest version of the Stanford model (Zirger and Maidique 1990) used discriminant analysis, a third level measure of dimensionality[5]. They are considered here, along with fourth level works using linear regression (Cooper 1981, 1985a, 1992; Cooper and de Brentani 1984), because they illustrate the field's most important parsimonious screening models which yield reasonably accurate success/failure forecasts.

2.3.5.1 Project NewProd

The first phase of Project NewProd (Cooper 1979a, see Figure 2-1, panel E) provided the conceptual framework (see Figure 2-2) for Cooper's success/failure initial screening forecasting models (Cooper 1979b, 1981). It does the same for this work as well. Developed to identify relevant variables from the myriad available for investigation, new product success or failure is determined, ultimately, by the interaction of the commercial entity (see Figure 2-2, panel #6) with the marketplace (#1). The commercial entity is the result of the new product process, a stage-wise series of activities (#4) and information acquisition functions (#5). The NPD environment into which the product is launched is uncontrollable at the project level. The NPD process is controllable at the project level.

Beginning with a seventy-seven variable data set developed from this framework, Cooper demonstrated parallel discriminant analysis (Cooper 1979b) and linear regression (Cooper 1981) forecasting functions which described the dimensions of success. The monomorphic NewProd models were reasonably accurate, were based on eleven and eight deterministic dimensions respectively and forecast success/failure accurately in approximately 84% of the cases. In both, the most important of these dimensions was product uniqueness/superiority. In the earlier study, market knowledge/marketing proficiency and technological resource compatibility were

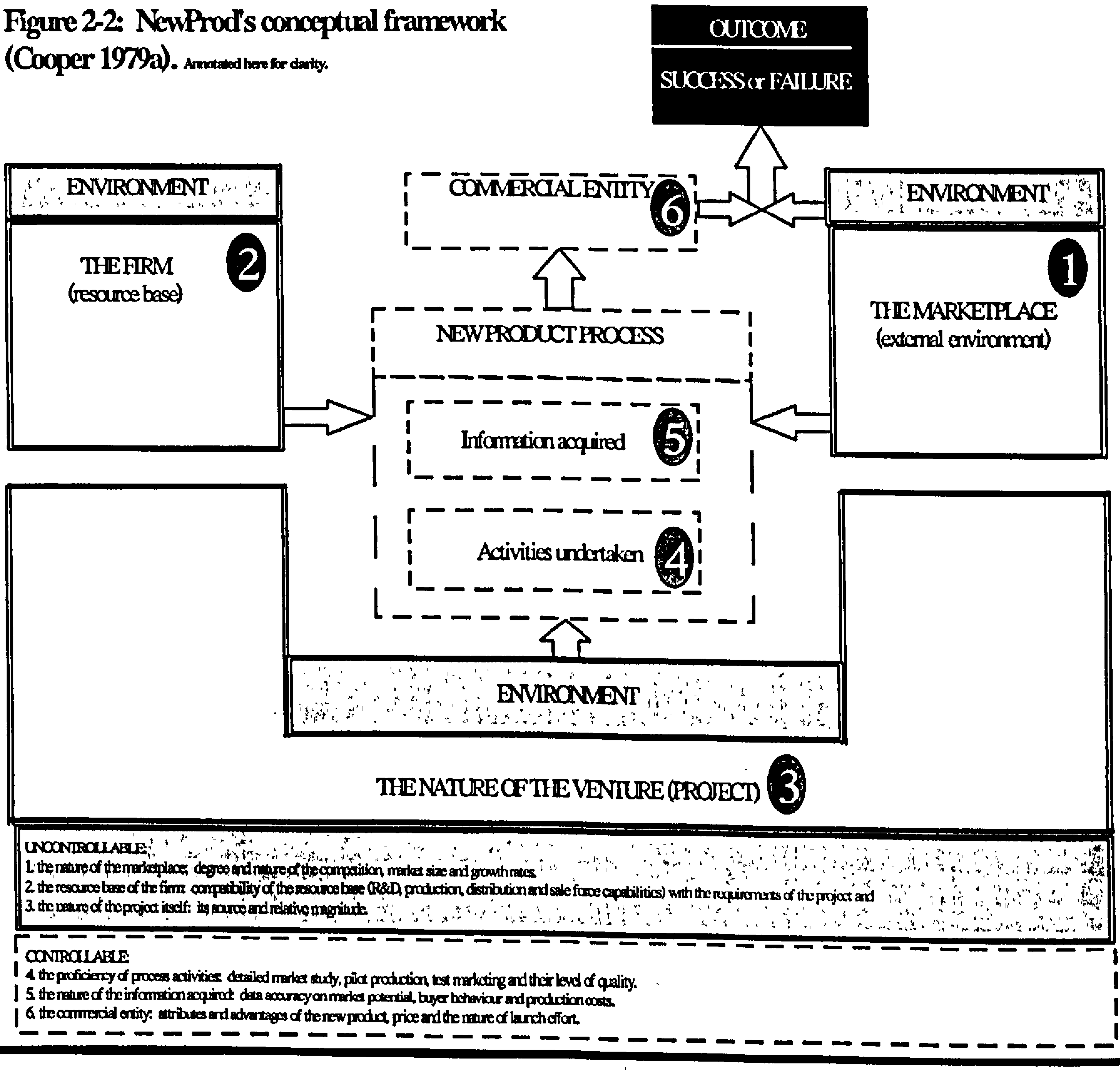
[5] There are four ascending levels: (1) descriptive; (2) tests of difference/similarity; (3) dimensionality and (4) interpretation of parameters (Montoya-Weiss and Calantone 1994).

second and third (see Table 2-2). Market dynamism detracted from success as did relative price of the product, marketing competitiveness and newness to the firm.

Table 2-2: NewProd discriminant analysis dimensions

Cooper, Robert G., The Dimensions of Industrial New product Success and Failure, *Journal of Marketing* Vol. 43 (Summer 1979b), 93-103. 77 variables reduced to 18 factors with Eigenvalue >1 explaining 71.3% of variance. 84.1%% correct. Success = 89.2%, Failure = 78.5%. Wilk's Lambda =.51, F=15.95 at .001 with 11df			
Factor Name/Factor #	***Standardised Function Coefficient***	***Wilk's Lambda***	***F to Enter or Remove***
Product Uniqueness/Superiority F4	.527	.859	31.66
Market Knowledge and Marketing Proficiency F2	.465	.730	33.95
Technological resource compatibility F1	.325	.680	14.13
Market Dynamism (Frequency of New Product Introductions) F14	-.264	.644	10.65
Market need, growth and size F8	.271	.610	10.49
Relative price of product F15	-.252	.576	10.62
Marketing and managerial synergy F6	.193	.557	6.49
Marketing competitiveness (and customer satisfaction) F5	-.186	.540	5.88
Newness to the firm F3	-.170	.517	3.24
Strength of marketing communications and launch effort F9	.137	.517	3.24
Source of idea/investment magnitude F18	.114	.510	2.27

Figure 2-2: NewProd's conceptual framework (Cooper 1979a). Annotated here for clarity.



Though it received only limited validation (see Table 2-3), this work and its follow-up using multiple linear regression (see Table 2-4) remain the most important work in initial screen modelling to date.

Table 2-3: NewProd validation and predictive proficiency[6]

1. ORIGINAL STUDY USING CROSS SPLIT-HALF METHOD WITH 195 cases and 84.1% reliability	Cooper, Robert G., An empirically derived new product project selection model, *IEEE Transactions on Engineering Management* EM-28:54-61 (August 1981)) *Cases used to generate = same to test*
2. NORTH AMERICAN STUDY 179 new cases 73% reliability.	Cooper, Robert G., Project NewProd: Factors in New Product Success, *European Journal of Marketing*, 1980b 14, 5/6 Cooper, Robert G., New Products: What Distinguishes the Winners, *Technology Management*, November-December 1990, P27-31 Cooper, R. G. and E. J., Kleinschmidt, New Products: The Key Factors in Success, Chicago, IL: American Marketing Assoc., 1990 Cooper, Robert G and Elko J Kleinschmidt, What Separates Winners from Losers?, *Journal of Product Innovation Management*, Vol. 4 Issue 3 Sept. 1987 pp. 169-184
3. DUTCH TEST 19 cases (all new) with 84% reliability	Bronnenberg, J. J.A. M. and L. A. van Engelen, A Dutch test with the NewProd-Model, *R&D Management*, 18(4): 321-332 1988
4. DANISH TEST 26 cases	Modified NewProd to create DanProd (all new cases)
5. PROCTOR & GAMBLE 60 cases with 80% reliability	Cooper, Robert G., Selecting Winning New Product Projects: Using the NewProd System, *Journal of Product Innovation Management*, 1985; 2:34-44

Cooper's linear regression application produced slightly different results. This was probably due to change in statistical technique[7] and using a distilled, forty-eight variable sub-set. Again he found that product quality, superiority and uniqueness together, are the single most important dimension of NPD success. This time however, overall project/company resource compatibility and market need, growth and size followed (see Table 2-4). The remaining variables were consistent with the earlier work.

Table 2-4: NewProd linear regression dimensions

Cooper, Robert G. An empirically derived new product project selection model. *IEEE Transactions on Engineering Management* EM-28:54-61 (1981) and Cooper, Robert G., Selecting Winning New Product Project: Using the NewProd System. *Journal of Product Innovation Management*, 1985; 2:34-44, Linear regression using 48 variables R=.648074, R^2=.420, Adj. R^2=.395, F =16.83 with 8df Standard error = 2.73			
Key factors or dimensions	*Reg. Coef*	*F value*	*Variables loading on factor*
Product superiority, quality and uniqueness	1.744	68.7	highly innovative, new to mkt. product has unique features for user product is superior to competing products product reduces customers' costs product does unique task for user product is higher quality than competitors
Overall project/co resource compatibility	1.138	30	adequate financial resources compatible R&D resources compatible engineering skills necessary marketing research skills needed managerial skills compatible production resources compatible sales force/distribution resources adequate advertising/promo skills
Market need, growth and size	.801	12.5	high need level by customers for product type large market ($ volume)

[6] from Cooper, Robert G. The NewProd System: The Industry Experience. *Journal of Product Innovation Management* 9:113-127 (June 1992).
[7] Third level measures of dimensionality such as discriminant analysis are not as refined as fourth level regression analysis (Montoya-Weiss and Calantone 1994) and may cause slight differences in results.

			high growth market
Economic advantage of product to end user	.722	10.2	product reduces customers' costs product is priced lower than competing products
Newness to the firm	-.354	2.9	new customers to firm new product class to firm new customer need to firm new production process to firm new product technology to firm new sales force/distribution to firm new advertising/promotion to firm new competition to firm
Technological resource compatibility	.342	2.5	compatible R&D resources & skills for project compatible engineering skills & resources
Market competitiveness	-.301	2.0	highly competitive market intense price competition in market many competitors many new product introduced into market changing user needs
Product customness/specialisation	-.225	.9	a market-derived new product idea a custom product a mass market for product
Constant	.328		

Following these two landmark studies, Cooper and de Brentani (1984; see Table 2-5) studied managerial accept/reject criteria. Generally consistent with NewProd, new factors perceived important to managers at the initial screen included financial potential, product life, domestic focus and types of strategy (market maintenance and diversification strategy). Comparison to Cooper's earlier work suggests that differences exist between perceived causes of success/failure and criteria perceived important to the managers' accept/reject decision. This is the first indication that a "reality check" (Calantone, Di Benedetto and Haggblom 1995) problem might exist in the forecasting branch of the literature.

Table 2-5: Linear regression results of accept/reject criteria

Cooper, Robert G. and Ulrike de Brentani, Criteria for Screening New Industrial Products, *Industrial Marketing management*, 1984 (13) 149-156. Adjusted $R^2 = .564$, $F = 54.3$, sig. at .0001			
Key factors or dimensions	***Reg. Coef***	***F value***	***Significance of F***
Financial Potential	1.390	158.2	.0001
Corporate Synergy	1.285	134.2	.0001
Technological and Production Synergy	.932	69.9	.0001
Product Differential Advantage	.881	62.7	.0001
Product Life	.576	26.7	.0001
Market Maintenance Strategy	.425	14.6	.0002
Size of Market	.384	12	.0006
Diversification Strategy	.270	5.8	.0161
Domestic Market	.223	4.1	.0450

Cooper and de Brentani's study of the financial services industry (1991) found dimensions consistent with those in previous industrial screening works, but in radically different order. This may indicate that model differences exist based on whether the product is a manufactured item or a service. Because the work did not utilise a forecasting methodology, it is not used as a basis of comparison here.

2.3.5.2 Stanford Innovation Project

The original Stanford Innovation Project (Maidique and Zirger 1984) had three parts: (1) collection of unstructured data for variable set determination[8]; (2) comparison of success/failure innovation pairs for fifty-nine innovations and (3) an in-depth case study of a twenty firm sub-set. The following circumstances were found to lead to new product success:

- The developing organisation through in-depth understanding of the customers and the marketplace, introduces a product with a high performance-to-cost ratio.
- The developing organisation is proficient in marketing and commits a significant amount of its resources to selling and promoting the product.
- The product provides a high contribution margin to the firm.
- The R&D process is well planned and executed.
- The create, make and market functions are well interfaced and co-ordinated.
- The product is introduced into the market early.
- The markets and technologies of the new product benefit significantly from the existing strengths of the developing business unit.
- There is a high level of management support for the product from the development stage through its launch to the marketplace.

No forecasting model was developed until the follow-up six years later (Zirger and Maidique 1990). Using discriminant analysis for dimension determination and forecasting (see Table 2-6), the high-tech biased, deterministic model found excellence of the R&D organisation to be the most important dimension of success. Superior technical performance and product value followed. Whilst superior product was not a distinct significant factor, its key constructs were found in other dimensions. Like NewProd, a weak competitive environment was important to success.

Table 2-6: Stanford Innovation Project discriminant analysis

Zirger, B. J. and Maidique, M. A. A Model of New Product Development: An Empirical Test *Management Science* 7:867-883 (1990). Wilk's Lambda = .51, Eigenvalue = .978, Canonical Correlation = .7		
Key factors or dimensions (factor name)	*Structure Coefficients*	*Constructs*
Excellent R&D Organisation	.80	Product had superior quality and reliability Product was developed by a highly competent engineering organisation Product development process was well planned Product was strongly supported by project management Co-ordination between engineers and manufacturing was good A clearly identified individual was an activist in promoting the product's development throughout the product development and the introduction cycle. Product was a good match with the customer's needs
Superior Technical Performance	.64	Co-ordination between marketing and engineering was good Product had superior technical performance
Product Value	.48	Product was priced lower than competitive alternatives Product provided superior benefit to cost Product concept developed form frequent interactions between the product development team, introduction team

8 despite the NewProd and SAPPHO studies, the authors thought the literature variable pool was lacking by industry.

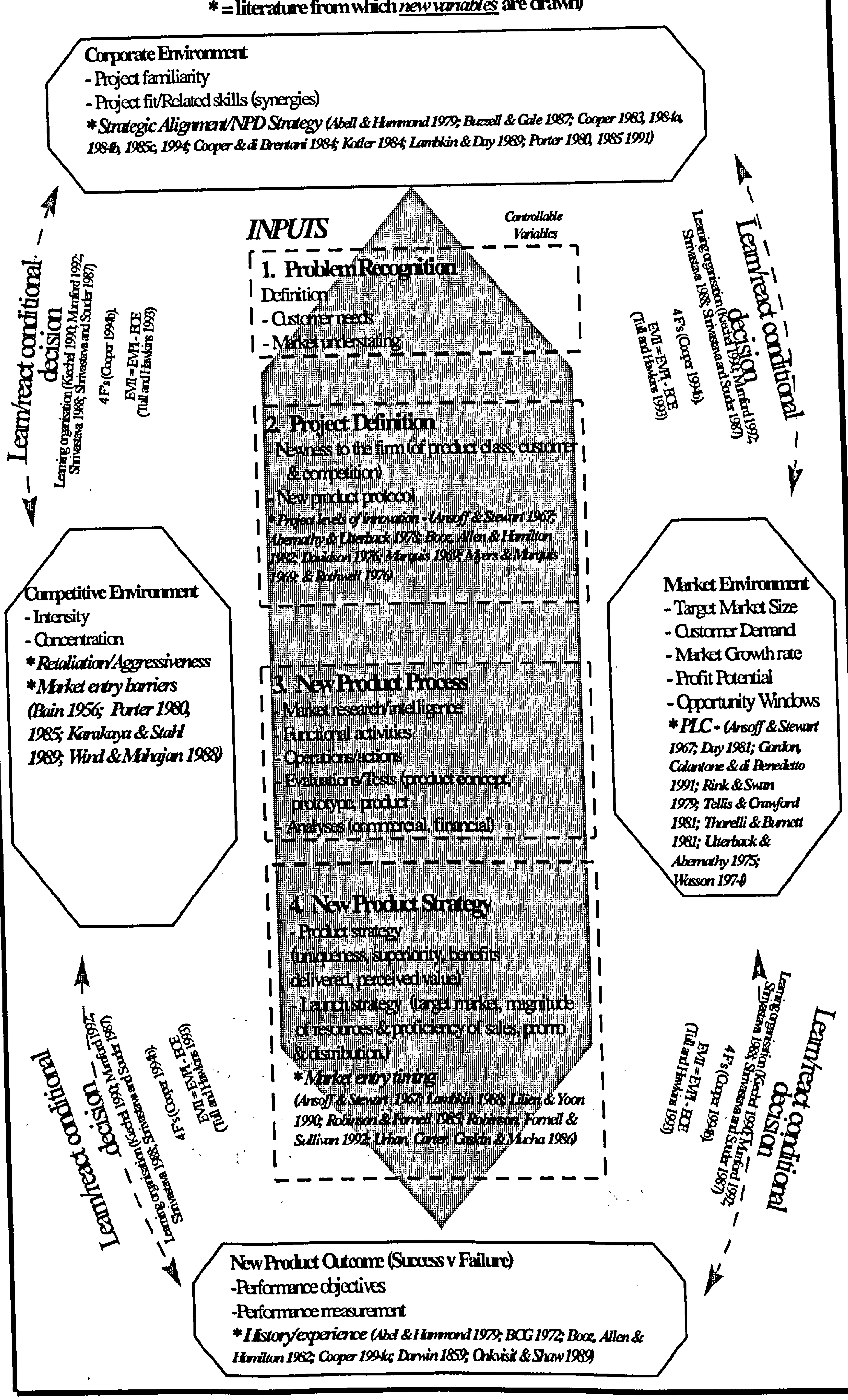
		and the customers
Synergy with Existing Competencies	.38	Product benefited from its closeness to the company's existing products Product benefited from its closeness to the company's existing markets Product benefited from its closeness to the company's technologies
Management support	.35	Product was strongly supported by general management
Competent Marketing & Manufacturing	.28	Co-ordination between marketing and manufacturing was good Product was manufactured by a highly competitive manufacturing organisation Product was introduced by a highly competent sales and marketing organisation
Weak Competitive Environment	.28	Product was first to the market Product was developed for a market with few strong competitors
Large & growing market	.27	Product was developed for a large market Product was developed for a rapidly growing market

2.4 Conceptual framework

New conceptual frameworks for screening/forecasting models must be grounded in Cooper's six variable groups (see Figure 2-2). This work is. However, this work's framework better addresses the problems of accounting for product evolution following the initial screen (Cooper 1992) and the parallel effects of an evolving marketing strategy (Crawford 1986). Key to the modification (see Figure 2-3) is the change in the expected value of the go/no-go decision at the initial screen as it evolves through infinite permutations vis-à-vis the learn/continue/react decision though one year post launch. The outcome possibilities are a function of: (1) initial probabilities of success; (2) expected values of success with no strategic response; (3) revised probabilities of success based on learned antecedent states of nature and (4) revised expected values of success based on type and magnitude of learned strategic response.

The post screening expected value calculation would actually involve infinite continuous calculations based on compounding internal and external environmental forces (Calantone and Di Benedetto 1990) over time. Since deterministic frameworks are inappropriate when time is a critical factor (Burns and Austin 1985), deterministic models used in changing (Albala 1975; Abell and Hammond 1979; Buzzell and Gale 1987; Crawford 1984, 1986; Kotler 1994; Lambkin and Day 1989; Lilien and Yoon 1990; Porter 1980, 1985, 1991; Utterback, Allen, Hollomon and Sirbu 1976) stochastic environments are also. Such frameworks produce models laden with measurement timing error which reduces the temporal validity of initial and intra-process dimensional prescription. The environmental changes in turn produce changes in the conditional expected value (Tull and Hawkins 1993) of the learn/continue/react decision. Such infinite compounding of posterior states of nature

Figure 2-3: Learn/react FRAMEWORK for evaluating factors of NPD success over time.
* = literature from which *new variables* are drawn)



is highly relevant today as many facets of business activity accelerate (Bayus 1994). Static frameworks can describe this dynamic conceptually, but they fail as a platform for its operationalisation, measurement and implementation. To measure the correction necessary to maintain infinite possible states of equilibrium, this framework links variable groups more directly to strategy. It does this by casting the type and magnitude of appropriate strategic reaction in the role of equilibrium (Kotler 1994) alignment mechanism. It does not abandon NewProd's application of early information in the creation of an early success forecast probability distribution and prescriptive strategy. However, success is not determined from initial strategy alone but from the interaction of the market environment with the evolving new product strategy (Cooper and Kleinschmidt 1987b; Crawford 1986). Accordingly, this framework acknowledges posterior probabilistic distributions in the form of post screen changing states of nature.

Clearly, adopting a framework embracing infinite expected values of imperfect information (EVII) seems more prudent today, than accepting one which leads to dynamic environment avoidance (Cooper 1979b, 1980b, 1981). Furthermore, it is harmonious with Cooper's proposals concerning new 3rd generation models featuring the 4F's[9] (Cooper 1994b). These characteristics are desirable because they should bring products to market faster and improve utilisation of scarce resources. Thus, this work's conceptual framework supports assessment of the entire portfolio's value as a function of the highest project/portfolio expected payoff for each state of nature. This permits a potential solution to "pipeline churn", the problem of too often changing development priorities and "pipeline balance", the ability to successfully develop new product platforms whilst extending existing product lines.

2.5 Hypotheses development

Most past efforts have been dedicated to identifying variables and proposing explanatory models rather than to testing models and hypotheses (Cooper and Kleinschmidt 1987b). This work tests seven hypotheses based on the conceptual model described above, in consideration of gaps in previous NPD forecasting research.

[9] (1) Fluid and adaptable with overlapping stages for greater speed; (2) Fuzzy gates where conditions are not absolute but can assume varying states that are conditional and situational; (3) Focused prioritsation to allow better resource management of the entire portfolio and (4) Flexible to allow each project a unique route through the process network.

Hypotheses H_1a through H_1d are related in their assumption that: (1) previously validated and new multi-disciplinary variables require replication for synthesis in field knowledge (Montoya-Weiss and Calantone 1994; Wind and Mahajan 1988) and (2) process and environmental variable groups related to NPD outcome evolve over the life of the process (Albala 1975; Abell and Hammond 1979; Buzzell and Gale 1987; Crawford 1984, 1986; Kotler 1994; Lambkin and Day 1989; Lilien and Yoon 1990; Porter 1980, 1985, 1991; Utterback, Allen, Hollomon and Sirbu 1976). Increasingly more elegant statistical tests are used to measure and analyse NPD managers' perception of variable states, first at the NPD process beginning (T_0, the initial screen) and then at the end (T_1, one year post launch). The procedures test the evolution of variables (H1a), normalised factors (H_1b), model dimensions (H_1c) and model predictive accuracy (H_1d) at two extreme points in the NPD process whilst techniques advance from simple ANOVA/t-tests, to factor analysis and linear regression.

Hypotheses H_2 and H_3 explore how the dual linear regression functions and dimensions established in the procedures in H_1c above, change conditionally by P_iLC and order/innovation. Finally, H_4 examines the NPD value of strategic planning as both an initial contributor and a learned reactive linking mechanism to dimensional alignment.

2.5.1 Hypothesis H_1a

Many variables relating to a new product's success are dynamic and perceived to evolve over the life of the NPD process.

This hypothesis tests the null form that there is no change in the perceived significance and/or magnitude of variables important to entry success over the life of the NPD process. It is important because "best practices" require replication, better statistical rigour and more comprehensive reporting, especially under conditions assessing their temporal stability (Montoya-Weiss and Calantone 1994). Evolution of managers' perception of NPD variable change over the life of the process has not been verified. Understanding this change is fundamental to uncovering reasons for practitioner under-utilisation of models. This is especially important in today's dynamic situations recommended for avoidance (Cooper 1980b) yet still considered important for field advancement (Mahajan and Wind 1992).

2.5.1.1 Core antecedent variables from NPD forecasting literature

In choosing variables for replication, this hypothesis acknowledges pioneering efforts (see Figure 2-1, A-E). However, only NewProd (Cooper 1979b, 1981), SAPPHO

(Rothwell et al 1974) and Stanford (Maidique and Zirger 1984, Zirger and Maidique 1990) are comprehensive enough in reporting information and supporting statistics (Montoya-Weiss and Calantone 1994). NewProd's original data set of seventy-seven process and environmental variables (Cooper 1979b) were comprehensive. These were reduced first to forty-eight (Cooper 1981, 1985a) and then to thirty (Cooper 1992). They capture homogeneous success/failure forecasting variation best (see variables labelled *COOPER 1992* in APPENDIX A). For validation and synthesis, this work adopts Cooper's core, supplemented from other seminal works as needed.

2.5.1.2 Supporting variables from other NPD forecasting literature

Additional multi-disciplinary, multi-functional antecedents need testing (Cooper 1976; Cooper and Kleinschmidt 1986; Montoya-Weiss and Calantone 1994; Wind and Mahajan 1988). Where conceptual gaps in Cooper's core existed, variables were borrowed from Cooper and de Brentani (1984) and Zirger and Maidique (1990). These forecasting works were closest in method and findings to NewProd and form the best basis of comparison for judging this work's validity and contribution.

Cooper and de Brentani (1984) found financial potential, product life and types of strategy important to manager's accept/reject decision (see table 2-5). These new variables uncovered, along with mutually inclusive dimensions reordered, suggests reality check/utilisation problems between scholarly findings and practitioner go-no-go criteria. All three variable concepts were operationalised for better precision and added to this work's core (see *Cooper and de Brentani 1984* in APPENDIX A).

Zirger and Maidique (1990) used a high technology sampling frame to study variables similar to NewProd (see table 2-6). In slightly different order due to R&D/organisational variable operationalisation, their findings tap dimensions similar to NewProd and support using the "Cooper 30". However, unlike Cooper, early entry was found related to success (Maidique and Zirger 1984). It was operationalised and added to the variable core data set (see *Zirger and Maidique 1990* in APPENDIX A).

2.5.1.3 New variables

New variables culled from theory important to adjunct fields are noted by an "*" in Figure 2-3. Also, one primary citation to justify their use is displayed in the postal survey instrument in APPENDIX A. Areas integrated with the core include: (1) New product development history/experience; (2) Market entry barriers and competitive retaliation; (3) PLC; (4) Market entry timing; (5) Project innovation levels and (6) Strategic action/reaction. Models not acknowledging these areas, despite being

(Rothwell et al 1974) and Stanford (Maidique and Zirger 1984, Zirger and Maidique 1990) are comprehensive enough in reporting information and supporting statistics (Montoya-Weiss and Calantone 1994). NewProd's original data set of seventy-seven process and environmental variables (Cooper 1979b) were comprehensive. These were reduced first to forty-eight (Cooper 1981, 1985a) and then to thirty (Cooper 1992). They capture homogeneous success/failure forecasting variation best (see variables labelled *COOPER 1992* in APPENDIX A). For validation and synthesis, this work adopts Cooper's core, supplemented from other seminal works as needed.

2.5.1.2 Supporting variables from other NPD forecasting literature

Additional multi-disciplinary, multi-functional antecedents need testing (Cooper 1976; Cooper and Kleinschmidt 1986; Montoya-Weiss and Calantone 1994; Wind and Mahajan 1988). Where conceptual gaps in Cooper's core existed, variables were borrowed from Cooper and de Brentani (1984) and Zirger and Maidique (1990). These forecasting works were closest in method and findings to NewProd and form the best basis of comparison for judging this work's validity and contribution.

Cooper and de Brentani (1984) found financial potential, product life and types of strategy important to manager's accept/reject decision (see table 2-5). These new variables uncovered, along with mutually inclusive dimensions reordered, suggests reality check/utilisation problems between scholarly findings and practitioner go-no-go criteria. All three variable concepts were operationalised for better precision and added to this work's core (see *Cooper and de Brentani 1984* in APPENDIX A).

Zirger and Maidique (1990) used a high technology sampling frame to study variables similar to NewProd (see table 2-6). In slightly different order due to R&D/organisational variable operationalisation, their findings tap dimensions similar to NewProd and support using the "Cooper 30". However, unlike Cooper, early entry was found related to success (Maidique and Zirger 1984). It was operationalised and added to the variable core data set (see *Zirger and Maidique 1990* in APPENDIX A).

2.5.1.3 New variables

New variables culled from theory important to adjunct fields are noted by an "*" in Figure 2-3. Also, one primary citation to justify their use is displayed in the postal survey instrument in APPENDIX A. Areas integrated with the core include: (1) New product development history/experience; (2) Market entry barriers and competitive retaliation; (3) PLC; (4) Market entry timing; (5) Project innovation levels and (6) Strategic action/reaction. Models not acknowledging these areas, despite being parsimonious and accurate, may be thought deficient (Lilien 1975) or "black box" (Mahajan and Wind 1992) by practitioners, thus leading to under-utilisation. Their validation would indicate future use in new product success/failure forecasting is warranted.

2.5.1.3.1 Product market history

The addition of product market historical experience is reasonable because:

- firms should exploit past experience (Abell and Hammond 1979; Boston Consulting Group 1972; Buzzell and Gale 1987; Cooper and de Brentani 1984; Cooper and Kleinschmidt 1987b; Crawford 1980, 1994; Lambkin 1988; Lilien and Yoon 1990; Peters and Waterman 1982; Schmalensee 1982). This leads to competitive advantage (Booz, Allen and Hamilton 1982).
- benchmarking (Griffin 1993) historic norms to create information tracking systems (Crawford 1994; Kotler 1994) is necessary for "focusing" on the expected value (Tull and Hawkins 1993) of the go/no-go/continue decision vis-à-vis the expected value of the entire portfolio (Cooper 1994).
- product market entry success is related to previous generation replacement history e.g. success of PC word processors proceeds from replacement history of electro-mechanical ⇒ manual typewriter product market history (Saunders and Jobber 1994).
- past product market history, possibly the industrial, multigenerational equivalent of natural selection (Darwin 1859), needs testing. Individual products are offsprings of "family" platforms enhanced over time. Successive platforms are the applied result of underlying core capabilities (Meyer and Utterback 1993). In well-managed firms, such core capabilities tend to be of much longer duration and broader scope than single product families or individual products. Unobservable in seminal, single product market generation work, project "nature"[10] may be a "family inheritance" relating to synergy. Embodying all past product market efforts and analogous to genetic family history, the nature of past project experience may affect initially, every "next" project's success. As with early childhood experience, these early, uncontrollable influences may last until modified by controllable "nurturing[11]" processes over time.
- variation may be the result of "dominant or recessive" product market characteristics unseen in single generation studies. Analogous to Mendel's[12] "hereditary units" (genes), project family ancestors and their ability to learn and teach from experience, may be the key to why projects fail despite seemingly "doing all the right things".

Though success, failure and kill ratios and characteristics have been included on rare occasions (Cooper 1984b, 1985b; Cooper and Kleinschmidt 1990a), very little has been done to establish the nature and extent of the link between this indirect measure of success and other dimensions (Hart 1993). Seminal omission of this certain

10 A human analogy is one's early "nature" affecting being e.g. family wealth, appearance, place of birth, body build, intelligence level and religion. are uncontrollable in the child. To some degree they affect early and later decision making.
11 Sooner or later one's own "nurturing" choices modify what nature has delivered on her own.
12 Gregor Johann Mendel.

deterministic dimension[13] from initial screening model development seems an oversight.

2.5.1.3.2 Competition and barriers to entry

Competition is intensifying in many industries (Griffin 1993; Hayes, Wheelwright and Clark 1988; Womack, Jones and Roos 1990). Though the nature of the competitive situation has been found to be only weakly related to success, (Cooper and Kleinschmidt 1993), "the environment" needs further study (Montoya-Weiss and Calantone 1994). Some suggest that environmental dimensions have less impact on success than process dimensions (Cooper 1979b, 1980b, 1981, Cooper and Kleinschmidt 1993) and that new products can be successful under a variety of market conditions (Cooper and Kleinschmidt 1987a). However, re-examination is important in today's increasingly competitive global environment because:

- past undercounting of market environment characteristics may result from products facing highly negative markets being killed early in their development (Cooper and Kleinschmidt (1987a). Long-term retrospectives exhibit survivour bias and may not capture these phenomena.
- being "environmentally ignorant" is a significant failure scenario (Calantone and Cooper 1979).
- competition for resources can cause failure (Calantone and Cooper 1979; Cooper 1975; Darwin 1859; Lambkin and Day 1989; Link 1987; Wind and Mahajan 1988) with some recommending dynamic (Cooper 1980b) and competitive (Cooper 1979b, 1981; Zirger and Maidique 1990) environments be avoided.
- competitive actions are related to strategic planning (Abell and Hammond 1979; Ansoff and Stewart 1967; Bain 1956; Booz, Allen and Hamilton 1982; Buzzell and Gale 1987; Nijssen, Arbouw and Commandeur 1995; Rogers 1983; Doyle, Saunders and Wong 1992; Wasson 1978), recognised as important by NPD managers (Maidique and Zirger 1984) and important in practitioners' definitions of success (Hart 1993).

Whilst new products aimed at markets with aggressive competitors seem to succeed or fail in spite of the situation (Cooper and Kleinschmidt 1993), the importance and type of the threat causing unique strategic responses goes unmeasured. Direct assessment of the *threat* of competition and important barriers to entry such as "incumbent cost advantages", "product differentiation", "brand identity", "customer switching costs", "capital requirements", "access to distribution channels", "absolute cost advantages" and "government policy" (Porter 1985) is warranted.

[13] If honestly assessed, past history has almost 0% chance of measurement error. i.e. it is a deterministic dimension. A deterministic mathematical model is expressed as $Y=B_0 + B_1X_1$. Given any value for X, the value of Y can be determined with precision. A stochastic model contains one or more random components that lead to errors in efforts to predict and is written as $Y=B_0 + B_1X_1 + e$ (epsilon/error) (Webster 1992).

2.5.1.3.3 Product Life Cycle (PLC)

PLC "surrogates variables" [14] have been found inferior to process variables for success prediction (Cooper 1979a) with length of PLC found only moderately important to project accept/reject decisions (Cooper and de Brentani 1984). However, PLC should be added to this work's core variable data set because:

- the citations suggesting its strategic importance are impressive (Ansoff and Stewart 1967; Buzzell 1966; Catry and Chevalier 1974; Day 1981; Dodge and Rink 1978; Doyle 1976; Gordon, Calantone and di Benedetto 1991; Kotler 1994; Luck 1972; Levitt 1965, 1966; Michael 1977; Rink and Swan 1979; Tellis and Crawford 1981; Thorelli and Burnett 1981; Utterback and Abernathy 1975; and Wasson 1978).
- it is thought to have a moderating impact on the NPD process (Cooper 1979b, 1981, 1984) with previously validated dimensions deserving more attention as moderators (Montoya-Weiss and Calantone 1994).
- with most NPD processes designed for long PLCs (Wind and Mahajan 1988), managers complain tools do not match their short cycle needs (Cooper and Kleinschmidt 1991). PLC has the potential to meet forecasting needs (Balachandran and Jain 1972; Cooke and Edmondson 1973; Kovac and Dague 1972; Parsons 1975) as an enabler (Day 1981). This might allow short-cuts and the improved accuracy requested (Wind and Mahajan 1988) in 3rd generation situational/conditional schemes (Cooper 1994b).
- construct validity problems (Montoya-Weiss and Calantone 1994) caused by surrogate error emanate, possibly, from using only surrogate variables (Cooper 1979a) to measure PLC. This needs correction using better operational definitions of PLC.

Prominence in the literature, under-examination of NPD-related moderating characteristics and surrogate measurement error compel replication using a better operationalisation of the PLC concept as a process enabler (Day 1981).

2.5.1.3.4 Market entry timing

Entry timing is related to level of project innovativeness (Crawford 1994), with both concepts in need of re-examination based on mixed findings.

- some find market entry timing is important to success (Ansoff and Stewart 1967; Lambkin 1988; Lilien and Yoon 1990; Robinson and Fornell 1985; Robinson, Fornell and Sullivan 1992). Pioneers develop sustainable competitive advantages (Lambkin 1988; Robinson 1988; Robinson and Fornell 1985; Robinson, Fornell and Sullivan 1992) with market share penalties paid by later entrants (Urban et al 1986). However,
- first-in advantages are based on the assumption of accumulated experience, marketplace positioning and stable preference patterns (Bain 1956). These are not as certain in today's short cycled markets where rapid diffusion reduces learning-based advantages (Liberman and Montgomery 1988).

[14] product homogeneity, intensity of competition, level of price competition, number of competitors.

- some indicate that final market share does not depend on order of entry at all (Fershtman, Mahajan and Muller 1990) or may be explained as much by other factors (Lilien and Yoon 1990; Miller, Gartner and Wilson 1989; Kerin et al. 1992) including scale of entry (Biggadike 1979).
- the best success/failure forecasting projects show mixed results. Cooper (1979b) and Cooper and Kleinschmidt (1993) did not find entry order a determinant of success in contrast to Maidique and Zirger's observation (1984).

Clarification of the relationship of entry order to success in initial screening models remains undecided, provocative and worth re-examination.

2.5.1.3.5 Market entry innovativeness

Findings covering the impact of innovativeness (see APPENDIX B) on performance are scattered and inconclusive:

- Myers and Marquis (1969) showed the great majority of five-hundred and sixty-seven successful incremental innovations were market derived (about 75% market pull) and only 21% were technology push. They did not produce a forecasting model however.
- Globe, Levy and Schwartz (1973) determined that radical innovations were dominated by internal and technical factors.
- early works have not found innovativeness a strong factor of success (Chakrabarti, O'Keefe and Soulder 1976; Kulvik 1977; Rothwell 1972, 1974).
- NewProd considered innovativeness a moderating variable only (Cooper 1979a, 1979b, 1980a, 1980b) emphasising that innovative products are not all that different from "me too" products.
- Cooper and de Brentani (1991) found highly innovative services marginally more successful, with Maidique and Zirger (1984, 1990) finding product innovativeness not to be a success dimension.

However, these findings need re-examination in light of the fact that:

- all previous linear NPD work failed to identify the curvilinear phenomena inherent in innovativeness (Kleinschmidt and Cooper 1991).
- Cooper recently found highly innovative products achieved an admirable track record (Cooper 1994a).
- innovation is an area lacking empirical confidence with only 31.9% of the research reporting the type of innovation studied. Thus, typically reported factors of success are called into question, with managerial guidelines by type of innovation needed (Montoya-Weiss and Calantone 1994).

In these increasingly dynamic times it is highly appropriate to re-examine success more precisely as a function of "new-to-the-world products", "new-product lines", "additions to existing product lines", improvements/revisions to existing products", "repositionings" and "cost reductions" (Booz, Allen and Hamilton 1982).

2.5.1.3.6 Strategic action/reaction

Booz, Allen and Hamilton (1982) argue that success favours those that implement company specific approaches driven by corporate objectives and strategies. Whilst this concept is not new, the link between objective attainment, type and magnitude of initial strategy based on early information and reactive strategy based on new learning has not been demonstrated. It should be since:

- new product strategy and execution result from the new product process activities moving the product from idea to launch in an environment of resources, experience and skills in marketing, production and technology (Cooper and Kleinschmidt 1987b). Strategy leads to performance (Buzzell and Gale 1987), as firms plan, anticipate and assemble resources and skills (Abell and Hammond 1979) to take advantage of the projected situation.
- traditional strategic approaches such as PIMS (Buzzell and Gale 1987)[15] usually deal with existing products and are of little help in NPD work (Cooper 1984a, 1984b).
- strategic typologies are linked to performance (Cooper 1984a, 1984b, 1985b) with new product outcomes determined, not from initial strategy alone, but from the interaction of the market environment with the new product strategy (Cooper and Kleinschmidt 1987b).
- the NPD strategic process (Cooper 1985a, 1985b) exhibits this interaction into the post launch period (Cooper 1992; Crawford 1986). Benchmarking strategic changes between the initial screen and one year post launch would allow observation of the strategic alignment process (Abell and Hammond 1979; Kotler 1994; Porter 1991).
- new product strategies link the NPD process to company objectives, which, in turn, loop back to provide guidelines for the next project's screening criteria (Booz Allen and Hamilton 1982). This conceptual "connective dynamic" needs better operationalisation, definition and clarification.

Beginning NPD strategy at the initial screening using historical experience and early information may be quite inappropriate in the later stages of the process. After downstream information becomes more certain, adjustments in strategic emphases and implementation are conceivable. Thus, assessing initial screen strategic profile and its evolutionary adjustment vis-à-vis "newness/innovativeness problems ", "barriers to entry problems", "resource problems", "project/newness problems", "final product problems" and "market problems" is apropos.

2.5.1.4 Core supporting and new antecedents may evolve

Information available early may evolve to a richer level during the later stages of the process (Albala 1975; Abernathy and Utterback 1978; Crawford 1984, 1986; Lambkin 1988; Ronkainen 1985). Successful innovation is facilitated by monitoring environmental evolution (Mintzberg 1983) and handling major changes related to technology and the marketplace as they occur (Calantone and Di Benedetto 1988, 1995; Cooper 1980a; Cooper and Kleinschmidt 1987b, 1988). Understanding the

[15] PIMS (profit impact of market strategy) strategic dimensions consist of strategy in the areas of product/service policies, pricing policies, marketing programs, investment strategy, work force productivity, vertical integration and R&D.

significance and magnitude of simple and compounding variable evolution, within and between categories (Calantone and Di Benedetto 1990), is fundamental to empirical demonstration of "must meet, should meet" stage and gate criteria and activities (Cooper 1990a). This evolution[16] has not been demonstrated, but would support those recommending its assessment (Abell and Hammond 1979; Buzzell and Gale 1987; Kotler 1994; and Porter 1980, 1985, 1991). And it may uncover conditional phenomena (Cooper 1994b) necessary to relative models (Lilien 1975) which are required for futuristic scenario analysis (Wind and Mahajan 1988).

2.5.2 Hypothesis H_1b

The factors constructed from screening variables are dynamic with respect to their construction, percent of variance, order and magnitude. They evolve over time from the initial screen to the end of the first year of market entry.

Hypothesis H_1b is a logical extension of H_1a above. It tests the null form that there is no difference between early and late normalised factorial environments. It flows methodologically from Schocker, Gensch and Simon's (1969) admonition to eliminate variable overlapping effects by reducing them to more manageable subsets of independent dimensions.

Factor analysis is well established in NPD research (Calantone and Cooper 1979; Cooper 1979b, 1981 1985a; Cooper and de Brentani 1984, 1991; Zirger and Maidique 1990). Investigations over the last three decades have generated awareness of the normalised environmental factors that facilitate or undermine new product success. Unfortunately, no work has observed normalised factor environmental change from the beginning to the end of the NPD process.

H_1b posits that there is a difference between beginning and ending factor analysis results. Validation is important because demonstrating a significant change in factor solutions would suggest multiple normalised environments are at work in the NPD process. This would support those suggesting that internal and external environmental changes occur (Abell and Hammond 1979; Buzzell and Gale 1987; Calantone and Di Benedetto 1988, 1995; Cooper 1980a; Cooper and Kleinschmidt 1987b, 1988; Kotler 1994; Porter 1980, 1985, 1991) thus affecting the expected value of success.

2.5.3 Hypothesis H_1c

Factors significant to a new product's successful introduction are dynamic. As more information becomes known to the team over time these significant factors

[16] also for normalised factors (H_1b), linear regression success dimensions (H_1c), accuracy improvement (H_1d) and strategic reaction (H_4).

evolve from an inadequate, incomplete, uncertain condition at the initial screen to a more adequate, more complete, more certain condition at the end of the first year of market entry. They change in their order and magnitude.

A logical extension of H_1a and H_1b above, this hypothesis tests the null form that there is no linear difference between beginning and ending dimensions perceived significant to success. It replicates Cooper's seminal methodology, integrates new heterogeneous dimensions and then re-examines factor selection and magnitude as they change over time. The aim is to understand internal temporal construct validity problems possible in static works.

2.5.3.1 Re-examination and validation of previous work

The link between project outcome, performing up-front activities (Cooper 1988, 1994b; Cooper and Kleinschmidt 1986, 1987b, 1994) and initial screening forecast reliability (Cooper 1979b, 1981, 1992; Zirger and Maidique 1990) has been established. However, for the field to evolve beyond the exploratory stage, replication is required (Montoya-Weiss and Calantone 1994). NewProd has received limited validation (see Table 2-3) and Stanford none. Therefore, re-construction and validation of the initial screening function and dimensions, using core and expanded data sets, is important.

2.5.3.2 NPD model evolution

Testing H_1c also responds to queries as to whether or not "best practices" are time invariant (Montoya-Weiss and Calantone 1994). Though dimensional evolution has been acknowledged to be a methodological problem (Cooper 1992; Crawford 1979), neither NewProd (see Table 2-2 and Table 2-4) nor Stanford (see Table 2-6) results have been tested for temporal stability.

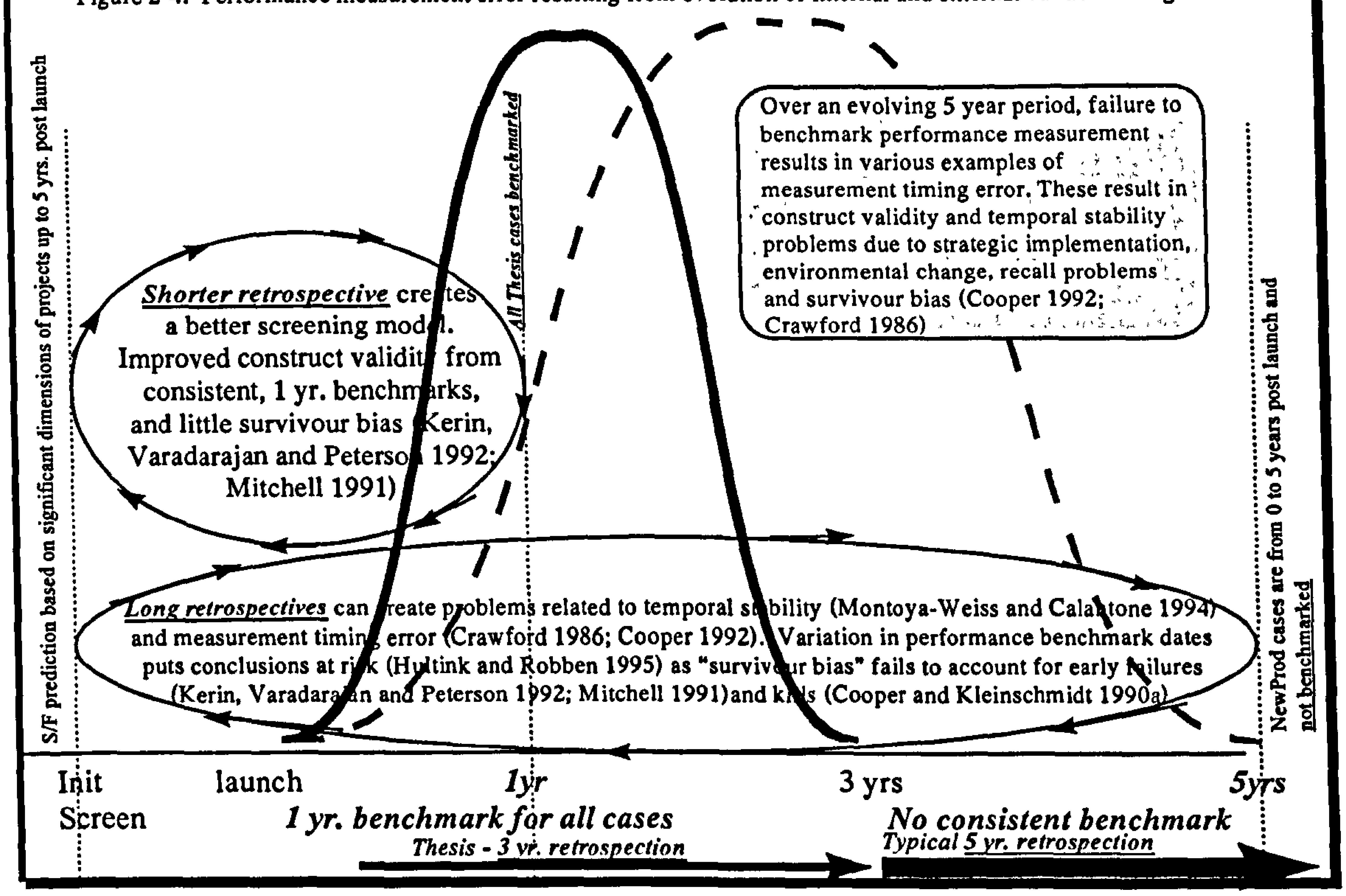
Some NPD evolution is recognised currently. For example: (1) conceptual changes are thought to represent continuous improvement in the quality of the data over time (Albala 1975); (2) product innovation techniques are thought to evolve over time into process innovation techniques (Abernathy and Utterback 1978; Calantone, Di Benedetto and Meloche 1988; de Bresson and Townsend 1981; Utterback 1981) and (3) project success is related to evolving technical and marketing skills and resources, either on hand or acquired over time (Calantone and Di Benedetto 1988, 1990, 1993; Cooper and Kleinschmidt 1987b, 1988). Therefore, it is reasonable to postulate that if the quality of data, innovation techniques, skills and resources needed change over time, then early dimensions of success may differ from later dimensions of success.

Importantly, if "best models" were demonstrated to differ over time, the GO/NO-GO and GO/CONTINUE decision would then be conditional[17]. "Fuzzy" decision making is thought desirable (Cooper 1994b). Thus, accepting H_1c would ultimately lead to more flexible models displaying unique critical paths (Lilien and Kotler 1983; Urban and Hauser 1980)[18] to success.

2.5.3.3 Seminal measurement timing error

A serious threat to the validity of the NewProd model comes from its long, imprecise retrospective measurement period. To establish dimensional construct validity, early NewProd work used factor analysis. Later both factor analysis and Chronbach alphas were used. However, factor analysis and Chronbach alphas are not panacea substitutes for establishing construct validity (Montoya-Weiss and Calantone 1994).

Figure 2-4: Performance measurement error resulting from evolution of internal and external variable changes



Measurement timing error occurs when measurements are made at an inappropriate time to properly reflect the characteristic being studied (Tull and Hawkins 1993). Cooper constructed the NewProd model from long retrospectives (see Figure 2-4)[19].

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17 Conditional probability is the likelihood that event "A" will occur given that, or on the condition that, event "B" has already occurred. $P(A|B) = P(A \text{ and } B) / P(B)$ (Webster 1992). The project might GO or CONTINUE given that significant early requirements have been achieved and those required later have a high conditional probability for later accomplishment based on evolving internal and external conditions.

18 see CPM in APPENDIX B. Similar to PERT, CPM refers to the critical path method of project management used for timely application of resources. The technique is similar, but possibly more useful to practitioners, than anecdotally determined stage-gates (Cooper 1990a). See also, Grossman, Don and Sri N. Gupta, Dynamic Time-Staged Model for R&D Portfolio Planning-A Real World Case, *IEEE Transactions on Engineering Management*, Vol. EM-21, No 4, November 1974.

19 NewProd's evolutionary problem is founded also, in the inconsistent manner of asking for the success/failure performance judgement e.g. the measurement of dimensional evolution varies from case to case depending on the point in time when the respondent decides independently, to measures success/failure. This can be misleading (Kerin, Varadarajan and Peterson 1992). In Calantone and Cooper (1979) the unit of analysis was a product new to the firm and a failure within the last 5 years. Unfortunately, in Cooper 1979a, 1979b and 1981, the term "recent" was used but not defined. The elapsed time benchmark date (from screening or from launch) was missing also. This work improves upon this using one year from

Asking company personnel to recall sets of new products over a five year period relies heavily on memory, is subjective in interpretation and may vary between operational functions. The results can be biased towards earlier products because there has been a longer time to achieve some degree of success (Crawford 1979). Clearly, the longer the retrospective the more serious such survivor bias (Kerin, Varadarajan and Peterson 1992, Mitchell 1991). Thus, because the product and marketing strategy evolve together (Crawford 1986) causal antecedents can be divorced from the ultimate success/failure result by strategic action/reaction (Cooper 1992). Further, since most performance measures vary with the timeframe specified, the failure to define precise performance measurement benchmark dates in seminal literature may limit the value of this type of result (Hultink and Robben 1995).

In testing H_1c measurement timing error and survivor bias are reduced by using a three year time frame (versus five years) and a one year performance benchmark date. Construct validity and temporal assessment (Montoya-Weiss and Calantone 1994) should improve proportionately.

2.5.4 Hypothesis H_1d

As the factors contributing to a new product's success evolve, the resulting new product screening model's predictive proficiency evolves also.

H_1d is a logical extension of H_1a, H_1b and H_1c. It tests the null form that there is no accuracy difference between the two linear functions created in H_1c above. Validation is important because it would support the evolution of environments theorised above and respond to requests for better forecasting accuracy (Mahajan and Wind 1992).

Screening accuracy is critical yet based on speculative (Cooper and de Brentani 1984; Albala 1975, Cooper and Kleinschmidt 1987b, 1990; Souder 1978) information. Up-front activities are poorly performed overall (Cooper 1988) with richer data emerging as the process evolves (Albala 1975). Practitioner under-utilisation may be due to manager disapproval of immature, uncertain forecasts based on expensive speculative information leading to low expected value from early model use[20]. If predictive proficiency is shown to rise over time, a multiple model (Albala 1975; Lilien 1975) simulation becomes an even more attractive NPD paradigm. These would be probabilistic rather than deterministic and would be more useful than current models

launch as the performance measurement date. For comparison, Cooper's "recent project" is assumed to be 5 years denoted in previous and later (Cooper and de Brentani 1991b; Cooper and Kleinschmidt 1993) works.

20 EVII = EVPI-ECE. Expected Value of Imperfect Information = Expected Value of Perfect Information minus Expected Cost of Errors (Tull and Hawkins 1993). The more speculative the model's information (increasing the cost of error based on speculative "a priori" information), the lower its expected value to the practitioner. The lower the value of the model to the practitioner the less it will be used.

in dealing with risk due to internal and external change. As such, they would allow complex diagnostic analyses using multiple performance criteria based on various types of strategic equilibrium adjustment.

2.5.5 Hypothesis H_2

Factors significant in contributing to a new product's successful introduction vary as a function of the length of the product's introductory life cycle.

The operational definition of PiLC is "the life expectancy of an introduction before modification is necessary". It is calculated in years and months and is in harmony with Day's argument that a product life cycle begins when a substantial change in technology, customer function or customer group occurs that is outside the scope of all or most of the current suppliers (Day 1981). Yet it avoids the empirically vague issue of beginning and end of PLC stages. Using PiLC in a conditioning/moderating role, H_2 tests the null form that there is no difference between short, medium and long product market dimensions of success.

Some have suggested that there may not be one set of NPD activities/processes common to all teams, conditions and situations (Calantone, Vickery and Droge 1995; Cooper 1985a, 1994b; O'Connor 1994). Accordingly, with short cycles (Griffin 1993; Qualls, Olshavsky and Michaels 1981) lessening management's ability to react quickly, thus forcing use of approximations (Ansoff and Stewart 1967), H_2 attempts to demonstrate how PiLC approximation alters dimensions under such conditions. Validation is important because, though PLC is recommended for determining strategy, few have examined how strategies actually change in response to product life cycle changes (Thorelli and Burnett 1981).

2.5.5.1 PLC in the general literature

Supporters of PLC's suggest the concept is fundamental to determining strategy (Hoffer 1975). They advise that it leads to better planning (Levitt 1965, 1966), is the simple and intuitive centrepiece of the marketing and planning literature (Thorelli and Burnett 1981) and though lacking empirical support, it is advocated by academics (Buzzell 1966, Catry and Chevalier 1974; Cox 1967; Doyle 1976; Kotler 1994; Luck 1972; Michael 1977; Polli and Cook 1969, Rink and Swan 1979; Staudt et al. 1976; Utterback and Abernathy 1975; Wasson 1978) as a framework for product management (Tellis and Crawford 1981).

Others disagree based on disappointing application (Thietart and Vivas 1984), propensity for self-fulfilling, premature product death (Dhalla and Yuspeh 1976) and lack of evidence concerning competitive processes accompanying market evolution (Lambkin and Day 1989). None-the-less, its true value as an enabling condition, a moderating variable, or a consequence of strategic decisions (Day 1981) has not been explored fully (Harrell and Taylor 1981).

2.5.5.2 PLC in the screening literature

Direct PLC impact assessment is conspicuously rare in the screening/forecasting literature. When acknowledged, support has been weak. NewProd (Cooper 1979a) found a gap between the venture outcome and product life-cycle surrogates. With none significantly related to success or failure, he argued for de-emphasising its strategic or predictive value. However, he did find it to moderate conditions of success (Cooper 1979b, 1981). Contrarily, Cooper and de Brentani (1984) later found length of PLC significant to managers' accept/reject decisions, but it ranked only fifth out of nine criteria (see Table 2-5). This may illustrate another "reality check" incongruity between modelers and practitioners (Calantone, Di Benedetto and Haggblom 1995).

2.5.5.3 Current short PLC imperative

Product life-cycles and/or symptoms are getting shorter (Bayus 1994; Booz Allen and Hamilton 1982; Griffin 1993; Guveritz, S. 1982; Qualls, Olshavsky and Michaels 1981; Rosenthal 1991). The evolution of the original twenty-five year typewriter PLC to the five year first-generation microprocessor-controlled model is an example (Saunders and Jobber 1994). Even more severe, computer hardware PLCs are estimated at six to eighteen months (Seymour 1995) with significant advances in graphics components estimated at ninety to one-hundred twenty days (Boudette 1993).

Decreasing product development cycle time is an important issue to US corporations (Griffin 1993) with many companies trying to shorten their time from ideation to launch (Ali, Krapfel and LaBahn 1995; Griffin 1993; Millson, Raj and Wilemon 1992). Currently, there is a veritable deluge of articles in the Journal of Product Innovation Management concerning shorter PLCs, cycle reduction time and issues ancillary (Bayus 1994; Carmel 1995; Cooper 1994b; Cooper and Kleinschmidt 1994; Nijssen, Arbouw and Commandeur 1995; Murmann 1994; Saunders and Jobber 1994; Rauscher and Smith 1995). However, most NPD processes are modelled on long PLCs. Flexible procedures allowing short-cuts need development (Wind and Mahajan 1988).

"The environment" requires further study (Montoya-Weiss and Calantone 1994). Validation of short, medium and long PiLC success dimensions is meaningful since little is understood of shrinking PLC effect on dimension variance. Further, all current models lack desirable third generation conditional/situational characteristics (Cooper 1994b) which could shorten cycle time based on PiLC conditions. Reducing requirements (Wind and Mahajan 1988) by limiting dimension consideration to only those appropriate to product market length would support early estimation of PLC (Levitt 1965, 1966), validate PLC as a moderator (Cooper 1979b, 1981; Day 1981) and be useful to NPD critical path modelling (Lilien and Kotler 1983; Urban and Hauser 1980).

2.5.6 Hypothesis H_3

Factors significant in contributing to a new product's successful introduction vary as a function of its order of entry/related level of innovativeness.

Since the general and NPD literature is mixed on the effects of speed to market and its contribution to success/failure under researched (Montoya-Weiss and Calantone 1994), re-examination is important. Inconsistent findings may be due to inadequate operationalisations of the concept, methodological inconsistencies and statistical inappropriateness. It is clear that no standardised set of NPD activities are perfect for all conditions (Calantone, Vickery and Droge 1995; Cooper 1994b; O'Connor 1994). Therefore, using order/innovation to moderate the aggregate factors is appropriate and useful to measure success through the 1st year after launch.

H_2 does not attempt to decide whether entry should be early, late, or somewhere in between. Rather, it investigates whether "high-tech" pioneers exhibit different success factors than "lower-tech" followers. With free and timely choice of order/innovation not always possible, a need exists to differentiate between early and late strategies (Montoya-Weiss and Calantone 1994).

2.5.6.1 Order/innovation in the general literature

The concept of ordered advantage is quite mature (Bain 1956; Stigler 1969), with Ansoff and Stewart (1967) suggesting technological strategy success comes from either: (1) being first to market based on technical leadership and risk taking; (2) following the leader stressing an ability to react quickly as the market starts its growth phase; (3) applying applications engineering to modify products in mature markets or (4) being "me-too", but stressing superior manufacturing efficiency and cost control.

Some find early entry important to success (Booz, Allen and Hamilton 1982; Hopkins and Bailey 1971; Lilien and Yoon 1990; Robinson, Fornell and Sullivan 1992). Pioneers have higher market shares (Robinson and Fornell 1985) for both start-up and adolescent businesses (Lambkin 1988), with a significant penalty paid by later entrants (Urban, Carter, Gaskin and Mucha 1986). These penalties, especially in high growth, short PLC and high price erosion environments, have caused profit declines from 17% to 35% over a five year period (Nijssen, Arbouw and Commandeur 1995).

Some find otherwise (Fershtman, Mahajan and Muller 1990; Miller, Gartner and Wilson 1989) suggesting successful entry may actually be more a condition of marketing positioning and advertising (Kerin, Varadarajan and Peterson 1992; Urban et al. 1986), delayed entry to improve the product and/or marketing effort (Lilien and Yoon 1990) or a function of industry related variables (semiconductor industry - Flaherty 1983; Spital 1983; high technology - Maidique and Zirger 1984; cigarettes - Whitten 1979; pharmaceuticals - Bond and Lean 1977). At best the general literature is mixed.

2.5.6.2 Order/innovation in the screening literature

Speed to market is one of the least studied factors of success (Montoya-Weiss and Calantone 1994). The existing evidence is mixed due probably to differences in variable selection, conceptual/operational definitions and/or inappropriate statistical methods.

The effects of innovation as it relates to order is also troublesome. Utterback (1974) examined factors affecting successful innovation. Later Abernathy and Utterback (1978) examined how response to innovative ideas changes as teams mature. Innovativeness is identified as important to new entries (Davidson 1976; Marquis 1969; Rothwell 1976) and to competitive advantage (Maidique and Zirger 1984) with Booz, Allen and Hamilton (1982) determining that ten percent of "new to market" products represent sixty percent of successes. This is inconsistent with those failing to find that being first to market is a significant determinant[21] (Cooper 1979b; Zirger and Maidique 1990). Complicating matters, Kleinschmidt and Cooper (1991) recanted previous findings on innovation because of the inappropriateness of linear methods. Then, ironically, they used linear techniques again (Cooper and Kleinschmidt 1993) to find order moderately significant to success. Such

21 this may be due to the methodological problem of averaging dimensions over long periods of time and failure to benchmark performance measurement dates consistently. Importantly, the survivor bias (see Figure 2-4) resulting would eliminate the significance of those who failed because of late entry.

inconsistencies support re-examination. The problem is still unresolved and provocative.

2.5.6.3 Complications with past findings

Changing new product development environments, methodological problems of past work and failure to identify, account and report innovation type requires re-evaluation of success discriminants as a function of innovation type (Montoya-Weiss and Calantone 1994). Environments are now characterised by new knowledge being applied faster, more new introductions, time between innovations decreasing, more variations available and failure to consistently remove products from the market (Bayus 1994; Saunders and Jobber 1994). Avoiding such environments (Cooper 1979b, 1980b) to attain a learning advantage is impractical today. Given that rapid diffusion rates reduce learning-based advantages (Liberman and Montgomery 1988), re-evaluation of order/innovation is more appropriate than ever.

Problematic also is the suggestion that order effects may vary between incumbents and newcomers (Mitchell 1991). Survivor bias (Kerin, Varadarajan and Peterson 1992) from five year retrospectives (see Figure 2-4) may exclude early failure. This casts some suspicion on the mixed order/innovation findings. This work's use of a cross-section of small, large, new and incumbent teams, benchmarked precisely at one year post launch, minimises survivor bias. The results from testing H_3 will represent pioneering failed case phenomena possibly missing in the NewProd and Stanford models.

2.5.7 Hypothesis H_4

Firms which develop precise initial strategies but react flexibly to deal with deficiencies in early assumptions of internal and external environments, are more successful than those that do not.

Suggesting that firms should plan and react accordingly is not original. Poor planning has been known to be a reason for failure for some time (Crawford 1977). However, few firms plan well (Abell and Hammond 1979) and no one has measured the direct effect of strategy's initial and later intra-process links to success. H_4 tests the null form that there is no difference in entry success based on the team's ability to plan and implement initial NPD strategy and then react appropriately over time.

2.5.7.1 Strategy in the general literature

Strategy at its simplest is static. It provides a blueprint for the pursuit of organisational objectives appropriate for sustained success (Thompson and Strickland 1987). This success is based on analysing: (1) customer segmentation and its requirements; (2) competitors and their strategies; (3) environmental trends; (4) market evolution of supply and demand and (5) company strengths and weaknesses (Abell and Hammond 1979). These factors must be reviewed in the context of size and historical experience vis-à-vis costs.

Strategy is also dynamic, with strategic windows for successful entry occurring when a market's key success requirements and specific firm competencies fit best (Abell 1978). Though the PIMS studies linked strategy to performance (Buzzell and Gale 1987), the phenomena of strategy guiding the fit between objectives, resources and opportunities over time (Porter 1991) has not been demonstrated. This learned reactive dynamic defined as alignment (Abell 1978; Kotler 1994) remains unexamined in an NPD context.

2.5.7.2 Strategy in the screening literature

Company specific new product programmes are a function of a well-defined new product strategy (Booz, Allen and Hamilton 1982). These link the NPD process to company objectives, provide focus for idea/concept generation and guide the establishment of screening criteria.

Modern NPD strategy has been studied (Cooper 1984a, 1984b, 1985b; Cooper and de Brentani 1984; Rothwell et al. 1974; Souder 1987, 1988) with Cooper finding programme strategy related to performance. This relationship was based on the types of new products developed, markets chosen, technologies employed and the nature, orientation and commitment of the process (Cooper 1984a, 1984b, 1985b). However, it is understudied in an NPD context (Montoya-Weiss and Calantone 1994) with no one accounting directly for the effects of less informed, early, strategic planning, evolving into more informed, later strategic reaction. Equilibrium maintenance and its link to success needs clarification.

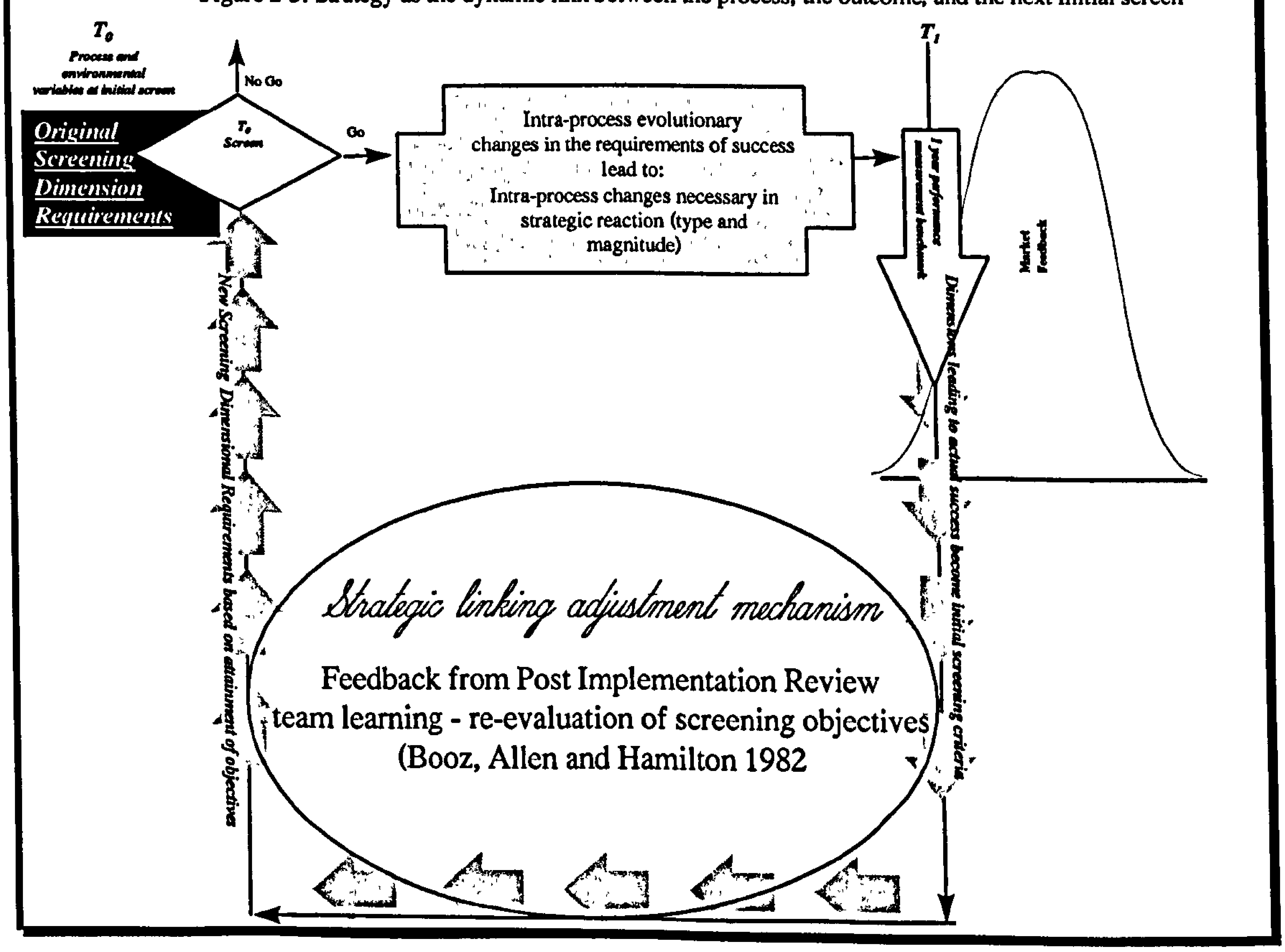
2.5.7.3 Strategy - the unmeasured NPD "dynamic link"

PIMS linked strategy to performance but has been criticised as overly simplistic formulae attempting to solve complex management problems (Lubatkin and Pitts 1985). Because PIMS treats NPD strategies peripherally, it is not adequate to address new product development programmes (Cooper 1984a, 1984b) or individual project strategy. Survivor bias reduces PIMS to analysing only late phenomena, as the effects of early exit from the market goes unexamined. And PIMS does not forecast which new products will succeed based on specific strategic variation. As such, it is inadequate for describing normative initial or reactive NPD success accomplishment. Better understanding of the temporal nature of NPD strategy is needed.

This work posits that the team's NPD strategy has both an initial and reactive role in assessing, reacting to and controlling process and environmental group equilibrium. This initial and ending "strategic state of nature" and its link to success, needs examination because:

- though strategic policies and decisions involving significant resource commitments are not easily reversible, they must be calibrated to fit the situation (Buzzell and Gale 1987). As situations change, strategic fit must change to optimise success.
- process and environmental strategy evolution is important. New posterior conditional information acquisition requires strategic adjustment (Kotler 1994). The type and magnitudinal impact of changing relationships between initial and ending strategic NPD requirements has not been established.
- well-defined strategy links the process to company objectives, establishing guidelines for screening criteria in return (Booz, Allen and Hamilton 1982; see Figure 2-5). However, this successful post launch strategic feedback process has never been demonstrated and requires delineation for its incorporation into initial screening model criteria.

Figure 2-5: Strategy as the dynamic link between the process, the outcome, and the next initial screen



Whilst correctly advising attention to controllable variables, NewProd and Stanford cannot empirically demonstrate the evolving calibration of strategy to dynamic situations. Recommended for avoidance (Cooper 1980b), dynamic situations requiring control are precisely where adaptive strategy is most critical and wanting. By failing to deliver dynamic advice, seminal models are strategically lacking.

Accordingly, H_4 posits that successful teams are better able to make dynamic, linking adjustments based on the results of group compounding interaction. Measuring the type and magnitude of the strategic link to evolving success is important, new to the field and demonstrated here.

2.6 Summary

H_1a - H_1d: Scholarly evidence indicates that whilst use of screening models could reduce failure rates, they are under-utilised by practitioners and need improvement (Cooper and de Brentani 1984; Cooper and Kleinschmidt 1988; Wind and Mahajan 1988; Mahajan and Wind 1992). Model inadequacy, low expected value from using priori methods only, naive models and/or inability to deal with the dynamics of the 1990's marketplace may explain why up-front actives are poorly performed.

Evidenced by scholarly calls for improvement and practical under-utilisation, testing H_1a through H_1d is important. Results should bridge gaps in the literature currently and add needed quantitative sophistication to overcome possible construct validity problems (Montoya-Weiss and Calantone 1994; Mahajan and Wind 1992) resulting, in part, from measurement timing error and survivor bias. Furthermore, these results could demonstrate flexibility characteristics cardinal to future third generation process models (Cooper 1994b).

H_2 - H_4: Re-examination of both PLC (H_2) and order/innovation (H_3) is especially important in today's dynamic environment. Mounting pressure to innovate fast and frequently make PLC and order/innovation conditioned models desirable, especially given the current trend to reduce cycle time.

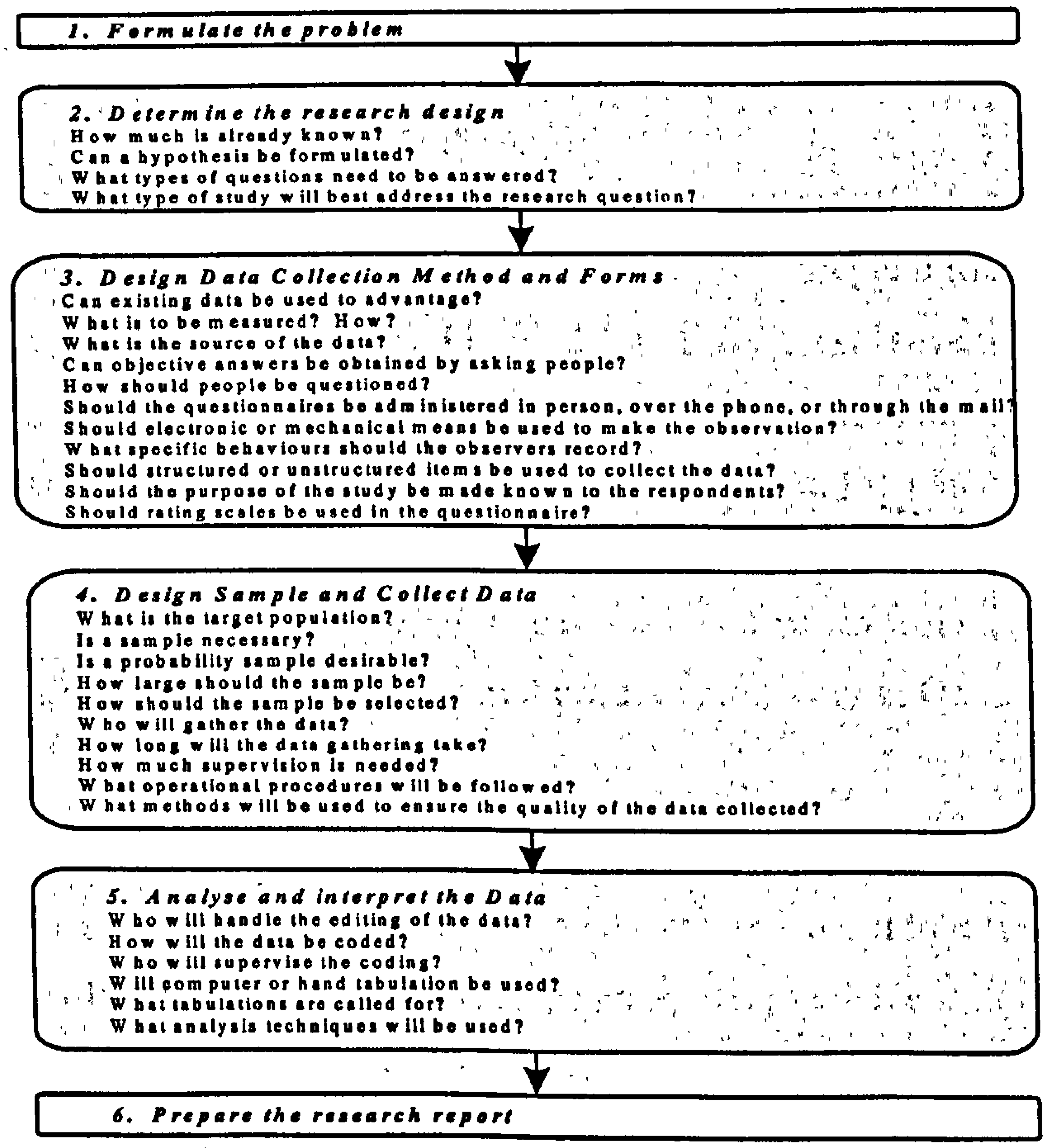
Finally, hypothesis H_4 is needed to demonstrate that successful teams are better able to make dynamic changes in initial screening strategy as markets and processes evolve over time. Given strategy's lack of validation in the NPD forecasting literature (Montoya-Weiss and Calantone 1994) combined with the calls for dynamic environment avoidance (Cooper 1980b), project level strategic reaction guidance is a worthy objective.

Chapter Three - Methodology

3.1 Introduction

This research utilises Churchill's (1991) six step sequence recommended for use in marketing research (see Figure 3-1). Chapter three explains the application of steps *two through five.* It describes the procedures used to examine all hypotheses listed in Chapter two. The chosen method emanates from seminal authors to allow a valid comparison.

Figure 3-1: Research process used (Churchill 1991)



3.2 Previous methodological designs

NPD methodology for go/kill determination has evolved from developing personal checklists via judgement (see Figure 2-1, panel B) to regressing perceived success and failure antecedents (Cooper 1979b, 1981, 1985a, 1992; Cooper and de Brentani 1984; Zirger and Maidique 1990; see Figure 2-1 panel F). Common designs should have developed to provide a replicative, integrated scientific approach for advancing the field. Unfortunately, there is a wide variation in research designs, methods and operationalisations of the dependent and explanatory variables used to study new product performance (Montoya-Weiss and Calantone 1994).

Simple first level designs employing descriptive statistics including means, frequencies and proportions are, unfortunately, still common in new work. They stand along side third and fourth level analysis[22]. The best overall design is the one used by Cooper in his early NewProd project work (Cooper 1979b, 1981). All others, except Rothwell et al (1974) and Maidique and Zirger (1984), either lack rigour or complete reporting for summarisation, replication and field improvement (Montoya-Weiss and Calantone 1994). This work is grounded in the NewProd design and modified only based on scholarly calls for improvement and published requests by practitioners.

3.2.1 NewProd methodology

In Cooper's earliest NewProd work (1979a) he developed a conceptual model of six new product development constructs (see Figure 2-2). From these, seventy-seven antecedents were selected for potential contribution to success and failure. A questionnaire was mailed to functionally neutral managers soliciting perceptions of antecedent importance vis-à-vis actual success or failure. One-hundred and ninety-five actual new product project success/failure cases were obtained from a government sampling frame of active industrial product producers in Ontario and Quebec Canada.

Respondents were asked to select two "recent" projects, one a clear cut commercial success and the other a similarly distinct failure[23]. They were asked to rate the project intervally from 0 to 10. Total agreement with the antecedent variable statement was a "10". Total disagreement was a "0" (see APPENDIX A, question #8). Benchmarks for performance measurement were not used[24] leading to probable measurement timing error and survivor bias. After telephone follow-up for "assistance and encouragement" and correction for "inappropriate or non-existent firms", a 69% response rate was achieved[25]. Cooper's analysis utilised simple designs stressing means, simple correlation and analysis of variance.

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22 Montoya-Weiss and Calantone (1994) suggest that the nature of statistical inference and deduction has improved over time with empiricism evolving from: (1) descriptive statistics (means, frequencies and proportions); (2) tests of differences/similarities (t-test, binomial test, ANOVA, MANOVA and X^2) (3) measures of dimensionality (factor analysis, cluster analysis and discriminant analysis) and (4) interpretation of parameters statistically (correlation analysis, canonical correlation analysis, regression analysis, path analysis and structural equation models).

23 projects that exceeded or fell short of minimum acceptable profitability for the type of project or investment, regardless of the way profitability was measured (scale from -5 to +5). This limited focus on profitability was later determined to be too narrow (Cooper and Kleinschmidt 1987a).

24 Crawford (1979) suggests a serious issue with failure studies revolves around how long a product is allowed to continue before success/failure is determined. Depending on industry, the setting and the buyer's decision process, strategy, management of the process and major expenditures of money can "fix problems" and thus affect the success ratio (see Cooper, Robert G., The NewProd System: The Industry Experience, Journal of Product Innovation Management, June, 1992, 9:113-127). If studies are (the typical) five year variety, researchers may be studying remedial marketing skills not success and failure of original innovation at the screen.

25 this "adjustment" is confusing given that the respondents were pre-screened.

Using the same data set, Cooper (1979b) advanced the methodology by applying factor analysis (Schocker, Gensch and Simons 1969) to eliminate the multicollinearity of the seventy-seven variable antecedents. Eighteen orthogonal (see APPENDIX B) factors with Eigenvalues greater than 1 were accepted followed by discriminant analysis (Simon and Freimar 1970) to forecast success/failure and determine the weightings of the factors in the screening model. Eleven of the eighteen factors differentiated well between new product success and failure. The model was validated using the split-half method.

Ultimately, these seventy-seven variables were reduced to forty-eight for his 1981 linear regression work and the interative 1985 work. Here he refined the procedure further by applying fourth level linear regression to thirteen orthogonal factors constructed using principal component analysis and varimax rotation. Eight were significant in predicting success. Chronbach alphas were not used to confirm internal consistency in any of these works.

With the exception of an occasional fourth level linear approach such as Calantone and Di Benedetto's 1990 use of canonical correlation (see APPENDIX B) to measure the interaction between and within the sets of variables, no other methodologies have made inroads in the field. As such, NewProd's method stands as the definitive methodology for retrospective, deterministic linear forecasting model development.

3.2.2 Other forecasting model methodology

To determine manager's accept/reject criteria Cooper and de Brentani (1984) used the same statistical methodology but chose variable sets differently. They studied screening factors from sixty-three industrial firms asking each to identify an "accept" and a "reject" proposal. Three-hundred and seventy projects were rated on each of eighty-six items using an eleven point Likert scale from -5 (strongly reject) to +5 (strongly accept). Using factor analysis with principal component extraction and varimax rotation, an eleven factor solution was chosen based on the scree test (see APPENDIX B, Cattel 1966). This, along with the use of Chronbach alpha scores to judge internal consistency, was new to these type screening studies and an important improvement.

Cooper and de Brentani's study of the financial services industry (1991) used and improved on the now evolving methodology. Like Cooper's early work, a conceptual framework was developed to describe the new service process and environment. Continuing the improvement of construct validation, Chronbach alphas tested internal consistency. However, the performance measurement technique was also improved by the use of a three level categorisation based on: (1) simple success/failure; (2) degree of success/failure and (3) level of objective attainment. Unfortunately, use of simple one way ANOVA of success/failure and Pearson product-moment correlations failed to enhance field statistical elegance.

The initial Stanford Innovation Project (Maidique and Zirger 1984) used a design which did not resemble NewProd. It began by: (1) collecting unstructured data for variable set determination; (2) constructing success/failure innovation pairs for fifty-nine innovations and (3) performing an in-depth case study of a twenty firm sub-set. The 1990 follow-up (Zirger and Maidique 1990) used factor analysis and discriminant analysis in a manner quite similar to NewProd (Cooper 1979b). This reaffirmed the eminence of third level designs for success prediction and analysis.

3.3 Thesis research design

This design resembles most closely the reasonably thorough NewProd project, because consistency of design, replication and synthesis is needed (Montoya-Weiss and Calantone 1994). It adheres to NewProd's methodological foundations so as to replicate, validate temporally and synthesise. However, adding new heterogeneous variables to the established homogeneous data set and then judging their relationship over time using a discrete simulation must be considered exploratory.

To advance the methodology incrementally, a maximum three year retrospective benchmarked at one year post launch was used in lieu of the traditional five years. This was done to reduce perceived measurement timing error and survivour bias. Second, third and fourth level statistical techniques encompassing tests of differences/similarities, measures of dimensionality and statistical parameters interpretation (Montoya-Weiss and Calantone 1994) were used for sound inferential generalisation to larger, similarly profiled active NPD populations.

3.3.1 Conceptual framework, sampling frame, sample selection and scope

This work is grounded in a modified version of the NewProd conceptual framework (see Figure 2-2 and Figure 2-3). This allows a comprehensive replicative analysis of seminal work. Still, it is flexible enough to support integration of new antecedent variables and assessment of their impact on the commercial outcome at both the initial screen and one year post launch.

The sampling frame chosen was *Compact Disclosure*, a CD ROM database containing 12,000 records of US public organisations having at least 500 shareholders of one class of stock or at least $5,000,000 in assets. A large non-probability (see APPENDIX B) sample (n=1300) was constructed from the frame of 1600, with the intention to acquire more NPD cases than the NewProd project (n=195 from 103 firms). Firms were selected only from manufacturing SIC codes 2000 through 4000. The large sample was necessary to lessen the expected impact of a low response rate. This was unavoidable due to the over-inclusion of firms normally inactive in NPD activities. This group of "probable low responses" was necessary to measure phenomena hypothesised in H_3[26] within the short three year time constraint. The frame over-represented industrial commercial machinery, electrical equipment, measurement instrumentation and chemicals whilst it under-represented "low technological" industry (see Figure 3-2). Hultink and Robben (1995) have found that background characteristics such as market served, product innovativeness, innovation strategy and general functional orientation of the firm do not influence the importance attached to measuring long-term and short-term new product success. Therefore, the heterogeneity of the sample should not bias the dependent variable.

Where?

3.3.2 Level of data collection and performance/functional perspective

Since the literature has skilfully side-stepped the issue of what the essence of new product success is (Hart 1993; Hultink and Robben 1995), this work used a combination of well established definitions. Consistent with NewProd, success/failure data was collected at the project level. Consistent again, performance was measured intervally from -5 to +5. This score represented the perceived level of performance in a single product market one year post launch. This period is consistent with those suggesting at least six months is necessary to measure entry strategy characteristics (Green, Barclay and Ryans 1995)[27].

The traditional operationalisation of success has been subjective and defined as the amount the project exceeded or fell short of minimum acceptable profitability (Cooper 1979b, 1981). Subjective measurement may be acceptable when accurate objective measures are unavailable or are very difficult to ascertain (Dess and Robinson 1984; Pearce, Robbins and Robinson 1987). Indeed, the experience of some authors encountering low response rates suggests that indirect measure may

[26] e.g. to compare high innovation characteristics of success against low innovation characteristics of success, sufficient numbers of high and low responses must be obtained for Duncan's multiple range test to be valid. Implicit in low innovation processes is the low rate of new product introduction, especially within a constrained three year period. Over soliciting from the stone, clay, glass and other commodity like industries unduly raises the non response rate and error potential.

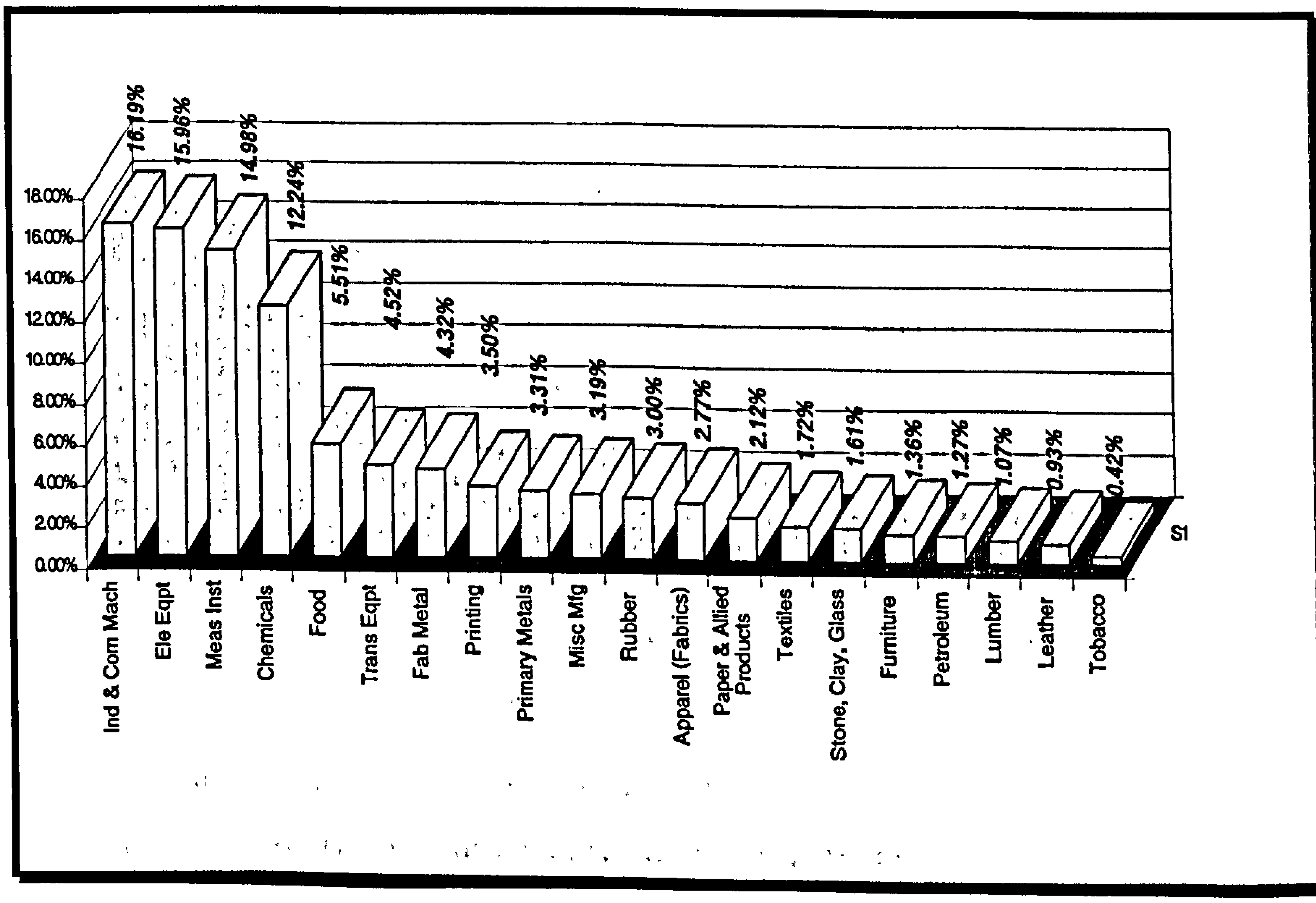
[27] In the pilot test new product managers indicated that they regarded "12 months after launch" as a reasonable reference point for evaluating market entry outcome and a good surrogate for the "end of the NPD process".

well be more fruitful in assessing data (Hart 1993). However, unlike NewProd, this work used multiple subjective measures rather than single measures of new product success.

The pilot study indicated that Griffin and Page's sixteen measures would be onerous or impossible to verify. This would have been especially true in a large postal survey susceptible to non-response and selection error. Since the determinants of new product success may be different depending on performance measurement operationalisation (Hart 1993; Hultink and Robben 1995), this work used "financial", "window of opportunity" and market impact measures. These have been found adequate to delineate performance (Cooper and Kleinschmidt 1987a) and have precedent in recent work (Cooper and de Brentani 1991). Hence, success/failure performance was established as follows:

1. *Success/failure* - a yes/no categorisation based on whether the project had met minimum criteria for success.
2. *Degree of success* - a measure of -5 to +5, where +5 meant a great success and -5 meant a great failure.
3. *Meeting specific criteria* - the degree of meeting financial, window of opportunity and/or market impact performance measurement criteria (0-10)[28].

Figure 3-2: Sampling Frame by Standard Industrial Classification Code



28 The 1-10 scale was used for consistency with the NewProd project antecedent measurement. The three performance measures were also necessary because long PLC projects with heavy front end capitalisation may not have been mature enough to measure using financial measures only. Conversely, short PLC projects may have been successful but off the market by 1 year post launch.

In measuring the antecedents of success as perceived by the NPD managers[29], it was important to select the two distant time frames (T_0 and T_1) to capture different information awareness/availability states. These were thought to be nebulous during the initial screening stage and more concrete after commercialisation.

3.3.3 Measurement technique, questionnaire construction, coding and editing

Crawford (1979) criticises surveys. Asking company personnel to recall sets of new products over a five year period is too memory intensive, subjective and may vary between functions such as marketing and R&D. Further, potential problems exist when using single key informants (Phillips 1981). However, whilst variables measured retrospectively may produce key informant after-the-fact rationalisation, objectively worded scales are common in this type of work and are thought to limit post-hoc bias (Cooper and Kleinschmidt 1994).

Figure 3-3: Potential sources of error in research information[30]

1. *Surrogate information error* - Variation between the information required to solve the problem and information sought by the researcher.
2. *Measurement error* - Variation between the information sought by the researcher and the information produced by the measurement process
3. *Experimental error* - Variation between the actual impact of the independent variables and the impact attributed to the independent variables
4. *Population specification error* - Variation between the population required to provide the needed information and the population selected by the researcher
5. *Frame error* - Variation between the population as defined by the researcher and the list of population members used by the researcher
6. *Sampling error* - Variation between a representative sample and the sample obtained by using a probability sampling method
7. *Selection error* - Variation between a representative sample and the sample obtained by using a non-probability sampling method
8. *Non-response error* - Variation between the selected sample and the sample that actually participates in the study

Postal surveys are rapid, anonymous, limit surrogate information error and are relatively inexpensive. The hope was to not to be as geographically limited as NewProd. In consideration of sample size requirements across a 3000+ mile US expanse, a postal survey was the only feasible method of data collection. This approach was least intrusive, allowed anonymity important to managers of failed projects and reduced experimental error (see Figure 3-3) and interviewer bias. It might have been better to perform a true longitudinal study tracking antecedents in real time (Cooper 1992). However, time was of the essence and longitudinal techniques are not without problems (Churchill 1991). Therefore, the trade-off in error potential was thought reasonable[31].

The questionnaire (APPENDIX A) emulates the NewProd instrument. It is appended only to examine additional antecedent relationships germane to the phenomenon

29 Consistent with NewProd, in small organisation this was the president. In large organisations it was the division manager or new product development officer.
30 Tull and Hawkins 1993.
31 Cooper argues that longitudinal studies are not possible given the expense, time involved and the high ratio of 500 projects screened to 100 projects launched and available ultimately, for study.

under study. Beginning with the "Cooper 30" variable subset (Cooper 1992), the questionnaire contained new variables essential to the validation of all hypotheses. The respondents were asked to choose either a successful or failed new product introduced within the last three years and to determine the extent to which the statement described the project at the initial screen (T_0) and one year post launch (T_1). Two different answers for the same question indicated that, over time, the perceive variable state of nature changed. This intellectually demanding technique extends the methodology incrementally but increases the probability of incomplete instruments, non-response error, experimental error from implied antecedent difference and/or measurement timing error from the retrospective approach. Therefore, vigilance was necessary in assessing the need for imputation[32] as well as in assessing possible experimental or measurement timing error. Here, experimental and measurement timing error have converse influence manifest in disproportionately high amounts of antecedent statistical difference or equivalence over time.

The final instrument was pre-tested by twenty local respondents to determine whether they could isolate precisely in memory, discrete states of nature by time period and whether the dual retrospective technique was "leading". All respondents were in general agreement that they could make the distinction with reasonable certainty[33] i.e. there was real difference for some but not for all variables over time. Further, they suggested that if the antecedent situation was stable over time, they felt no obligation to change their answer based on implied difference. However, most did indicate that the instrument was laborious. After minor editing, the pilot test was determined to be quite valid and thought to measure precisely what was intended.

The two page questionnaire (APPENDIX A, one page back and front) using Cooper's scaling technique allowed the direct comparison of results. Performance, again like project NewProd, was measured on a continuous scale from -5 through +5 (Cooper and Kleinschmidt 1987a). -5 meant a great failure, falling far short of the minimum criteria and +5 meant a great success, far better than the minimum. Individual response scaling, whilst not normally distributed[34], was internally consistent for each data set.

[32] assigning attributes to the non-respondents (of a survey) based on the characteristics of the respondents in order to adjust for non-response (Tull and Hawkins 1993).

[33] some stated that, in many cases, complete documentation was still available for reference.

[34] Insinga suggests that studies which ask only one person to complete this type questionnaire using Cooper's scaling method are subject to a wide confidence interval, perhaps jeopardising conclusions. Further, the scale produces non-normally distributed responses (Insinga 1986). His recommendation for smaller, more clearly defined scales from a larger number of respondents per firm, though preferable, would have reduced the validity of comparison and been impractical.

3.3.4 Implementation

The first mailing (S_1) was sent with a cover letter to the firm's Vice President of Marketing. Consistent with Hultink and Robben (1995), it was to be passed along to the new product development manager or a staff member most knowledgeable in a clearly successful or failed project. As an incentive, study results were offered on floppy disk in the form of a PC compatible decision support system, *Product-Wars*©. A follow-up reminder letter with an additional questionnaire was sent approximately two weeks later to increase response further. "In every survey involving mail questionnaires, there should be a provision for at least one follow-up questionnaire so that any bias in the answers of original respondents can be partially corrected and so that some estimate of the probable answers of non-respondents can be made from the two groups of respondents" (Lambert and Harrington 1990 p8). The same procedure was used in the second wave (S_2) sent approximately three months later.

Using a one way ANOVA at p=.05, a 6.6% difference in 151 variable distribution means was observed between sample collection dates. Methodologically consistent with Song and Parry (1994), separate factor analyses results were compared by time period to determine if this minimal antecedent difference would produce an unstable factor analysis by sample. Sample S_1 at T_0 explained 72.2% of variation compared with 78.4% explained for S_2 at T_0. Factors with Eigenvalues > 1 were almost identical though in slightly different order. Factor analysis of sample S_2 at T_0 explained 71.6% of variation compared with 78.5% explained for S_2 at T_1. Again, factors were almost identical. These slight differences suggests minimal imputation (Tull and Hawkins 1993, see APPENDIX B) is required for non-respondent result adjustment (Armstrong and Overton 1977; Pace 1939)[35]. Furthermore, Suchman (1962) believes that non-response bias in certain situations may be to the researcher's advantage, especially in extreme circumstances when the emphasis is upon the phenomena being studied and not upon its distribution to the general population. Here extrapolation to the general population is not desired since the primary interest is in active NPD population phenomena. Therefore, the minimal non-response bias was judged not to be a significant problem and the samples were combined. This yielded a final SPSS data file of 260 valid and complete cases.

This SPSS data file analysed contained one-hundred and fifty-one independent intervally scaled variables. Seventy-five used Cooper's eleven point scale and

[35] Response is related to early versus later respondent interest in the subject. Late respondents are thought closer to actual non responders and answering because of increased stimuli of follow-ups, incentives etc..

comprised data set A, the retrospective perceptions of new product development managers at the initial screen (T_0). Seventy-six[36] comprised data set B, the retrospective perceptions of these same managers at one year post launch (T_1). NPD product market history[37], along with time from screen to launch and length of PiLC were scaled metrically. The remainder were nominally scaled or qualitative data representing industrial demographics.

Two-hundred and ninety three questionnaires were returned. Thirty-three were incomplete or otherwise unusable yielding 190 success cases and 70 failure cases. This success/failure ratio is comparable to that achieved in previous comparative studies (de Brentani 1986; Cooper and Kleinschmidt 1993). After correcting for inappropriate, non-existent, subsidiary and/or duplicate firms, the final response rate was determined to be 21.7% based on an adjusted sample size of 1198. Since significant numbers of companies do not conduct new product development activities (Wind and Mahajan 1988), this is reasonable given the broad dimensions of the research, the necessity of including non-active firms for comparison and testing in H_2 and H_3 and the demanding questionnaire (as reported by respondents and non-respondents alike). Further, this rate is quite consistent with Robertson, Eliashberg and Rymon's (1995) comparison of US and UK rates[38] and with other industrial marketing research field studies reported recently (Achrol and Stern 1988; Anderson, Chu and Weitz 1987; Gatignon and Robertson 1989; Heil and Walters 1993; Puto, Patton and King 1985; Sujan 1986).

Instrument coding was pre-tested and governed by dBASE/PARADOX⇒SPSS import syntax. Pilot and early responses were cross-tabulated and sample analyses performed to insure all tests required by the hypotheses were possible, valid and ran reliably. Cross-checks of results were performed at regular intervals to insure the data entry integrity.

3.4 Statistical analysis and models

A combination of second, third and fourth level procedures apply to the seven hypotheses tested.

3.4.1 Second level tests - ANOVA and paired-samples t-tests (see APPENDIX B)

To test whether two or more population means are equal, H_1a uses:

36 one question referred to only data set B at T_1.
37 aggregate success, failure and kill performance in the specific product market over the previous three year period.
38 In their study, the US response rate was 23.3% and the UK rate was 20.2%

1. ANOVA to test the null hypothesis that data come from an NPD population in which the mean of the variable tested is equal for both successful and failed cases. i.e. determines which variables are significant to success at T_0 and at T_1.
2. the two-tail, paired-samples t-test to examine the null hypothesis that the data come from an NPD population in which the means of two related variables are equal. i.e. determines which variables experience significant perceived changes in magnitude between T_0 and T_1.

The combined results are used to argue for acceptance of H_1a.

Since by definition, all factors constructed from orthogonal factor analysis methods have a distribution mean of 0 and a standard deviation of 1, these techniques were not possible to test for H_1b or H_1c. In the aggregate, they display no variance between factors. As such, ANOVA procedures are impossible. Therefore, H_1b and H_1c use observation of important output statistics along with distribution factor and residual error differences by success/failure to determine differences. H_1d uses a one-way ANOVA to test for differences in predictive distribution accuracy.

In support of H_2 and H_3, Duncan's multiple range test was used to determine significant differences in success factor distribution and residual accuracy due to PiLC and order/innovation conditions among and between time periods. H_4 uses a paired-samples t-test to determine differences in strategic reaction ability over time by success and failure cases individually.

3.4.2 Third level tests - Factor analysis (see APPENDIX B)

Consistent with Schocker, Gensch and Simons (1969), factor analysis was used to reduce the number of variables to a smaller set of independent factors for use in linear regression. The SPSS for Windows 6.0 algorithm for conducting factor analysis first computes the "ith" standardised variable expressed as: $X_i = Ai_1 + Ai_2F_2 + \ldots + A_{ik}F_l + U_i$. The "Fs" represent the common factors with all variables being expressed as functions of these variables. The "As" are the coefficients used to combine the factors and the "U" represents the unique factor, the part of the function which cannot be explained by the common factors. Utilising the result from this formula, X_i, the "ith" standardised variable is then used in the general expression below, for estimating the "jth" factor:

$$Fj = \sum_{i=1}^{p} W_{ji}X_i = W_{j1}X_1 + W_{j2}X_2 + \ldots + W_{jp}X_p \,.$$

The "Wi(s)" are the factor score coefficients and "p" is the number of variables (Norusis 1993). The results are subsets of highly correlated variables within factors and conversely, no correlation between orthogonal factors.

Two separate factor analysis were performed, one at T_0 and the other at T_1. These were then analysed separately to determine the quality of each result and to establish if differences existed between factorial solutions by time period. Parsimonious, intuitively logical solutions in support of the research objectives were sought using different extraction[39] and rotation[40] techniques. Solution quality was based on:

- high factor loadings
- high factor Chronbach alpha scores[41]
- amount of common factor variance explained by the solution
- Eigenvalues greater than 1
- factorial consistency with past work
- an appropriate levelling of the scree (and)
- parameter normalcy with past work.

3.4.3 Fourth level tests - Linear regression (see APPENDIX B)

Linear regression using stepwise selection of the orthogonal factors resulting from the factor analysis was used to study relationships important in the model. The SPSS for Windows 6.0 algorithm for conducting a multiple linear regression analysis is defined as follows: $Yi = B_0 + B_1X_{1i} + B_2X_{2i} + \ldots + B_pX_{pi} + e_i$. "$X_{pi}$" indicates the value of the "p^{th}" independent variable for case "i". e_i is the error component. The model assumes that there is a normal distribution of the dependent variable for every combination of values of the independent variables (Norusis 1993). This assumption is violated by Cooper's NewProd linear regression model (Cooper 1981). The forward stepwise method of independent variable inclusion was used with a probability of F to enter of .05 and a probability of F to remove of .10. This is a very conservative stepping method and minimises the likelihood of arbitrary variables entering or being removed from the model by chance.

3.5 Hypotheses testing decision rules

Hypotheses H_1a, H_1b, H_1c and H_1d deal with the evolution of individual variables, factors constructed from these variables, significant dimensions of success and model accuracy as they are perceived by managers to evolve over the NPD process. Acceptance should be based on the significance of difference between time periods, along with the magnitude of the demonstrable change. Hypotheses H_2, H_3 and H_4 deal with conditional changes in success dimensions based on product life cycle, order of entry/level of innovation and ability to deal with strategic requirements over the life

39 principal components, un-weighted least square, generalised least squares, maximum likelihood, principal axis factoring, alpha factoring and image factoring.
40 varimax, equimax, quartimax and direct oblique.
41 Chronbach alpha scores measure internal consistency. Whilst those > .5 are considered satisfactory (Cooper and de Brentani 1991b), factors with scores <.5 were allowed to remain in the solution because of the exploratory requirements of heterogeneous data integration (Montoya-Weiss and Calantone 1994).

of the process. Acceptance of H_2 and H_3 should be based on changes in success dimensions, as conditions are applied to the aggregate models developed in H_1c, both within and between time periods. Acceptance of H_4 should be based on strategic reaction differences observed in dimensions and variables between successful and failed cases.

3.5.1 Rules for testing hypotheses H_1a

H_1a should be accepted and the null form rejected if either:

- the variables shown significant to success at T_0 are different than those shown significant at T_1. Demonstration of significant difference for a large selection of variables using a one-way ANOVA at p.<.05 constitutes acceptable proof (or)
- a change in magnitude from T_0 to T_1 is demonstrated in a large selection of the variables. Demonstration of significant magnitudinal change for a large selection of variables using a paired samples t-test at a 95% confidence interval constitutes acceptable proof.

3.5.2 Rules for testing hypotheses H_1b, H_1c and H_1d

Neither ANOVA or related pair t-tests is appropriate to test H_1b or H_1c. Therefore, H_1b should be accepted and the null form rejected if:

- by observation, differences exists over time based on manual item by item analysis of factor set construction, Eigenvalue, percent of variance, loadings and/or factor Chronbach alpha scores.

To test H_1c, ANOVA is impossible again. Therefore, H_1c should be accepted and the null form rejected if:

- in the aggregate, the linear regression models and dimensions of success, at p=.05 to enter and p=.1 to remove, are observably different over time. This should be demonstrated by important differences in model analysis of variance/validity, regression coefficient selection/order/size/error, model standard error and/or significance level.
- this should be supplemented by differences in factor and residual distributions by success/failure.

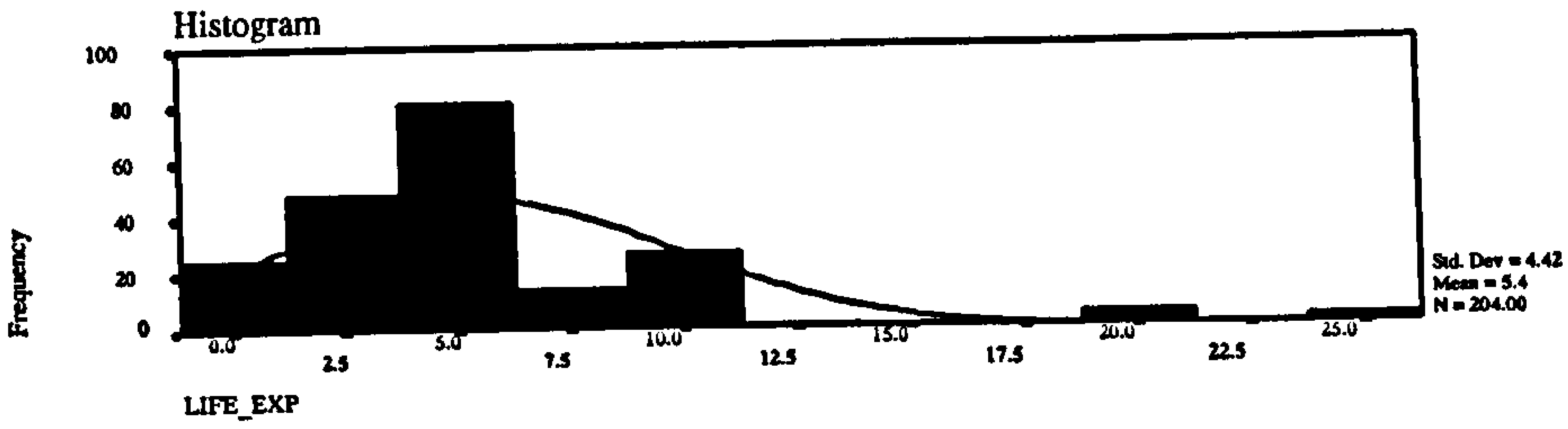
H_1d attempts to validate a significant difference in the predictive accuracy of each function constructed in H_1c. Therefore, H_1d should be accepted and the null form rejected if:

- after using a paired-samples t-test at a 95% confidence interval, a significant difference in accuracy exists in the aggregate T_0 and T_1 linear regression predictive distributions.

3.5.3 Rules for testing hypotheses H_2, H_3 and H_4

H_2 deals with changes in factors of success when conditioned by P_iLC. Because the PLC variable was not normally distributed (see Figure 3-4), the PiLC variable was re-

Figure 3-4: actual P_iLC distribution



Mean	5.411
Std err	.309
Median	5.000
Mode	5.000
Std dev	4.419
Variance	19.526

Kurtosis	6.360
S E Kurt	.339
Skewness	2.186
S E Skew	.170
Range	24.750
Minimum	.250
Maximum	25.000

P_iLC Percentile at 33.33% = 3 yrs.
P_iLC Percentile at 66.67% = 5 yrs.

computed into three categories; short (0-3 years, n = 71), medium (3.001 years to 4.999 years, n = 76) and long (5 years and longer, n = 57[42]).

Based on comparing model and dimensional differences within and between time periods categorically, H_2 should be accepted and the null form rejected if:

- the categorical linear regression models and dimensions of success at p=.05 to enter and p=.1 to remove, are different within and between time periods. This would be demonstrated by observing important differences in model ANOVA/validity and coefficient selection/order/size/error, model standard error and/or significance level.
- further, this difference should be confirmed, ideally, by significant differences between common factor and residual error distributions demonstrated using Duncan's multiple range test at p=.05[43] by success/failure.

H_3 deals with changes in factors of success when they are conditioned by order/innovation[44]. Consistent with Crawford's affirmation of innovativeness as a function of timing (Crawford 1994), before conducting the linear regression analysis at T_0 and T_1, the SPSS file was categorised by the normally distributed "1st in" factor at both periods. Data sets A and B were divided into: (1) high levels of innovation for products entering early (top 1/3 of the normalised factor at T_0 and T_1); (2) medium levels of innovation for products entering somewhere in the middle (middle 1/3 of the normalised factor at T_0 and T_1) and (3) low levels of innovation for products entering

42 the PiLC analysis is of 204 cases. 56 respondents failed to give PiLC estimates in months and years.
43 The categorisation produces 6 non-normal distributions. Because these exhibit variance, Duncan's multiple range test is appropriate.
44 Kleinschmidt and Cooper (1991) used a *subjective* process classifying: (1) highly innovative products as "new-to-the-world" and "product lines innovative to the company"; (2) moderately innovative products as "lines new to the firm but not new to the world" along with "new items in existing product lines" and (3) low innovative products as "all modifications, redesigns, repositionings and minor extensions". In this hypothesis, the phenomena of order of entry and relative level of innovation were treated as related because they tapped the same dimension. Three categories of high/1st, medium/middle and low/late related innovativeness with entry timing was logical and consistent with Crawford (1994) i.e. the first-in a new product market is implicitly, the most innovative.

late (bottom 1/3 of the normalised factor at T_0 and T_1). To operationalise this concept, frequency distributions of the normalised ORDER factor were obtained at T_0 (factor 5, Figures 3-5a) and the normalised ORDER factor at T_1 (factor 6, Figure 3-5b).

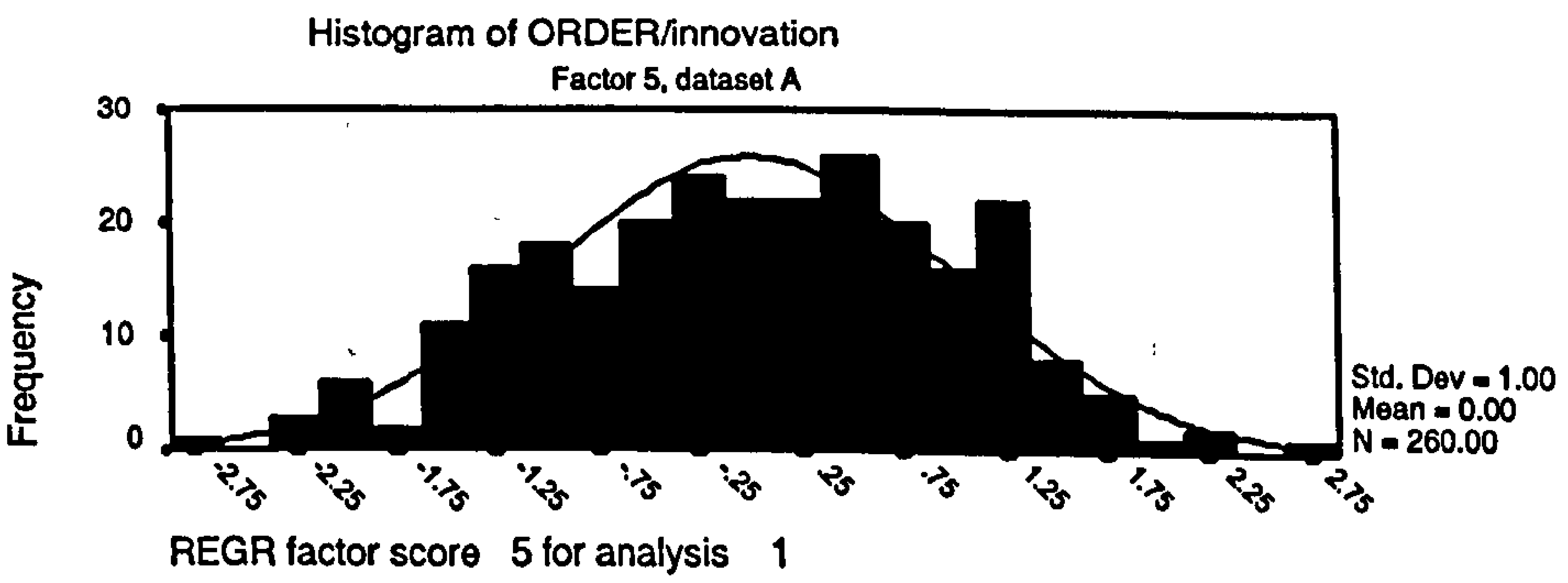
H_3 should be accepted and the null form rejected if:

- categorical linear regression models and dimensions of success, at p=.05 to enter and p=.1 to remove, are different within and between time periods. This would be demonstrated by observing important differences in model ANOVA/validity and coefficient selection/order/size/error, model standard error and/or significance level.
- further, this difference should be confirmed, ideally, by significant differences between common factor and residual error distributions demonstrated using Duncan's multiple range test at p=.05 by success/failure.

H_4 deals with the effects of initial and reactive strategy. It should be accepted and the null form rejected if:

- the aggregate linear regression strategic reaction factor is significant at both T_0 and T_1 and there is an obvious increase or decrease in the factor's importance over time (or)
- the individual strategic reaction variables constituting the factor change in statistically significant and different ways over time for success versus failure cases. This must be demonstrated by significant magnitudinal difference using the paired samples t-test procedure at a 95% confidence interval.

Figure 3-5 (a)

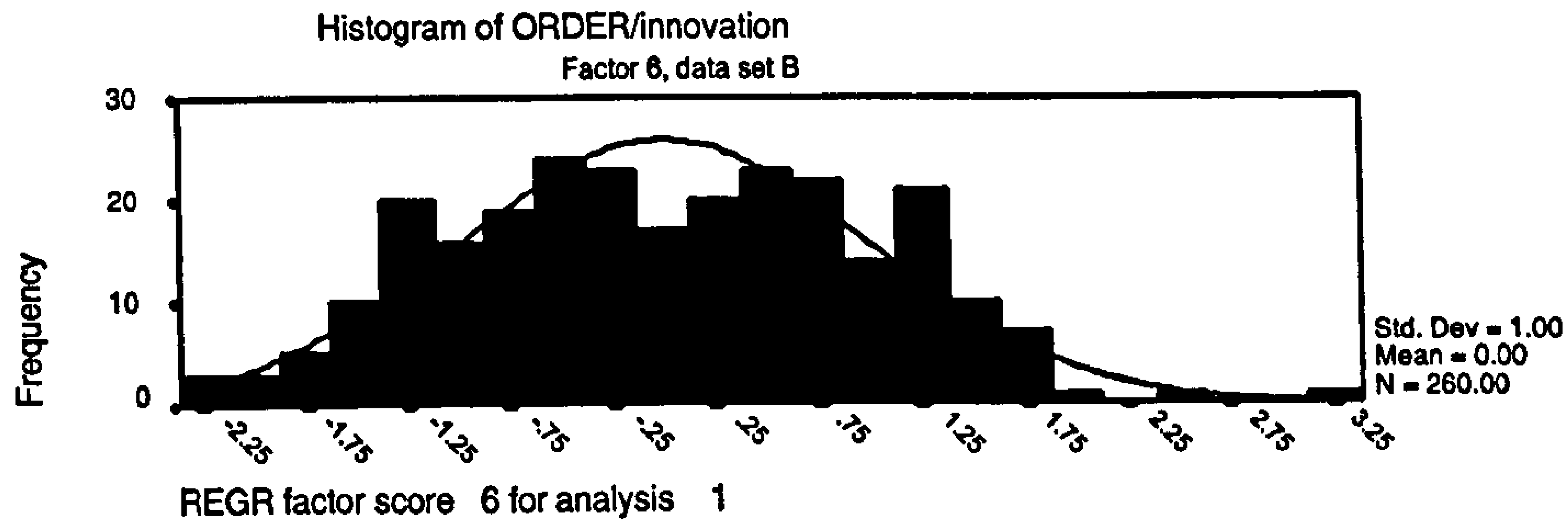


ORDER Percentile at 33.33% = -.471
ORDER Percentile at 66.67% = +.542

Mean	.000
Std err	.062
Median	.003
Mode	-2.800
Std dev	1.000
Variance	1.000

Kurtosis	-.444
SE Kurt	.301
Skewness	-.111
SE Skew	.151
Range	5.610
Minimum	-2.800
Maximum	2.810

Figure 3-5(b)



ORDER Percentile at 33.33% = -.453
ORDER Percentile at 66.67% = +.521

Mean	.000
Std err	.062
Median	.000
Mode	-2.354
Std dev	1.000
Variance	1.000

Kurtosis	-.501
S E Kurt	.301
Skewness	.023
S E Skew	.151
Range	5.559
Minimum	-2.354
Maximum	3.205

3.6 Strengths and limitations

The strength of this methodology lies in its continuation and incremental improvement of techniques developed by Cooper and others. Whilst experimental in its use of discrete simulation, inter-disciplinary factor integration and constraints used to produce conditional models, all methodological components emulate established methods, thus satisfying calls for replication, temporal validation and synthesis (Montoya-Weiss and Calantone 1994).

Never the less, NewProd's methodology does have important weaknesses. There is always the potential for population specification and selection error when using a postal survey. Acknowledged by Cooper (1979a, 1979b, 1981), this plus potential non-response error is equally important here. More problematic is the possibility of measurement timing error and post hoc bias based on changes in the product, its environment and strategy following the initial screen (Cooper 1992). Between the initial screen and the time of performance measurement, products may languish and/or receive marketing adjustment before catching on. This creates models favouring earlier projects (Crawford 1979) laden with measurement timing error and survivor bias (Kerin, Varadarajan and Peterson 1992; Mitchell 1991). A real time longitudinal study would limit measurement timing error. However, these are not possible for large samples given data collection expense, time consumed and the 5/1 ratio of concepts to valid cases (Cooper 1992). Further, though regularly recommended, a fixed panel supporting a longitudinal validation has weaknesses of its own. Problems include non-representativeness due to high dropout/mortality rates and compensation bias, as well as significant differences noted between data generated by mail panel versus telephone interviewing (Churchill 1991).

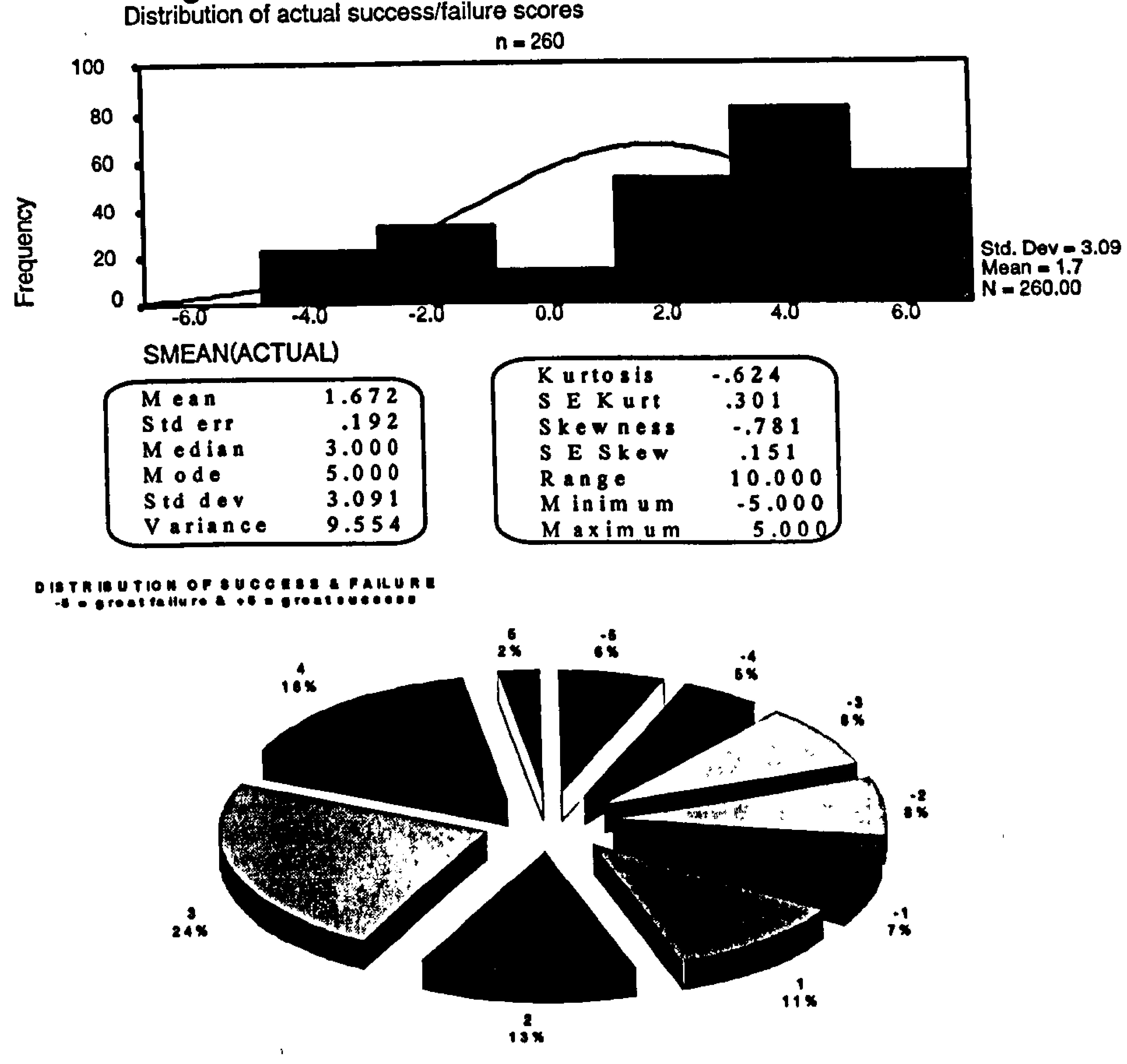
This work is more precise than other retrospectives. It limits the sample to three rather than five year old projects and measures performance consistently for the entire sample at one year post launch. This minimises survivor bias by including more failed products and those marginally successful but killed shortly after launch. This is the first time kill phenomena, regularly overlooked (Cooper and Kleinschmidt 1990a), have been knowingly measured. Contrarily, this method creates "beginner bias". Thus it is unable to account for projects judged a success or failure at one year post launch but which fail or succeed over the long-term.

Chapter Four - Analyses and findings (H_1a, H_1b, H_1c and H_1d)

4.1 Introduction

This chapter enumerates the findings of this research based on the methodologies presented in Chapter 3. Definitions of the statistical tests used are found in APPENDIX B.

Figure 4-1: success/failure distribution



4.1.1 Adequacy of the dependent variable

Two-hundred and ninety three questionnaires were returned. Thirty-three were unusable. The data from the remaining 260 instruments were judged to be valid, very representative of the sampling frame and appropriate to the phenomena studied. Figure 4-1 displays the dependent variable's aggregate frequency distribution and proportion by answer. The aggregate mean performance measurement on the -5 through +5 scale was 1.62. The success mean was 3.351 (n=190) and the failure mean was -2.886 (n=70). With a kurtosis of -.624 and a skewness of -.781, like NewProd, the success/failure distribution was not normal. This may be due to Cooper's scaling technique (Insinga 1986).

4.1.2 Definition of performance

Subsets of the sixteen established measures of performance (Griffin and Page 1993) can change from conceptualisation to commercialisation (Ronkainen 1985) and over the life of the product (Hultink and Robben 1995). Therefore, the actual definition of success and the point in the NPD process at which success is measured, is quite important. This work used recent field precedent in defining success types (Cooper and de Brentani 1991). These were: (1) simple success *or* failure - a categorical yes/no answer; (2) interval degree of success - a measure from -5 to +5 and (3) performance assessment as the degree of "financial", "window of opportunity" and/or "impact" measured intervally from 0 to 10. "Financial" measurement was defined as project profit, ROI and/or payback. "Window" measurement was defined as new markets and/or product categories opening as a result of the project. "Impact" measurement was defined as the project's effect on domestic and/or foreign market share (Cooper and Kleinschmidt 1987a). All three were measured retrospectively at both the initial screen and at one year post launch.

4.1.3 Relationship of performance measures

Problematic for the field is that measuring success in one of the three recommended ways does not translate into success on the other two (Cooper 1984a, 1984b; Cooper and Kleinschmidt 1987a). In fact, strategy leading to certain types of success may even prevent other types from occurring (Hultink and Robben 1995). Therefore, averaging the three criteria would only dilute useful variation. More pertinent to establishing the validity of the dependent variable are tests of significance and direction of linear association of all three measures over time.

All intervally scaled success/failure scores of -5 through +5 matched the categorical choice of success *or* failure absolutely. To determine whether "financial", "window" and/or "impact" accomplishment was related to success/failure categorical choice, a Chi-square (X^2) test of independence was conducted. The test results are illustrated in Table 4-1a. Table 4-1b illustrates the results of a two tailed bivariate correlation procedure. It relates the direction and strength of the -5 to +5 intervally scaled measure of success with the 0 to 10 measure of performance criteria. Table 4-1c illustrates a paired-samples t-test used to determine if performance criteria results differed significantly over time. Table 4-1d displays significant differences in performance measurement criteria by success/failure cases by time period.

Pearson's chi-square statistics and Likelihood ratios in Table 4-1a test the null hypothesis that there is no relationship between the categorical level success/failure choice and interval level performance criteria by time period. Overall results of using three success measures, rather than just financial measures, were favourable and consistent with previous recommendations and findings (Cooper de Brentani's 1991; Cooper and Kleinschmidt 1987a; Maidique and Zirger 1985). At T_0, none of the measures are significant at p=.05. This is not surprising since early information is tentative at best. None-the-less, two of the three X^2 values approach significance with "impact" significant at p=.07. This is not surprising either given Cooper and Kleinschmidt's (1987a) finding that protocol - "defining customer needs, wants, preferences and the target market prior to initiating product development" - is correlated with success measured as "impact". It also supports Hultink and Robben's (1995) finding that short term success is measured on product-level measures such as speed-to-market, whether the product gets launched on time and product developmental costs. It is apparent, even at this early point in the process, that the idea's perceived impact on share is consequential to it being judged a successful project to be passed along to the next stage/gate.

All three measures are significant at T_1. This indicates that the performance criteria are related to the success/failure categorical selection by one year post launch. Their different and increasing significance over time is consistent with Hultink and Robben's accepted hypotheses (1995) that a firm's time perspective influences the core measures of success and with Ronkainen's (1985) explanation that go/no-go/continue criteria change across development stages.

Table 4-1a: Chi-square (X^2) results of success/failure relationship to performance criteria

Criteria	*Pearson X^2*	*Significance*	*Likelihood Ratio*	*Significance*
Financial T_0	15.135	.127	16.075	.098
Financial T_1	***19.875***	***.03***	***19.048***	***.04***
Window T_0	12.457	.33	12.041	.361
Window T_1	***25.523***	***.004***	***25.000***	***.05***
Impact T_0	16.940	.076	16.852	.078
Impact T_1	***32.205***	***.000***	***30.570***	***.001***

Table 4-1b illustrates the two-tailed bivariate Pearson's r statistic. This is a measure of linear association between the simple interval measure of success/failure and the interval measure of performance criteria. The results support the X^2 categorical results above. The consistent positive correlation between actual performance scaled -5 through +5 and all three performance criteria scaled 0 through 10 at both T_0 and T_1 supports the validity of all performance measurement criteria. Their increasing strength over time suggests they are valid measures of an evolving success/failure dynamic.

Consistent again with Hultink and Robben (1995) the time perspective did influence the measures of success. However, the moderate strength of the correlation coefficients between "financial" and "impact" measures at T_0 and "financial" and "window" measures at T_1 is at odds with their counterintuitive conclusion that few significant associations exist among financial and non-financial measures of NPD success. Clearly there is a relationship between early "impact" and "financial" performance as well as later "financial" and "window" performance.

Table 4-1b: Performance measurement correlation analysis*

Measure	*Actual*	*Financial T_0*	*Financial T_1*	*Window T_0*	*Window T_1*	*Impact T_0*	*Impact T_1*
Actual	1.0000	.0705	***.2039***	.0254	***.2604***	***.1681***	***.2942***
Financial T_0	.0705	1.0000	***.7196***	***.1430***	***.1579***	***.3262***	.1018
Financial T_1	***.2039***	***.7196***	1.0000	.0803	***.3399***	***.1961***	***.3198***
Window T_0	.0254	***.1430***	.0803	1.0000	***.4663***	***.3459***	***.2261***
Window T_1	***.2604***	***.1579***	***.3399***	***.4663***	1.0000	***.3788***	***.5933***
Impact T_0	***.1681***	***.3262***	***.1961***	***.3459***	***.3788***	1.0000	***.6531***
Impact T_1	***.2942***	.1018	***.3198***	***.2261***	***.5933***	***.6531***	1.0000

* ***bold italics*** indicates significance at p=.01, 2-tail test

Table 4-1c panel ***C*** displaying the aggregate paired-samples t-test seems to suggest there is no statistically significant change in performance over time. In the aggregate, window of opportunity criteria decline and financial and market share performance rises slightly. Though sensible, none change at statistically significant levels. However, when sorted by success/failure, "financial" and "window" measure decreases are observed for failures at p=.07 (see Table 4-1c panel ***B***). This is more meaningful when combined with statistically significant success case increases for financial criteria accomplishment at p=.05. Once again this supports Hultink and Robben's (1995) and Ronkainen (1985) that performance measurements are perceived to differ over time. Additionally, it supports Hultink and Robben's finding that financial achievement, profitability, margins, and ROI are key foci in longer term performance measurement.

The significant "financial" success case change over time is noteworthy for NPD model developers. This supports Cooper and de Brentani's (1984) finding that financial measures are the most important managerial accept/reject criterion. Further, it is consistent with an 88% agreement by practitioners (Calantone, Di Benedetto and Haggblom 1995) that financial risk assessment should be incorporated into new product project evaluation (Cardozo and Smith 1983; Page 1993) and with

Ronkainen's findings (1985) that financial variables are critical in the go/no-go/continue decision-making processes.

Table 4-1c: Performance measurement criteria change

	MEAN[a] Success n=190 (73.1%) *A*			MEAN[a] Failure n=70 (27.1%) *B*			MEAN[a] n=260 (100%) *C*		
Measures of performance	T_0	T_1	*sig.* [b]	T_0	T_1	*sig.* [b]	T_0	T_1[b]	sig.[b]
Financial performance (0-10)	*6.8105*	*7.1211*	*.052*	*6.5143*	*5.9714*	*.072*	6.7308	6.8115	.571
Window of opportunity (0-10)	6.5053	6.5632	.707	*6.3714*	*4.7143*	*.071*	6.4692	6.0654	.137
Market share impact (0-10)	6.7158	7.0105	.117	5.4286	4.9714	.159	6.3692	6.4615	.571

[a] Mean values across projects of performance measurement criteria (0=strongly disagree to 10=strongly agree)
[b] Significance level of the difference in mean performance measurement criteria over time (ANOVA, two-tail t-test)

Table 4-1d is consistent with all evidence above. It displays the results of aggregate independent t-test performance differences by success/failure. Though financial and window criteria were not significantly different for success/failure cases at T_0, all three criteria were different by one year post launch. The significance of "impact" to success at T_0 reinforces the finding supporting Cooper and Kleinschmidt (1987a) and Hultink and Robben (1995) above. It confirms that a project can be promoted to the next stage/gate evaluation if its early "impact" score at T_0 is acceptable.

Table 4-1d: Performance measurement criteria differences by success/failure

	Aggregate independent t-test performance differences by success/failure
Financial T_0	p = .4863
Financial T_1	*p = .0076*
Window T_0	p = .8429
Window T_1	*p = .0000*
Impact T_0	*p = .0030*
Impact T_1	*p = .0000*

These combined results are in harmony with those suggesting an evolution of go/no-go/continue criteria is normal (Hultink and Robben 1995; Ronkainen 1985). Moreover, they caution that failing to meet early performance measurement criteria should not necessarily kill an otherwise acceptable project. Even if a project's financial and window of opportunity criteria are nebulous at the initial screen, its T_0 *impact* score may be enough to move it along - *if it can meet financial criteria by one year post launch*. This is quite significant because giving a project a GO! based first on meeting minimum impact criteria and then based on meeting financial performance *conditions* by one year post launch is the literature's first empirical demonstration of *fuzzy* performance measurement (Cooper 1994b).. Using temporal benchmarking techniques (Griffin 1993) to discover other fuzzy relationships can lead to cycle time reduction (Cooper 1995) which is fundamental to competitive strategy in many industries (Carmel 1995).

4.2 Hypothesis H_1a

Many variables relating to a new product's success are dynamic not static and are perceived to evolve over time from the initial screen to the end of the first year of market entry.

4.2.1 Introduction

Table 4-2 illustrates the results of the one way ANOVA for all cases, success cases only and failure cases only. The asterisks (*) indicate the time period in which the variable was significant to success and level of significance[45]. If variables changed in significance over time, either absolutely or by degree of significance, the change is noted in the last column.

Results from the paired-samples t-test are displayed in Table 4-4. Again, the number of asterisks defines the significance level. An arrow in the last column indicates the direction of magnitudinal change over time.

4.2.2 ANOVA findings

The one way analysis of variance indicates that many variables do change in perceived significance by time period.

Table 4-2: 1 Way ANOVA at T_0 and T_1[46]

	*T0 Sig. =.05 * =.10*	*T1 Sig. **=.05 * =.10*
F_PCERCN	**	**
K_PCERCN		
S_PERCNT	**	**

	*T0 Sig. **=.05 * =.10*	*T1 Sig. **=.05 * =.10*	*Changed from T0 to T1*
NEWNESS/INNOVATIVENESS			
This product was (please rate ALL types of new products:)			
1. • New-to-the-world (a true innovation in the product marketplace listed above)		**	changed
2. • A new product line			
3. • An addition to an existing product line		*	changed
4. • Improvement in or revision to an existing product			
5. • A repositioning	**	**	
6. • A cost reduction			
7. Our firm developed clear strategies to deal with deficiencies/problems in the area of Newness/Innovation		**	changed
SUCCESS FACTORS/STRATEGY			
8. After the 1 year entry period, this product was considered a Failure/Success (-5=great failure +5=great success)			
BARRIERS TO ENTRY			
The following were important in the GO/NO GO decision process (please rate ALL barriers to entry):			
24. • Cost advantages of incumbents (economies of scale)			
25. • Product differentiation (proprietary product differences) of the incumbents			
26. • Brand identity	**	**	
27. • Customer switching costs			
28. • Capital requirements			
29. • Access to distribution channels			
30. • Absolute cost advantages (learning curve, access to inputs, proprietary design etc.)			
31. • Government Policy			
32. • Expected retaliation			
33. Expected speed of competitive retaliation was an important consideration in this market	**	**	

45 ** = p<.05; * = p<.1.

46 *Bold italics* = new to the NPD forecasting literature in this form.

entry decision			
34. Expected magnitude of competitive retaliation was an important consideration in this market entry decision	**	**	
35. The product would have done better if marketed by almost any of our major competitors	**	**	
36. Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry	**	**	
RESOURCES REQUIRED			
37. Our company's financial resources were more than adequate for this project			
38. Our company's R&D skills & people were more than adequate for this project	**	**	
39. Our company's engineering skills & people were more than adequate for this project	**	**	
40. Our company's marketing research skills & people were more than adequate for this project	**	**	
41. Our company's management skills were more than adequate for this project	**	**	
42. Our company's production resources or skills were more than adequate for this project			
43. Our company's sales force &/or distribution resources & skills were more than adequate for this project	**	**	
44. Our company's advertising & promotion resources & skills were more than adequate for this project		**	**changed**
45. Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements	**	**	
NATURE OF PROJECT/NEWNESS TO FIRM			
46. Our product was highly innovative - totally new to the market			
47. The product specifications - exactly what the product will be - were very clear		*	**changed**
48. The technical aspects - exactly how the technical problems will be solved - were very clear	**	**	
49. The potential customers for this product were totally new to our company	*		**changed**
50. The product class or type of product itself was totally new to our company	**	**	
51. We had never made or sold products to satisfy this type of customer need or use before	**	**	
52. The competitors we face in the market were totally new to our company	**	**	
53. The product "fit in" with a family of products we already had on the market	**	**	
54. The product which entered the market was significantly different than that approved at the initial screen			
55. Our firm developed clear strategies to deal with deficiencies in the Nature of the Project	**	**	
THE FINAL PRODUCT			
56. Compared to competitive products (or whatever the customer was using) our product offered a number of unique features, attributes or benefits to the customer	**	**	
57. Our product was clearly superior to competing products in terms of meeting customer needs	**	**	
58. Our product permitted the customer to reduce his/her costs, when compared to what he/she was using		**	**changed**
59. Our product permitted the customer to do a job or do something that he/she could not do with what was available on the market		**	**changed**
60. Our product was of higher quality - however quality is defined in this market - than competing products		**	**changed**
61. Our product was priced considerably higher than competing products			
62. Our firm developed clear strategies to deal with deficiencies in the Final Product	**	**	
THE MARKET FOR THE PRODUCT			
63. Potential customers had a great need for this class or type of product	**	**	
64. The dollar size of the market (either existing or potential market) for this product was large		**	**changed**
65. The market for this product was growing very quickly	**	**	
66. The market was characterised by intense price competition			
67. There were many competitors in this market	*		**changed**
68. There was a strong dominant competitor- with a large market share - in this market			
69. Potential customers were very satisfied with the products (competitors' products) they were currently using	**	**	
70. Users' needs changed quickly in this market - a dynamic market situation			
71. We were the first to market this product		**	**changed**
72. We were not first to market this product; we followed close behind however			
73. We entered the market in its late growth stage	*	**	
74. We entered the market somewhere between its maturity and decline			
75. The fast rate of technological change was important in this product market			
76. Competitors introduced new products into this market very quickly			
77. Competitors withdrew products from this market very quickly			
78. R&D in this market produced many advancements in the production process and ensuing products			
79. Production methods in this market changed very quickly			
80. The amount of change (technological leap/boundary distance) was important in this product market			
81. New products introduced into this market were much more technologically sophisticated than those replaced			
82. R&D in this market produced significant advancements in the production process and ensuing products			
83. This product had a long life cycle in its original form (before modifications were		*	**changed**

necessary)			
84. We spent a long time on the market research for this product		**	changed
85. Market cyclicality was important in the decision to enter this market			
86. Market seasonality was important in the decision to enter this market			
87. The contribution margin was important in the decision to enter this market		**	changed
88. The primary market for this product was domestic (over 50% in US)			
89. Our firm developed clear strategies to deal with difficulties inherent in this market	**	**	

At p=.1, 30 variables out of the 75 tested (40%) were significant to success at T_0[47]. At T_1, 41 variables (54.67%) were significant to success[48]. Of the 30 variables significant at T_0, 28 are significant at T_1 also (93.3%). In large part, individual variables significant to success at the initial screen are perceived to remain significant over time. This argues for acceptance of the null hypothesis. On the other hand, 13 of 75 variables (17.33%) did not become significant until time T_1. This represents a 43.3% change in the original significant 30 variable environment and a 46.43% change based on the 28 variable, mutually inclusive environments. This argues for rejection of the null form and acceptance of the alternative hypothesis of change over time.

Table 4-3 illustrates the difference between the two environments. The left column contains the 28 variables significant to success at both periods. The right column contains the 13 variables that managers perceive become significant only over time. Of the mutually inclusive variables significant at both time periods, 13 of 28 (46.43%) are newly demonstrated in the NPD forecasting literature. Of those which become significant only over time, 6 of 13 (46.15%) are new. Clearly, managers perceive a significant change in NPD antecedents of success over time.

Table 4-3: Comparison of common versus unique variables over time (summary of temporal stability/instability over time) *Bold italics = new to the field in this form*

The 26 variable statements significant to success/failure at both time periods i.e. STABLE ANTECEDENTS	*The extra 13 variables statements that become significant to success/failure only over time i.e. UNSTABLE ANTECEDENTS (Montoya-Weiss and Calantone 1994)*
HISTORY ***Failure %*** ***Success %***	
INNOVATION ***5. This product was a repositioning***	INNOVATION ***1. This product was new-to-the-world*** ***3. This product was an addition to an existing product line*** ***7. Our firm developed clear strategies to deal with deficiencies/problems in the area of Newness/Innovation***
BARRIERS ***26. The following were important in the GO/NO GO decision process - brand identity*** ***33. Expected speed of competitive retaliation was an important consideration in this market entry decision*** ***34. Expected magnitude of competitive retaliation was an important consideration in this market entry decision*** ***35. The product would have done better if marketed by almost any of our major competitors*** ***36. Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry***	BARRIERS
RESOURCES	RESOURCES

47 27 variables at p<.05 (36%).
48 38 variables at p<.05 (37.3%).

38. Our company's R&D skills & people were more than adequate for this project 39. Our company's engineering skills & people were more than adequate for this project 40. Our company's marketing research skills & people were more than adequate for this project 41. Our company's management skills were more than adequate for this project 43. Our company's sales force &/or distribution resources & skills were more than adequate for this project ***45. Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements***	44. Our company's advertising & promotion resources & skills were more than adequate for this project
PROJECT 48. The technical aspects - exactly how the technical problems will be solved - were very clear 50. The product class or type of product itself was totally new to our company 51. We had never made or sold products to satisfy this type of customer need or use before 52. The competitors we face in the market were totally new to our company 53. The product "fit in" with a family of products we already had on the market ***55. Our firm developed clear strategies to deal with deficiencies in the Nature of the Product***	PROJECT 47. The product specifications - exactly what the product will be - were very clear
FINAL PRODUCT 56. Compared to competitive products (or whatever the customer was using) our product offered a number of unique features, attributes or benefits to the customer 57. Our product was clearly superior to competing products in terms of meeting customer needs ***62. Our firm developed clear strategies to deal with deficiencies in the Final Product***	FINAL PRODUCT 58. Our product permitted the customer to reduce his/her costs, when compared to what he/she was using 59. Our product permitted the customer to do a job or do something that he/she could not do with what was available on the market 60. Our product was of higher quality - however quality is defined in this market - than competing products
MARKET 63. Potential customers had a great need for this class or type of product 65. The market for this product was growing very quickly 69. Potential customers were very satisfied with the products (competitors' products) they were currently using ***73. We entered the market in its late growth stage*** ***89. Our firm developed clear strategies to deal with difficulties Inherent in this market***	MARKET 64. The dollar size of the market (either existing or potential market) for this product was large ***71. We were the first to market this product*** ***83. This product had a long life cycle in its original form (before modifications were necessary)*** 84. We spent a long time on the market research for this product ***87. The contribution margin was important in the decision to enter this market***

4.2.3 Paired samples t-test findings

In addition to determining whether variables are significant at T_0, T_1 or both, the examination of changes in variable magnitude is important as an indicator of direction and emphases. Results for the paired samples t-test for all cases, failure cases and success cases are displayed in Table 4-4. Figure 4-2, 4-3 and 4-4 illustrate graphically, this difference and direction[49] at the p=.10 level by all, by success and by failure cases. Because of the lack of comprehensive reporting (Montoya-Weiss and Calantone 1994), means, t values, r values, degrees of freedom and significance are reported for all variables by successes, failures and in the aggregate.

Because most levels of significance are at p=.05, the change in variable distribution means of over time is likely not to be caused by chance. With respect to all cases (n=260), 27 of 72[50] variables (37.5%) changed in magnitude (see Figure 4-2). For

[49] The increase (⇑) or decrease (⇓) in the variable's importance over time is indicated at the .05 (⇑⇑) or .1 (⇑) level. Up or down arrow direction must be interpreted as favourable or unfavourable respectively, in the context of the variable statement.
[50] success, failure and kill variables do not change over time i.e. 72 not 75 variables.

success cases (n=190), 25 of 72 (34.7%) variables changed in magnitude (see Figure 4-3). For failure cases (n=70), 29 of 72 (40.3%) variables changed in magnitude (see Figure 4-4). This difference illustrates at least two similar but critically different environments affecting the new product development process from T_0 to T_1. The implications of this are discussed in section 4.6.

Table 4-4: Paired samples t-test & correlation - T_0 (minus)T_1

A=All cases (the aggregate) *F=Failures only* *S=Successes only*	*mean T0*	*mean T1*	*T0-T1*	*r*	*Paired-samples T-test*	*Unequal .05 = ** .10 = **	*Up Dn*
1. • New-to-the-world (a true innovation in the product marketplace listed above)	A: 5.7654	5.3769	0.39	.904	t=3.84 at .000/259df	**	⇓⇓
	F: 5.3143	4.4857	0.83	.855	t=3.48 at .001/69df	**	⇓⇓
	S: 5.9316	5.7053	0.23	.923	t=2.16 at .032/189df	**	⇓⇓
2. • A new product line	A: 6.3423	5.9923	0.35	.892	t=3.13 at .002/259df	**	⇓⇓
	F: 6.8714	6.2000	0.67	.899	t=3.36 at .001/69df	**	⇓⇓
	S: 6.1474	5.9158	0.23	.891	T=1.73 at .084/189df	*	⇓
3. • An addition to an existing product line	A: 4.3385	4.2538	0.08	.932	t=.88 at .377/259df		
	F: 3.6571	3.4571	0.20	.938	t=1.18 at .243/69df		
	S: 4.5895	4.5474	0.04	.929	t=.37 at .715/189df		
4. • Improvement in or revision to an existing product	A: 3.5192	3.4269	0.09	.925	t=.95 at .345/259df		
	F: 3.0571	2.7714	0.29	.828	t=1.12 at .267/69df		
	S: 3.6895	3.6684	0.02	.952	t=.22 at .824/189df		
5. • A repositioning	A: 2.3231	2.3538	-0.03	.878	t=-.30 at .765/259df		
	F: 1.3714	1.6286	-0.26	.852	t=-1.47 at .146/69df		
	S: 2.6737	2.6211	0.05	.882	t=.42 at .674/189df		
6. • A cost reduction	A: 2.0692	1.9962	0.07	.895	t=.77 at .439/259df		
	F: 1.7429	1.7857	-0.04	.882	t=-.24 at .812/69df		
	S: 2.1895	2.0737	0.12	.898	t=1.04 at .299/189df		
7. Our firm developed clear strategies to deal with deficiencies/problems in the area of Newness/Innovation	A: 5.1885	4.8615	0.33	.389	t=.86 at .392/259df		
	F: 4.8571	2.6714	2.19	.405	t=1.65 at .103/69df	*	⇓
	S: 5.3105	5.6684	-0.36	.725	t=-2.18 at .030/189df	**	⇑⇑
24. • Cost advantages of incumbents (economies of scale)	A: 4.6038	4.600	0.00	.867	t=.04 at .972/25		
	F: 4.4286	4.3571	0.07	.852	t=.33 at .746/69df		
	S: 4.6684	4.6895	-0.02	.872	t=-.17 at .865/189df		
25. • Product differentiation (proprietary product differences) of the incumbents	A: 6.7308	6.6577	0.07	.787	t=.55 at .581/259df		
	F: 6.7429	6.4143	0.33	.695	t=1.1 at .275/69df		
	S: 6.7263	6.7474	-0.02	.821	t=-.15 at .884/189df		
26. • Brand identity	A: 5.5154	5.6808	-0.17	.840	t=-1.33 at.184/259df		
	F: 4.5857	4.6286	-0.04	.860	t=-.19 at .850/69df		
	S: 5.8579	6.0684	-0.21	.826	t=-1.42 at .158/189df		
27. • Customer switching costs	A: 3.7192	3.8769	-0.16	.827	t=-1.35 at .177/259df		
	F: 3.3714	3.3571	0.01	.780	t=.06 at .954/69df		
	S: 3.8474	4.0684	-0.22	.843	t=-1.68 at .094/189df	*	⇑
28. • Capital requirements	A: 4.6423	4.7077	-0.07	.792	t=-.48 at .630/259df		
	F: 4.6429	5.0286	-0.39	.769	t=-1.42 at .160/69df		
	S: 4.6421	4.5895	0.05	.802	t=.34 at .736/189df		
29. • Access to distribution channels	A: 5.1462	5.4154	-0.27	.866	t=-2.35 at .019/259df	**	⇑⇑
	F: 5.3714	5.4571	-0.09	.753	t=-.31 at .760/69df		
	S: 5.0632	5.4000	-0.34	.901	t=-2.85 at .005/189df	**	⇑⇑
30. • Absolute cost advantages (learning curve, access to inputs, proprietary design etc.)	A: 4.8231	4.95	-0.13	.804	t=-1.04 at .299/259df		
	F: 4.6857	4.6714	0.01	.742	t=-.05 at .958/69df		
	S: 4.8737	5.0526	-0.18	.826	t=-1.33 at .186/189df		
31. • Government Policy	A: 2.0500	2.2192	-0.17	.895	t=-1.85 at .065/259df	*	⇑

A=All cases (the aggregate) F=Failures only S=Successes only	mean T_0	mean T_1	T_0-T_1	r	Paired-samples T-test	Unequal .05 = ** .10 = *	Up Dn
	F: 2.0000	2.1571	-0.16	.875	t=-.87 at .390/69df		
	S: 2.0684	2.2421	-0.17	.901	t=-1.64 at .102/189df	*	⇑
32. • Expected retaliation	A: 2.5615	2.7154	-0.15	.837	t=-1.45 at .149/259df		
	F: 2.2143	2.4714	-0.26	.869	t=-1.42 at .161/69df		
	S: 2.6895	2.8053	-0.12	.826	t=-.90 at .371/189df		
33. Expected speed of competitive retaliation was an important consideration in this market entry decision	A: 3.8115	4.0192	-0.21	.828	t=-1.71 at .089/259df	*	⇑
	F: 2.7143	2.7143	0.00	.866	t=0.0 at 1.0/69df		
	S: 4.2158	4.5000	-0.28	.809	t=-1.86 at .065/189df	*	⇑
34. Expected magnitude of competitive retaliation was an important consideration in this market entry decision	A: 3.3769	3.5538	-0.18	.807	t=-1.44 at .151/259df		
	F: 2.4857	2.4571	0.03	.744	t=.12 at .905/69df		
	S: 3.7053	3.9579	-0.25	.816	t=-1.76 at .080/189df	*	⇑
35. The product would have done better if marketed by almost any of our major competitors	A: 2.9423	3.1154	-0.17	.894	t=-1.80 at .073/259df	*	⇑
	F: 3.6000	4.1714	-0.57	.855	t=-2.44 at .017/69df	**	⇑⇑
	S: 2.7000	2.7263	-0.03	.912	t=-.27 at .787/69df		
36. Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry	A: 4.2308	4.4077	-0.18	.789	t=-1.43 at .154/259df		
	F: 3.4143	3.0429	0.37	.687	t=1.50 at .138/69df		
	S: 4.5316	4.9105	-0.38	.808	t=-2.71 at .007/189df	**	⇑⇑
37. Our company's financial resources were more than adequate for this project	A: 6.6846	6.1423	0.54	.840	t=4.51 at .000/259df	**	⇓⇓
	F: 6.7571	5.7000	1.06	.822	t=4.16 at .000/69df	**	⇓⇓
	S: 6.6579	6.3053	0.35	.855	t=2.65 at .009/189df	**	⇓⇓
38. Our company's R&D skills & people were more than adequate for this project	A: 7.0346	6.6692	0.37	.776	t=2.88 at .004/259df	**	⇓⇓
	F: 6.4143	5.7286	0.69	.810	t=2.94 at .004/69	**	⇓⇓
	S: 7.2632	7.0158	0.25	.755	t=1.65 at .101/189df	*	⇓
39. Our company's engineering skills & people were more than adequate for this project	A: 6.8538	6.5500	0.30	.807	t=2.58 at .010/259df	**	⇓⇓
	F: 6.1429	5.5000	0.64	.857	t=3.04 at .003/69df	**	⇓⇓
	S: 7.1158	6.9368	0.18	.777	t=1.28 at .203/189df		
40. Our company's marketing research skills & people were more than adequate for this project	A: 5.9115	5.8385	0.07	.756	t=.59 at .556/259df		
	F: 5.2143	4.6714	0.54	.711	t=2.23 at .029/69df	**	⇓⇓
	S: 6.1684	6.2684	-0.10	.762	t=-.70 at .482/189df		
41. Our company's management skills were more than adequate for this project	A: 6.2115	5.9269	0.28	.703	t=2.11 at .036/259df	**	⇓⇓
	F: 5.4143	4.5714	0.84	.506	t=2.55 at .013/69df	**	⇓⇓
	S: 6.5053	6.4263	0.08	.763	t=.58 at .563/189df		
42. Our company's production resources or skills were more than adequate for this project	A: 6.6923	6.4308	0.26	.702	t=1.89 at .060/259df	*	⇓
	F: 6.6429	6.0286	0.61	.778	t=2.59 at .012/69df	**	⇓⇓
	S: 6.7105	6.5789	0.13	.676	t=.79 at .432/189df		
43. Our company's sales force &/or distribution resources & skills were more than adequate for this project	A: 6.2615	5.7923	0.47	.742	t=3.58 at .000/259df	**	⇓⇓
	F: 5.5571	4.7000	0.86	.788	t=3.63 at .001/69df	**	⇓⇓
	S: 6.5211	6.1947	0.33	.714	t=2.09 at .038/189df	**	⇓⇓
44. Our company's advertising & promotion resources & skills were more than adequate for this project	A: 5.5731	5.3731	0.20	.829	t=1.77 at .078/259df	*	⇓
	F: 5.1571	4.4286	0.73	.828	t=3.4 at .001/69df	**	⇓⇓
	S: 5.7263	5.7211	0.01	.832	t=.04 at .968/189df		
45. Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements	A: 4.3692	4.2538	0.12	.784	t=.96 at .340/259df		
	F: 3.7429	3.1714	0.57	.737	t=2.34 at .022/69df	**	⇓⇓
	S: 4.6000	4.6526	-0.05	.796	t=-.38 at .702/189df		
46. Our product was highly innovative -	A: 6.0846	5.8846	0.20	.894	t=1.99 at .048/259df	**	⇓⇓

A=All cases (the aggregate) *F=Failures only* *S=Successes only*	*mean T_0*	*mean T_1*	*T_0-T_1*	*r*	*Paired-samples T-test*	*Unequal .05 = ** .10 = **	*Up Dn*
totally new to the market							
	F: 6.0571	5.3286	0.73	.880	t=3.45 at .001/69df	**	⇓⇓
	S: 6.0947	6.0895	0.01	.905	t=.05 at .962/189df		
47. The product specifications - exactly what the product will be - were very clear	A: 6.6500	6.7500	-0.10	.736	t=-.74 at .462/259df		
	F: 6.3714	6.2286	0.14	.740	t=.59 at .554/69df		
	S: 6.7526	6.9421	-0.19	.734	t=-1.16 at .248/189df		
48. The technical aspects - exactly how the technical problems will be solved - were very clear	A: 6.0231	5.9192	0.10	.630	t=.67 at .503/259df		
	F: 5.4571	4.8000	0.66	.735	t=2.56 at .013/69df	**	⇓⇓
	S: 6.2316	6.3316	-0.10	.580	t=-.53 at .595/189df		
49. The potential customers for this product were totally new to our company	A: 3.8846	3.8962	-0.01	.918	t=-.12 at .903/259df		
	F: 4.5286	4.4429	0.09	.972	t=.76 at .450/69df		
	S: 3.6474	3.6947	-0.05	.893	t=-.39 at .699/189df		
50. The product class or type of product itself was totally new to our company	A: 4.7846	4.5154	0.27	.943	t=3.21 at .001/259df	**	⇓⇓
	F: 5.8714	5.5857	0.29	.945	t=1.84 at .07/69df	*	⇓
	S: 4.3842	4.1211	0.26	.940	t=2.64 at .009/189df	**	⇓⇓
51. We had never made or sold products to satisfy this type of customer need or use before	A: 4.5308	4.4385	0.09	.917	t=.88 at .378/259df		
	F: 5.8143	5.7286	0.09	.981	t=.9 at .369/69df		
	S: 4.0579	3.9632	0.09	.890	t=.68 at .496/189df		
52. The competitors we face in the market were totally new to our company	A: 3.0077	3.1115	-0.10	.934	t=-1.25 at .211/259df		
	F: 4.0000	4.1571	-0.16	.959	t=-1.14 at .257/69df		
	S: 2.6421	2.7263	-0.08	.920	t=-.83 at .408/189df		
53. The product "fit in" with a family of products we already had on the market	A: 6.3423	6.2692	0.07	.880	t=.64 at .524/259df		
	F: 5.2571	4.7857	0.47	.900	t=2.3 at .025/69df	**	⇓⇓
	S: 6.7421	6.8158	-0.07	.867	t=-.54 at .589/189df		
54. The product which entered the market was significantly different than that approved at the initial screen	t-test not applicable						
55. Our firm developed clear strategies to deal with deficiencies in the Nature of the Project	A: 4.0154	4.3615	-0.35	.611	t=-2.25 at .025/259df	**	⇑⇑
	F: 3.3714	3.3143	0.06	.465	t=.18 at .855/69df		
	S: 4.2526	4.7474	-0.49	.639	t=-2.83 at .005/189df	**	⇑⇑
56. Compared to competitive products (or whatever the customer was using) our product offered a number of unique features, attributes or benefits to the customer	A: 7.9808	7.7731	0.21	.622	t=1.51 at .131/259df		
	F: 7.4714	6.5429	0.93	.663	t=3.36 at .001/69df	**	⇓⇓
	S: 8.1684	8.2263	-0.06	.595	t=-.38 at .707/189df		
57. Our product was clearly superior to competing products in terms of meeting customer needs	A: 7.3538	6.9231	0.43	.669	t=3.00 at .003/259df	**	⇓⇓
	F: 6.7143	5.1143	1.60	.623	t=5.31 at .000/69df	**	⇓⇓
	S: 7.5895	7.5895	0.00	.691	t=0.0 at 1.0/189df		
58. Our product permitted the customer to reduce his/her costs, when compared to what he/she was using	A: 5.8846	5.5231	0.36	.866	t=3.09 at .002/259df	**	⇓⇓
	F: 5.8286	4.6714	1.16	.789	t=4.24 at .000/69df	**	⇓⇓
	S: 5.9053	5.8368	0.07	.902	t=.58 at .564/189df		
59. Our product permitted the customer to do a job or do something that he/she could not do with what was available on the market	A: 6.2192	5.8038	0.42	.491	t=1.35 at .177/259df		
	F: 6.2857	4.5286	1.76	.198	t=1.6 at .113/69df		
	S: 6.1947	6.2737	-0.08	.920	t=-.77 at .440/189df		
60. Our product was of higher quality - however quality is defined in this market - than competing products	A: 7.1962	6.7346	0.46	.397	t=1.25 at .213/259df		
	F: 6.1286	5.4857	0.64	.800	t=2.98 at .004/69df	**	⇓⇓

A=All cases (the aggregate) F=Failures only S=Successes only	mean T_0	mean T_1	T_0-T_1	r	Paired-samples T-test	Unequal .05 = ** .10 = *	Up Dn
	S: 7.5895	7.1947	0.39	.352	t=.79 at .431/189df		
61. Our product was priced considerably higher than competing products	A: 4.8308	4.8385	-0.01	.900	t=-.08 at .935/259df		
	F: 4.9571	5.0000	-0.04	.896	t=-.23 at .816/69df		
	S: 4.7842	4.7789	0.01	.901	t=.05 at .962/189df		
62. Our firm developed clear strategies to deal with deficiencies in the Final Product	A: 4.7077	4.8808	-0.17	.767	t=-1.40 at .161/259df		
	F: 3.8429	3.3857	0.46	.589	t=1.6 at .114/69df		
	S: 5.0263	5.4316	-0.41	.810	t=-3.16 at .002/189df	**	⇑⇑
63. Potential customers had a great need for this class or type of product	A: 6.9885	6.6385	0.35	.657	t=2.50 at .013/259df	**	⇓⇓
	F: 6.3429	5.0000	1.34	.555	t=4.0 at .000/69df	**	⇓⇓
	S: 7.2263	7.2421	-0.02	.705	t=-.11 at .909/189df		
64. The dollar size of the market (either existing or potential market) for this product was large	A: 6.8846	6.6231	0.26	.705	t=1.96 at .051/259df	**	⇓⇓
	F: 6.5857	5.4571	1.13	.729	t=4.08 at .000/69df	**	⇓⇓
	S: 6.9947	7.0526	-0.06	.706	t=-.40 at .691/189df		
65. The market for this product was growing very quickly	A: 5.8808	5.7192	0.16	.740	t=1.19 at .236/259df		
	F: 4.6857	4.1143	0.57	.682	t=1.88 at .065/69df	*	⇓
	S: 6.3211	6.3105	0.01	.741	t=.07 at .943/189df		
66. The market was characterised by intense price competition	A: 4.6192	4.9038	-0.28	.900	t=-3.02 at .003/259df	**	⇑⇑
	F: 4.9000	4.9429	-0.04	.943	t=-.30 at .763/69df		
	S: 4.5158	4.8895	-0.37	.884	t=-3.18 at .002/189df	**	⇑⇑
67. There were many competitors in this market	A: 4.6731	4.6192	0.05	.413	t=.13 at .894/259df		
	F: 5.9143	4.8714	1.04	.409	t=.80 at .424/69df		
	S: 4.2158	4.5263	-0.31	.508	t=-1.12 at .263/189df		
68. There was a strong dominant competitor- with a large market share - in this market	A: 5.0577	5.1731	-0.12	.913	t=-1.19 at .233/259df		
	F: 5.2429	5.4000	-0.16	.908	t=-.82 at .415/69df		
	S: 4.9895	5.0895	-0.10	.915	t=-.89 at .373/189df		
69. Potential customers were very satisfied with the products (competitors' products) they were currently using	A: 4.9038	4.9308	-0.03	.888	t=-.31 at .754/259df		
	F: 5.6714	5.9857	-0.31	.887	t=-2.05 at .044/69df	**	⇑⇑
	S: 4.6211	4.5421	0.08	.885	t=.77 at .440/189df		
70. Users' needs changed quickly in this market - a dynamic market situation	A: 3.5692	3.6769	-0.11	.918	t=-1.38 at .169/259df		
	F: 3.4286	3.3571	0.07	.983	t=1.04 at .30/69df		
	S: 3.6211	3.7947	-0.17	.896	t=-1.68 at .095/189df	*	⇑
71. We were the first to market this product	A: 5.5462	5.4269	0.12	.932	t=1.24 at .218/259df		
	F: 4.9143	4.3000	0.61	.887	t=2.68 at .009/69df	**	⇓⇓
	S: 5.7789	5.8421	-0.06	.949	t=-.64 at .523/189df		
72. We were not first to market this product; we followed close behind however	A: 2.9346	2.8077	0.13	.919	t=1.54 at .125/259df		
	F: 3.3429	3.2857	0.06	.913	t=.35 at .728/69df		
	S: 2.7842	2.6316	0.15	.920	t=1.6 at .111/189df		
73. We entered the market in its late growth stage	A: 2.9654	2.8846	0.08	.938	t=1.13 at .259/259df		
	F: 3.5714	3.600	-0.03	.939	t=-.19 at .850/69df		
	S: 2.7421	2.6211	0.12	.937	t=1.51 at .134/189df		
74. We entered the market somewhere between its maturity and decline	A: 2.0269	2.2385	-0.21	.613	t=-.89 at .373/259df		
	F: 2.1571	2.1000	0.06	.914	t=.38 at .703/69df		
	S: 1.9789	2.2895	-0.31	.569	t=-.97 at .332/189df		
75. The fast rate of technological change was important in this product market	A: 4.4308	4.5731	-0.14	.904	t=-1.52 at .131/259df		
	F: 4.0714	4.000	0.07	.949	t=.54 at .591/69df		
	S: 4.5632	4.7842	-0.22	.889	t=-1.86 at .064/189df	*	⇑
76. Competitors introduced new products into this market very quickly	A: 3.8423	4.2115	-0.37	.841	t=-3.30 at .001/259df	**	⇑⇑
	F: 3.9000	4.0286	-0.13	.906	t=-.76 at .452/69df		
	S: 3.8211	4.2789	-0.46	.818	t=-3.28 at .001/189df	**	⇑⇑

A=All cases (the aggregate) *F=Failures only* *S=Successes only*	*mean T_0*	*mean T_1*	*T_0-T_1*	*r*	*Paired-samples T-test*	*Unequal .05 = ** .10 = **	*Up Dn*
77. Competitors withdrew products from this market very quickly	A: 2.6038	2.6308	-0.03	.926	t=-.39 at .698/259df		
	F: 2.7571	2.7143	0.04	.982	t=.6 at .552/69df		
	S: 2.5474	2.6000	-0.05	.900	t=-.58 at .564/189df		
78. R&D in this market produced many advancements in the production process and ensuing products	A: 3.8115	4.0846	-0.27	.876	t=-2.84 at .005/259df	**	⇑⇑
	F: 3.8429	3.9000	-0.06	.926	t=-.39 at .698/69df		
	S: 3.8000	4.1526	-0.35	.858	t=-2.94 at .004/189df	**	⇑⇑
79. Production methods in this market changed very quickly	A: 2.8154	3.0269	-0.21	.907	t=-2.87 at .004/259df	**	⇑⇑
	F: 2.8571	3.1286	-0.27	.899	t=-1.64 at .105/69df		
	S: 2.8000	2.9895	-0.19	.911	t=-2.35 at .020/189df	**	⇑⇑
80. The amount of change (technological leap/boundary distance) was important in this product market	A: 4.4654	4.6577	-0.19	.860	t=-1.76 at .080/259df	*	⇑
	F: 4.2286	4.2857	-0.06	.913	t=-.33 at .745/69df		
	S: 4.5526	4.7947	-0.24	.838	t=-1.79 at .075/189df	*	⇑
81. New products introduced into this market were much more technologically sophisticated than those replaced	A: 5.3692	5.2000	0.17	.647	t=.69 at .492/259df		
	F: 5.3571	5.3000	0.06	.937	t=.35 at .724/69df		
	S: 5.3737	5.1632	0.21	.587	t=.63 at .526/189df		
82. R&D in this market produced significant advancements in the production process and ensuing products	A: 4.2385	4.3846	-0.15	.869	t=-1.46 at .144/259df		
	F: 4.0714	4.1286	-0.06	.928	t=-.39 at .701/69df		
	S: 4.3000	4.4789	-0.18	.845	t=-1.43 at .155/189df		
83. This product had a long life cycle in its original form (before modifications were necessary)	A: 5.7654	5.3692	0.40	.823	t=3.40 at .001/259df	**	⇓⇓
	F: 5.7429	4.8000	0.94	.818	t=3.95 at .000/69df	**	⇓⇓
	S: 5.7737	5.5789	0.19	.832	t=1.49 at .137/189df		
84. We spent a long time on the market research for this product	A: 3.3231	3.4615	-0.14	.849	t=-1.44 at .152/259df		
	F: 3.1000	2.8429	0.26	.872	t=1.52 at .132/69df		
	S: 3.4053	3.6895	-0.28	.844	t=-2.48 at .014/189df	**	⇑⇑
85. Market cyclicality was important in the decision to enter this market	A: 2.1462	2.1308	0.02	.946	t=.27 at .791/259df		
	F: 2.1857	2.0571	0.13	.956	t=1.17 at .244/69df		
	S: 2.1316	2.1579	-0.03	.942	t=-.39 at .700/189df		
86. Market seasonality was important in the decision to enter this market	A: 1.6808	1.7231	-0.04	.935	t=-.7 at .487/259df		
	F: 1.4286	1.3571	0.07	.969	t=.93 at .357/69df		
	S: 1.7737	1.8579	-0.08	.925	t=-1.08 at .282/189df		
87. The contribution margin was important in the decision to enter this market	A: 5.7000	5.7500	-0.05	.861	t=-.47 at .638/259df		
	F: 5.4429	4.9000	0.54	.875	t=2.61 at .011/69df	**	⇓⇓
	S: 5.7947	6.0632	-0.27	.860	t=-2.24 at .026/189df	**	⇑⇑
88. The primary market for this product was domestic (over 50% in US)	A: 7.6231	7.4308	0.19	.850	t=1.76 at .080/259df	*	⇓
	F: 7.5714	7.5000	0.07	.892	t=.39 at .70/69df		
	S: 7.6421	7.4053	0.24	.833	t=1.77 at .078/189df	*	⇓
89. Our firm developed clear strategies to deal with difficulties inherent in this market	A: 4.9538	4.8077	0.15	.782	t=1.18 at .240/259df		
	F: 3.5857	2.9429	0.64	.689	t=2.48 at .016/69df	**	⇓⇓
	S: 5.4579	5.4947	-0.04	.785	t=-.27 at .791/189df		

4.2.4 Conclusion

From the one way ANOVA above it is clear that there is a sizeable carry over effect of variables significant at both T_0 and T_1. This argues for the acceptance of the null form i.e. the two environments are equal. However, there exists also a set of

Figure 4-2: Aggregate significant variable magnitude change over time.

p=.1, n=260

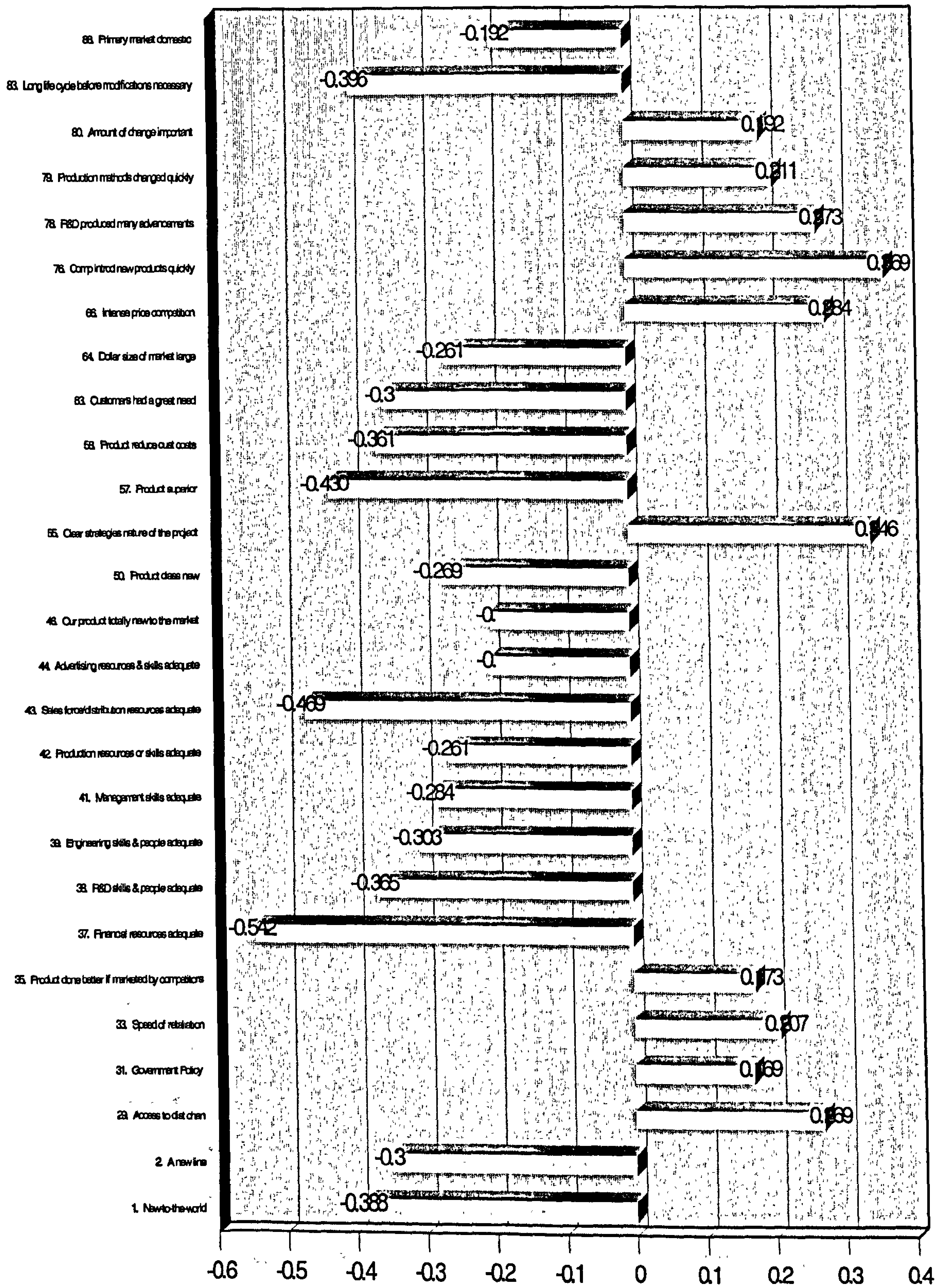


Figure 4-3: Success case significant variable magnitude change over time.

p=1, n=190

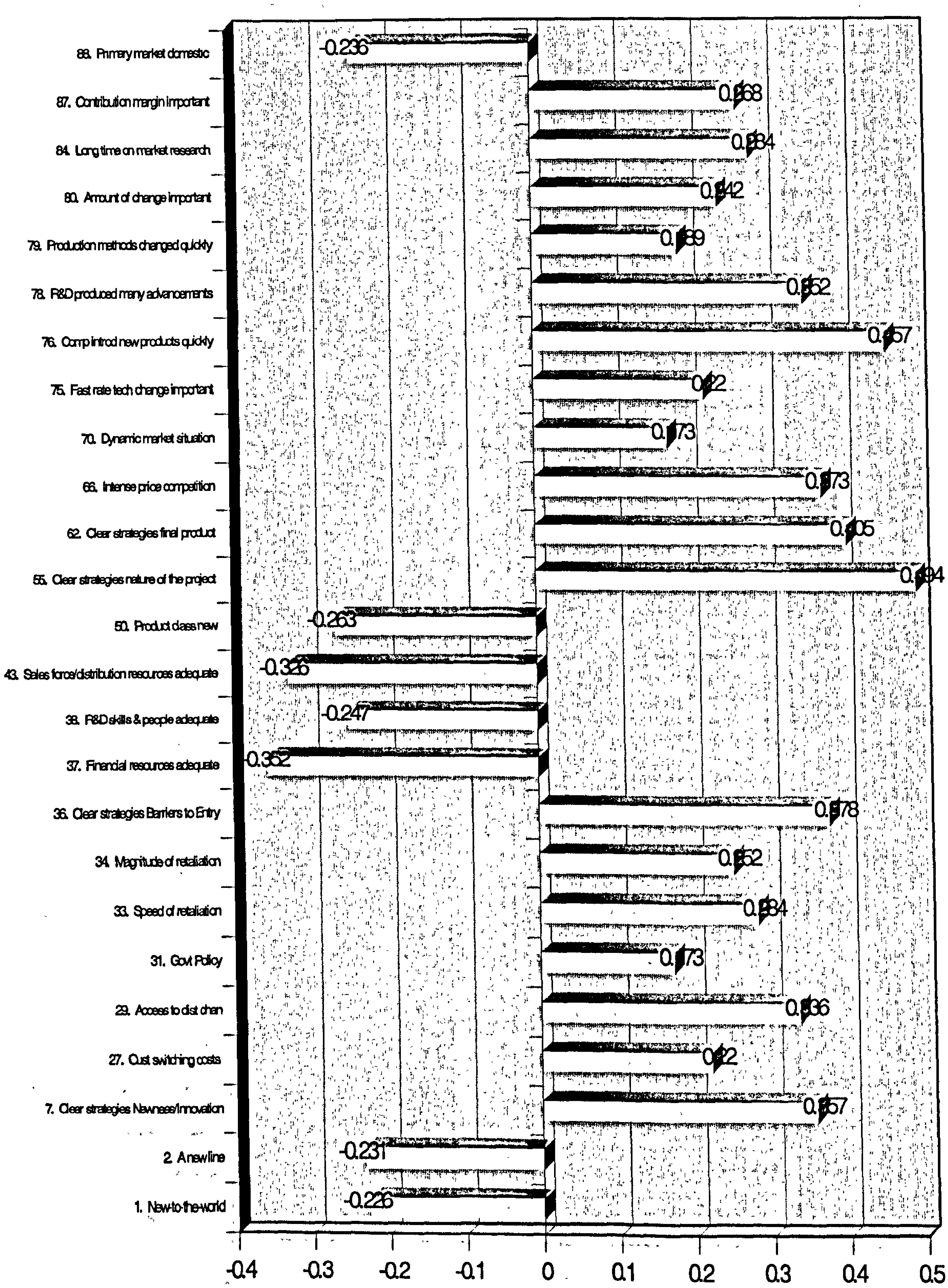
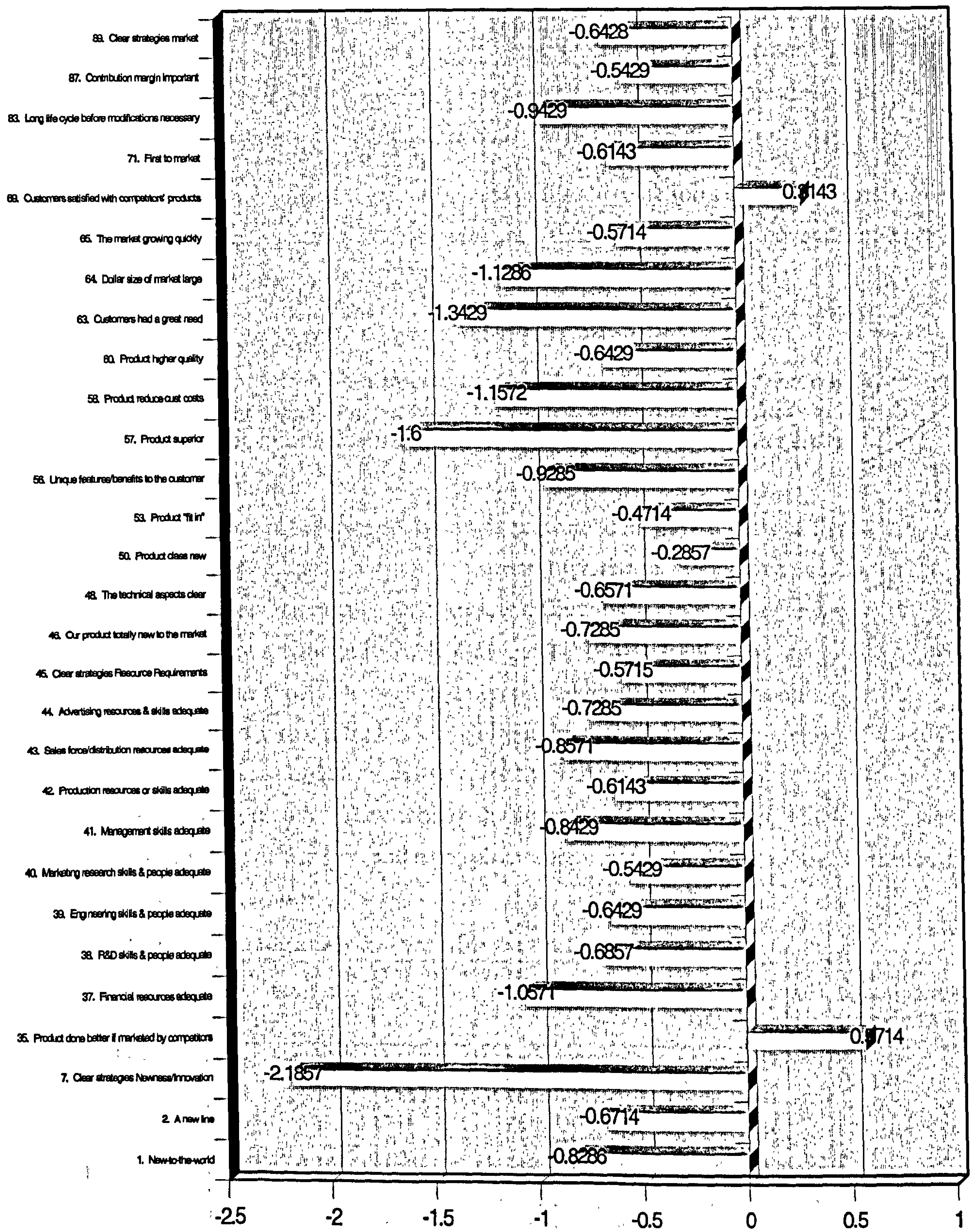


Figure 4-4: Failure case significant variable magnitude change over time.

p=1, n=70



distinctly different variables at work during this period which are significant over time. This argues for concluding that a difference does exist, rejection of the null form and acceptance of the alternate form. These differences are augmented by the results of the paired-samples t-test and support the conclusion that significant magnitudinal evolution does occur in aggregate, success and failure cases. This argues even more strongly for acceptance of the alternate form, as this change in selection and emphases affects the final outcome of the process.

These conclusive results require acceptance of the alternate form of the hypothesis, that many variables relating to a new product's success *are* dynamic not static and are perceived to evolve over time. The null form is thus rejected.

4.3 Hypothesis H_1b

The factors constructed from screening variables are dynamic, not static with respect to their construction, percent of variance, order and magnitude and evolve over time from the initial screen to the end of the first year of market entry.

4.3.1 Introduction

To test hypothesis H_1b, factor analysis was performed on the data sets at T_0 and T_1 independently. Factors, Eigenvalues, percents of variance, cumulative percents of variance, variables statements, their loadings, Chronbach alpha scores and average loading per factor are found in Table 4-5a and Table 4-5b for time T_0 and T_1 respectively. These describe well, the normalised dimensional environments at the initial screen and 1 year after launch. Since normalised factors have a mean of 0 and a standard deviation of 1, a paired-samples t-test of factors to determine significant difference is impossible. Therefore, in the aggregate, factor by factor analysis, t-tests of factor loading differences and scree plots were necessary to determine if T_0 results differed from T_1 results.

Table 4-5a: Factor analysis - variable set "A" at T_0

Factor	*Eigen*	*% Var.*	*Cum %*	*Variable Description*	*Variable loadings*	*Factor Chronbach alpha/avg loading*
1: Dynamic change in fast growing market	8.88	11.8	11.8	The amount of change (technological leap/boundary distance) was important in this product market	.79693	.8289 /.6397[51]
				R&D in this market produced significant advancements in the production process and ensuing products	.77981	
				Production methods in this market changed very quickly	.72506	
				The fast rate of technological change was important in this product market	.71265	
				R&D in this market produced many advancements in the production process and ensuing products	.70537	
				Users' needs changed quickly in this market - a dynamic market situation	.57894	

51 absolute values of factor loadings.

Factor	*Eigen*	*% Var.*	*Cum %*	*Variable Description*	*Variable loadings*	*Factor Chronbach alpha/avg loading*
				New products introduced into this market were much more technologically sophisticated than those replaced	.56640	
				Competitors introduced new products into this market very quickly	.47835	
				The market for this product was growing very quickly	.41347	
2: Strategic reaction capability	5.45	7.3	19.1	Our firm developed clear strategies to deal with deficiencies in the Final Product	.79772	.8349 /.6583
				Our firm developed clear strategies to deal with deficiencies in the Nature of the Project	.71614	
				Our firm developed clear strategies to deal with difficulties inherent in this market	.70756	
				Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements	.64650	
				Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry	.64225	
				We spent a long time on the market research for this product	.43936	
3: Overall project /company resource compatibility	4.94	6.6	25.7	Our company's sales force &/or distribution resources & skills were more than adequate for this project	.75936	.8209 /.6587
				Our company's marketing research skills & people were more than adequate for this project	.69001	
				Our company's management skills were more than adequate for this project	.68941	
				Our company's advertising & promotion resources & skills were more than adequate for this project	.67934	
				Our company's production resources or skills were more than adequate for this project	.62877	
				Our company's financial resources were more than adequate for this project	.50542	
4: New to the firm, didn't fit in	3.23	4.3	30.0	We had never made or sold products to satisfy this type of customer need or use before	.78503	.8022 /.6963
				The competitors we face in the market were totally new to our company	.77670	
				The potential customers for this product were (not) totally new to our company	.69618	
				The product class or type of product itself was totally new to our company	.69049	
				The product (did not) "fit in" with a family of products we already had on the market (negative)[52]	-.53329	
5: 1st in new, highly innovative market	2.87	3.8	33.8	We were the first to market this product	.78447	.7842 /.6917
				New-to-the-world (a true innovation in the product marketplace listed above)	.72419	
				Our product was highly innovative - totally new to the market	.68572	
				We were not first to market this product; we followed close behind however (negative)	-.57228	
6: Superior unique product meeting needs in large market	2.8	3.7	37.6	Our product was clearly superior to competing products in terms of meeting customer needs	.74770	.6662 /.5707
				Compared to competitive products (or whatever the customer was using) our product offered a number of unique features, attributes or benefits to the customer	.67551	
				Potential customers had a great need for this class or type of product	.67474	
				Our product permitted the customer to reduce his/her costs, when compared to what he/she was using	.54366	
				Our product permitted the customer to do a job or do something that he/she could not do with what was available on the market	.42724	
				The dollar size of the market (either existing or potential market) for this product was large	.35555	
7: Alertness to threat of competitive retaliation	2.2	2.9	40.5	Expected magnitude of competitive retaliation was an important consideration in this market entry decision	.84702	.8225 /.7699
				Expected speed of competitive retaliation was an important consideration in this market entry decision	.83638	
				Expected retaliation	.62642	
8:	2.0	2.6	43.1	Our company's R&D skills & people were more than	.78978	.7878

52 Cooper and Kleinschmidt (1994, p389) state that "Some variables are reverse-scale types (i.e. the less the better)". See also Cooper 1976, 1981, 1984, 1985b; Cooper and de Brentani 1984. Such reversals, usually shown as (negative)and/or reworded in the context of the factor, provide no inconsistency given the context of the statement. Such negative variable constructs are quite common in the literature (see Table 4-5c) and correctly indicate the effect of the variable on the factor.

Factor	*Eigen*	*% Var.*	*Cum %*	*Variable Description*	*Variable loadings*	*Factor Chronbach alpha/avg loading*
Technological resource adequacy				adequate for this project Our company's engineering skills & people were more than adequate for this project The technical aspects - exactly how the technical problems will be solved - were very clear	 .78641 .58147	/.7192
9: Satisfied, competitive market	1.9	2.5	45.6	Potential customers were very satisfied with the products (competitors' products) they were currently using There was a strong dominant competitor- with a large market share - in this market The market was characterised by intense price competition The product would have done better if marketed by almost any of our major competitors	.71161 .68621 .60927 .27695	.6291 /.5710
10: Exogenous timing variables	1.76	2.4	48.0	Market cyclically was important in the decision to enter this market Market seasonally was important in the decision to enter this market Competitors withdrew products from this market very quickly	.75213 .74769 .48119	.6448 /.6603
11: Moderate innovation	1.65	2.2	50.2	An addition to an existing product line Improvement in or revision to an existing product A new product line (negative)	.69737 .64962 -.62576	.6196 /.6576
12: Incremental innovation	1.57	2.1	52.3	A cost reduction A repositioning Cost advantages of incumbents (economies of scale)	.76912 .66642 .34859	.5564 /.5947
13: Innovative strategy in highly competitive market	1.52	2.0	54.3	Our firm developed clear strategies to deal with deficiencies/problems in the area of Newness/Innovation There were many competitors in this market	.87792 .87303	.8351 /.8755
14: Late market entry	1.41	1.9	56.2	We entered the market somewhere between its maturity and decline We entered the market in its late growth stage	.74528 .72510	.6532 /.7352
15: Differentiation barriers	1.39	1.9	58.1	Brand identity Access to distribution channels Absolute cost advantages (learning curve, access to inputs, proprietary design etc.) Product differentiation (proprietary product differences) of the incumbents	.67985 .66497 .43315 .33398	.4860 /.5280
16: NPD history of kills and success	1.28	1.7	59.8	In the last 3 years in this product market we have had ______Kills % (negative) ______Success %	 -.90616 .76658	.7492 /.8364
17: NPD history of failure	1.25	1.7	61.5	In the last 3 years in this product market we have had ______Failure % (negative)	 -.87497	1.0[53] /.8750
18: Government capital barriers	1.14	1.5	63.0	Government Policy Capital requirements	.63361 .55164	.2538[54] /.5926
19: Domestic markets	1.13	1.5	64.5	The primary market for this product was domestic (over 50% in US)	.71834	1.0 /.7183
20: Long life cycle, high price/high quality, strategy	1.11	1.5	66.0	This product had a long life cycle in its original form (before modifications were necessary) Our product was priced considerably higher than competing products Our product was of higher quality - however quality is defined in this market - than competing products	.68837 .59347 .34003	.2669 /.5406
21: Clear product specs	1.06	1.4	67.4	The product specifications - exactly what the product will be - were very clear	.48237	1.0 /.4824
22: Contribution margin	1.03	1.4	68.8	The contribution margin was important in the decision to enter this market Customer switching costs (negative)	.79463 -.34996	.1673 /.5723

53 In his factor analysis Cooper (1984) labels 5 of 11 single variable factors as "univariate dimensions". "1.0 is by definition, because only one measure was included for this construct" (Green, Barclay and Ryans 1995 p. 9).

54 NPD field Chronbach alpha scores have been used only since 1984. Though some report Chronbach alpha's <.5 (Cooper and de Brentani 1984), this is the minimum considered satisfactory (Cooper and de Brentani 1991). However, according to Cooper (1985a, p35) "The criteria used in the screening decision should reflect the corporation's overall objectives, and in particular, its goals for its new product program. Not all of these criteria are quantifiable, nor are they necessarily internally consistent". Nevertheless, if not for the exploratory nature of heterogeneous data integration and the importance of measuring their integrative effects on PLC and order/innovation constrained models, factors 18 through 22 would have been eliminated for reasons of internal inconsistency and parsimony.

Table 4-5b: Factor analysis - variable set "B" at T_1

Factor	*Eigen*	*% Var.*	*Cum %*	*Variable Description*	*Variable loadings*	*Factor Chronbach alpha/avg loading*
1: Dynamic change	10.14	13.3	13.3	The amount of change (technological leap/boundary distance) was important in this product market	.82154	.8572 /.6752
				R&D in this market produced significant advancements in the production process and ensuing products	.78378	
				New products introduced into this market were much more technologically sophisticated than those replaced	.74754	
				Production methods in this market changed very quickly	.72233	
				R&D in this market produced many advancements in the production process and ensuing products	.71093	
				The fast rate of technological change was important in this product market	.68817	
				Users' needs changed quickly in this market - a dynamic market situation	.52726	
				Competitors introduced new products into this market very quickly	.39979	
2: Strategic reaction capability	5.17	6.8	20.2	Our firm developed clear strategies to deal with deficiencies in the Final Product	.81096	.8577 /.6701
				Our firm developed clear strategies to deal with deficiencies in the Nature of the Project	.77957	
				Our firm developed clear strategies to deal with difficulties inherent in this market	.77011	
				Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry	.67059	
				Our firm developed clear strategies to deal with deficiencies/problems in the area of Newness/Innovation	.66200	
				Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements	.54572	
				We spent a long time on the market research for this product	.45160	
3: Superior product in large rapid growth market	5.12	6.7	26.9	Our product was clearly superior to competing products in terms of meeting customer needs	.76320	.8223 /.5839
				Compared to competitive products (or whatever the customer was using) our product offered a number of unique features, attributes or benefits to the customer	.73035	
				Our product permitted the customer to do a job or do something that he/she could not do with what was available on the market	.63634	
				Our product was of higher quality - however quality is defined in this market - than competing products	.61294	
				Potential customers had a great need for this class or type of product	.60473	
				Our product permitted the customer to reduce his/her costs, when compared to what he/she was using	.46619	
				The market for this product was growing very quickly	.43605	
				The dollar size of the market (either existing or potential market) for this product was large	.42104	
4: Technological resource compatibility (synergy)	3.39	4.5	31.4	Our company's R&D skills & people were more than adequate for this project	.81307	.8220 /.6450
				Our company's engineering skills & people were more than adequate for this project	.81157	
				Our company's production resources or skills were more than adequate for this project	.60966	
				The technical aspects - exactly how the technical problems will be solved - were very clear	.59845	
				Our company's financial resources were more than adequate for this project	.55909	
				The product specifications - exactly what the product will be - were very clear	.47791	
5: New to the firm, didn't fit in	2.97	3.9	35.3	We had never made or sold products to satisfy this type of customer need or use before	.80463	.7879 /.6895
				The competitors we face in the market were totally new to our company	.76480	
				The product class or type of product itself was totally new to our company	.72503	
				The potential customers for this product were totally new to our company	.68536	
				The product (did not) "fit in" with a family of products we already had on the market (negative)	-.46791	

Factor	*Eigen*	*% Var.*	*Cum %*	*Variable Description*	*Variable loadings*	*Factor Chronbach alpha/avg loading*
6: 1st in new, highly innovative market	2.54	3.3	38.6	We were the first to market this product New-to-the-world (a true innovation in the product marketplace listed above) Our product was highly innovative - totally new to the market We were not first to market this product; we (didn't) follow close behind (negative)	.78369 .74554 .69682 -.58039	.7932 /.7016
7: Marketing & management resource compatibility (synergy)	2.25	3.0	41.6	Our company's sales force &/or distribution resources & skills were more than adequate for this project Our company's advertising & promotion resources & skills were more than adequate for this project Our company's marketing research skills & people were more than adequate for this project Our company's management skills were more than adequate for this project	.73766 .71065 .66635 .53766	.8063 /.6631
8: Alertness to threat of competitive retaliation	2.03	2.7	44.3	Expected speed of competitive retaliation was an important consideration in this market entry decision Expected magnitude of competitive retaliation was an important consideration in this market entry decision Expected retaliation	.80881 .79754 .65937	.8137 /.7552
9: Exogenous timing variables	1.98	2.6	46.9	Market seasonality was important in the decision to enter this market Market cyclicality was important in the decision to enter this market Competitors withdrew products from this market very quickly	.78150 .74417 .38239	.6577 /.6360
10: Intense market competitiveness	1.89	2.5	49.3	There were many competitors in this market The market was characterised by intense price competition	.79799 .70215	.7083 /.7501
11: Satisfied customer with dominant competitor	1.64	2.2	51.5	Potential customers were very satisfied with the products (competitors' products) they were currently using There was a strong dominant competitor- with a large market share - in this market The product would have done better if marketed by almost any of our major competitors	.64010 .62984 .46411	.5397 /.5780
12: Moderate level of product innovation	1.59	2.1	53.6	Improvement in or revision to an existing product An addition to an existing product line (Not) a new product line (negative)	.70835 .68596 -.52022	.5777 /.6382
13: Financial barriers	1.50	2.0	55.6	Capital requirements Absolute cost advantages (learning curve, access to inputs, proprietary design etc.) Customer switching costs Cost advantages of incumbents (economies of scale)	.74310 .62640 .44307 .44120	.6122 /.5634
14: NPD history of kills and success	1.41	1.8	57.4	In the last 3 years in this product market we have had ______Kills % ______Success % (negative)	.92170 -.78354	.7492 /.8526
15: NPD history of failure	1.29	1.7	59.1	In the last 3 years in this product market we have had ______Failure % (negative)	-.83617	1.0 /-.83617
16: Incremental innovation	1.27	1.7	60.8	A cost reduction A repositioning	.82708 .57605	.5572 /.7016
17: Differentiation barriers	1.18	1.6	62.3	Access to distribution channels Brand identity Product differentiation (proprietary product differences) of the incumbents	.71599 .55290 .33706	.3783[55] /.5353
18: Relative high price of product	1.16	1.5	63.9	Our product was priced considerably higher than competing products	.75897	1.0[56] /.7590
19: Late market entry	1.12	1.5	65.4	We entered the market somewhere between its maturity and decline We entered the market in its late growth stage	.73468 .66118	.4715 /.6979
20: Domestic markets	1.07	1.4	66.8	The primary market for this product was domestic (over 50% in US)	.39041	1.0 /.3904

55 If not for the exploratory nature of data integration and its effects on PLC and order/innovation constrained models, factors 17 and factors 19 through 22 would have been eliminated.
56 This factor was found to be a "univariate dimension" both by Cooper (1984, 1985b) and by Song and Parry (1994).

Factor	Eigen	% Var.	Cum %	Variable Description	Variable loadings	Factor Chronbach alpha/avg loading
21: Government barriers	1.05	1.4	68.1	Government Policy This product had a long life cycle in its original form (before modifications were necessary)	.75140 .41841	.1948 /.5849
22: Contribution margin	1.01	1.3	69.5	The contribution margin was important in the decision to enter this market	.77585	1.0 /.7759

4.3.2 Adequacy of the factor analysis

Consistent with Cooper and de Brentani (1984) and Zirger and Maidique (1990), principle components extraction with varimax rotation yielded the best overall solution. Both factor analyses gave a good intuitive description of the underlying dimensions. Consistent with Cooper (1979b, 1984a), an Eigenvalue >1 was used as the primary determinant of factor inclusion. However, there is no one correct method to determine the number of factors from a data set (Kim and Mueller 1978). Therefore, comparison with significant work is appropriate here.

Table 4-5c compares the parameters of this work's factor analyses with field results over the last twenty years. Both factor analyses are quite normal and were accepted for the following reasons: (1) the factor loadings of the variables averaged .6444836 at T_0 and .653177 at T_1; (2) the amount of common factor variance explained by the 22 factors was 68.8% and 69.5% for T_0 and T_1 respectively; (3) alternative extraction and rotation procedures yielded similar groupings for each factor in both T_0 and T_1 cases; (4) all the factors had an Eigenvalue greater than one; (5) the variable groupings were intuitively logical and meaningfully described the items captured in the conceptual model of the new product decision process and (6) the scree plot of the variance associated with each factor showed an appropriate levelling between the key factors and the rest of the scree (Cattell 1966). The only characteristics needing explanation are low variances per factor and low Chronbach alpha scores towards the end of the scree.

Factors exhibiting low variance and low Chronbach alpha scores were acceptable due to the exploratory nature of heterogeneous inter-disciplinary data integration and their potential usefulness in testing H_2 and H_3.. There is a need to publish results even if they are not significant, so that knowledge of the principal drivers of new product performance may progress beyond an exploratory, descriptive nature (Montoya-Weiss and Calantone 1994). Furthermore, lower Chronbach alpha scores are normal for "extra factors" at the end of any scree. Here, these result from requested inter-disciplinary data integration (Cooper 1976; Cooper and Kleinschmidt 1986; Wind and

Mahajan 1988) as heterogeneous new data produce low inter correlation with more homogeneous marketing variables. This is not seen in less integrative work where lowly correlated variable constructs are removed for the sake of parsimony and higher Chronbach alpha scores. Unfortunately, established models produced from these highly correlated but narrow homogeneous dimensions have not been well accepted by practitioners. Therefore, this more comprehensive approach is warranted. Nevertheless, those factors not significant in this work's linear regression functions, their variable constructs and variable constructs loading on significant factors at <.5 should be eliminated from future aggregate model building. This would put the variable/factor ratios between 4 and 6%, well within field boundaries.

Table 4-5c: Comparison of factor analysis characteristics in seminal work versus Thesis *nr=not reported. vars=variables loading on constructs. %<.5=% of variables loading on construct at less than .50. Neg = negative loadings. Shaded areas show extremes in literature compared to this work.*

	Variance /factor	*vars*	*factors*	*vars/ factor*	*%<.5*	*Neg*	*3 vars /factor*	*2 vars /factor*	*1 variable/factor Univariate[57] dimensions*
Cooper 1976[a]	11.1%	17	6	2.8	47.1%	11.8%	50%	33.3%	0
Cooper 1979b[b]	4%	82	18	4.6	31.7%	2.4%	22.2%	33.3%	0
Calantone and Cooper 1979[a]	11.1%	17	6	2.8	41.1%	11.8%	50%	33.3%	0
Cooper 1981[c]	5.3%	52	13	4	28.9%	5.8%	38.5%	23.1%	0
Calantone and Cooper 1981[b]	4%	82	18	4.6	31.7%	2.4%	22.2%	33.3%	0
Cooper and de Brentani 1984[d]	4.5%	58	11	5.3	2.1%	3.4%	27.3%	0%	0
Cooper 1984a[e]	4%	64	19	3.4	20.3%	1.6%	16%	11%	32%
Cooper 1985b[e]	nr	70	19	3.7	27.1%	1.4%	21.1%	11%	21.1%
de Brentani 1986[d]	4.5%	58	11	5.3	2.1%	3.4%	27.3%	0%	0
Cooper and Kleinschmidt 1987b[f]	nr	46	10	4.6	50%	0%	20%	0%	0%
Zirger and Maidique 1990[g]	8.8%	23	8	2.9	8.7%	0%	37.5%	37.5%	12.5%
Cooper and de Brentani 1991[h]	nr	77	18	4.2	nr	nr	27.8%	11.1%	0%
Cooper and Kleinschmidt 1994[i]	nr	72	10	7.2	46%	0%	0%	0%	0%
Song and Parry 1994[j]	4.9%	82	16	5.1	11%	12.2%	12.5%	18.8%	25%
Thesis A	3.1%	75	22	3.4	17.3%	6.7%	27.3%	22.7%	13.6%
Thesis B	3.2%	76	22	3.5	19.7%	7.9%	22.7%	27.3%	13.6%

[a] oddly, though these use the same data and generate the same number of constructs, they report different loadings.
[b] 82 variable constructs load from 77 variables i.e. some load on more than one factor.
[c] 52 variable constructs load from 48 variables i.e. some load on more than one factor.
[d] In both of these works a Chronbach alpha <.5 is reported. Scores ranged from .46 to .90.
[e] In these works different factor analysis results are reported from the same data. "Univariate dimensions" are defined. 64 and 70 variable constructs load from 86 variables respectively.
[f] some constructs overlapped each other in factors 7, 8 and 9. Chronbach alpha scores ranged from .5 to .98. 46 variable constructs load from 43 variables i.e. some load on more than one factor.

[57] Cooper (1984) published five factors and Cooper (1985b) published four factors comprising only one variable construct. These were accepted in the factor analysis solution because they aided interpretation and had eigenvalues >1. Cooper defined them as "univariate dimensions".

[g] The "product value" factor had one factor Eigenvalue of .87 i.e. usually eigenvalues <1 are not acceptable.
[h] Chronbach alpha scores ranged from .527 to .841. 77 variable constructs load from 65 variables i.e. some load on more than one factor.
[i] Chronbach alpha scores ranged from .605-.889
j 82 variable constructs load from 77 variables i.e. some load on more than one factor.

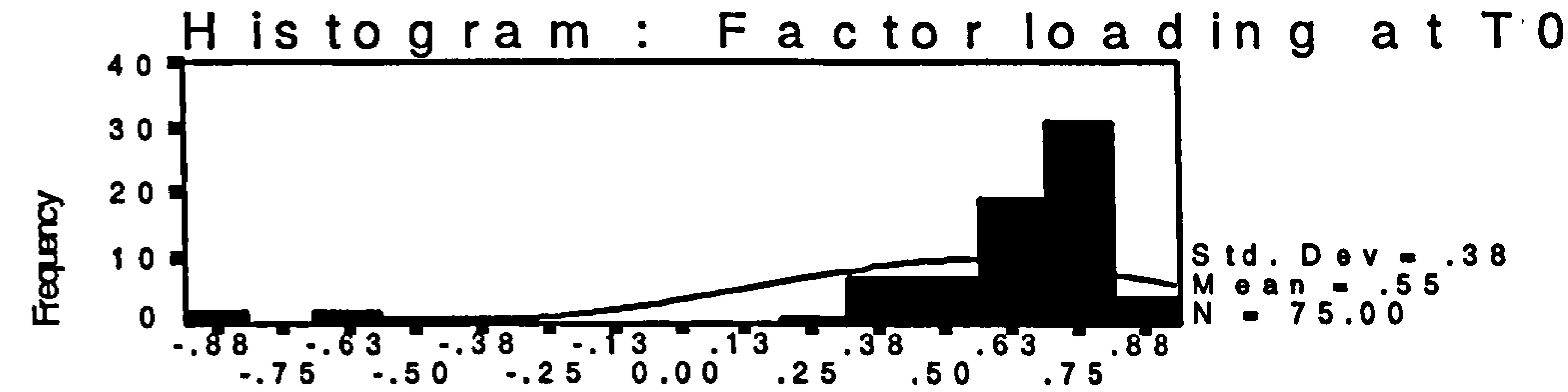
4.3.3 Factor analysis findings at T_0 versus T_1

The 22 factor solutions found at T_0 and T_1 explain 68.8% and 69.5% of the variance respectively. This rise may be a function of perceived information coalescing in explanation of stochastic processes. This compares to 71.3% explained for Cooper's original NewProd (1979b), 69% for Zirger and Maidique (1990) and 49.1% for Cooper and de Brentani (1984). If homogeneity and parsimony rather than heterogeneous factor integration was the goal, a 17 factor solution would have been chosen in both cases. This compares to Cooper's 18 factors, Zirger and Maidique's 8 factors and Cooper and de Brentani's 11 factors. Elimination of five factors would be argued on the basis of: (1) the two scree plots (see Figure 4-6) being virtually identical and tailing off after the 17^{th} factor; (2) a good amount of variance being explained (61.5% and 62.3%) and (3) a pattern of internal inconsistency beginning at the 18^{th} factor. However, this research responded to calls for expanding the variable/factor base (Montoya-Weiss and Calantone 1994) and greater interdisciplinary perspective (Wind and Mahajan 1988). Thus, lower ordered factors were not removed in order to test their relationship to time (H_1c), PiLC (H_2), order/innovation (H_3), the need to publish even insignificant data to progress beyond the exploratory stage and the need for more broad-based studies that include multiple factors from diverse categories (Montoya-Weiss and Calantone 1994).

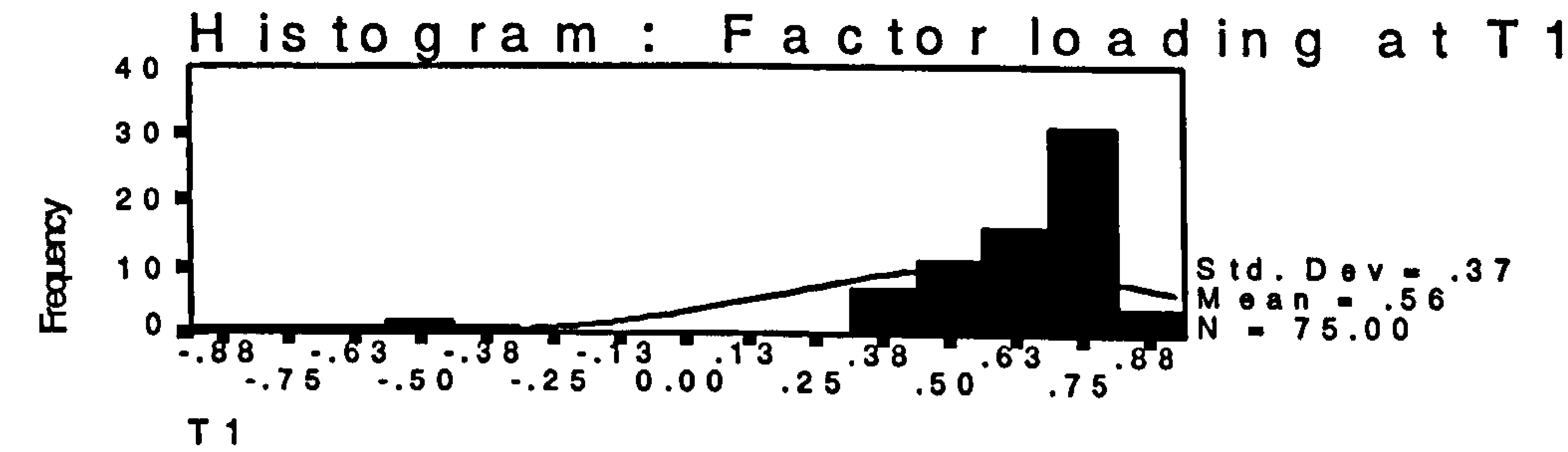
As seen in Figure 4-5, the loading distributions are almost identical, with the mean and standard deviation almost unchanged over time. A paired sample t-value of -.05 at p=.961 indicates factor mean distributions are statistical equivalents. This suggests that in the aggregate, normalised environmental factors do not change over time. This supports acceptance of the null hypothesis.

The characteristics of the factor analyses suggest absolute differences between the two environments. For example, the actual order of factors is quite different between T_0 and T_1. Of 22 factors only the first two, "dynamic change in fast growing market" and "strategic reaction capability" are ordered the same at both time periods i.e. only 9.1% of the factors fall at the same location by time period. Conversely, 90.9% show a change in factorial order. Even the two common factors (F1 and F2) have slightly different construction and loading order at each time period. However, reordering differences might be considered minor, since when matched logically by the

Figure 4-5: Factor loading distributions at T_0 v T_1

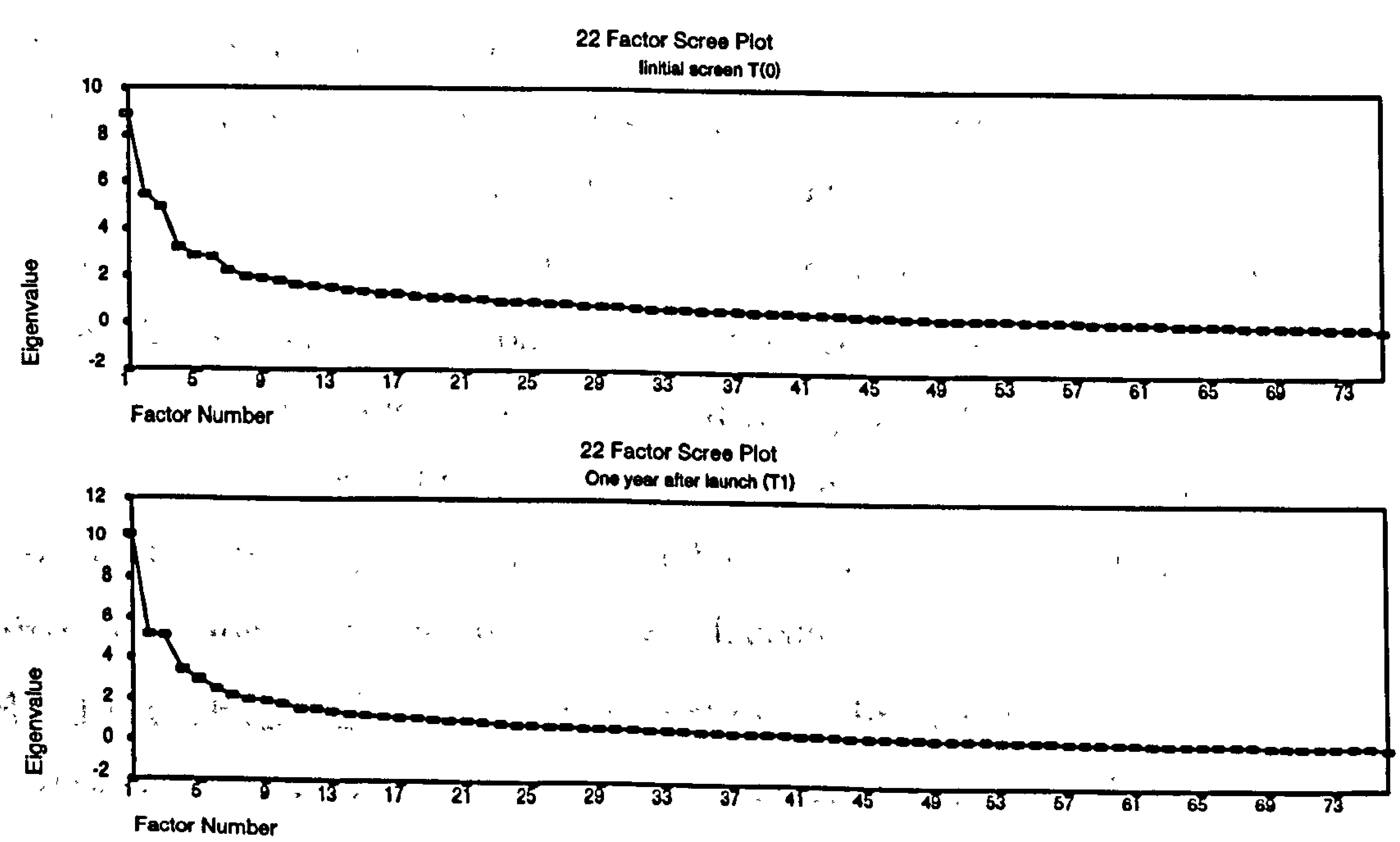


Mean T0	.548	Std err	.044	Median	.680
Mode	-.906	Std dev	.383	Variance	.146
Kurtosis	6.568	S E Kurt	.548	Skewness	-2.639
S E Skew	.277	Range	1.784	Minimum	-.906
Maximum	.878	Sum	41.130		



Mean	.556	Std err	.043	Median	.671
Mode	-.836	Std dev	.370	Variance	.137
Kurtosis	6.264	S E Kurt	.548	Skewness	-2.580
S E Skew	.277	Range	1.758	Minimum	-.836
Maximum	.922	Sum	41.674		

Figure 4-6: 22 Factor scree plot



dimensions they portend, 20 factors can be matched reasonably well. Absolute differences are observed in Eigenvalues, percent variance explained per factor, average variable loadings and Chronbach alpha scores. However, this gives only weak support to rejection of the null form. More likely, the normalised environment at T_0 and the normalised environment at T_1 tell essentially the same environmental story. An argument for intrinsic difference thus falls short.

4.3.4 Conclusion

Side by side, the technical parameters of the factor analysis are different absolutely. "Common factors" such as superior product do add/remove variables over time. However, variable loading distributions, whilst rising absolutely, are not different at p=.05. This lack of variation combined with similar pairing and almost identical scree plots requires this research to reject hypothesis H_1b and accept the null form. Probably due to the normalisation process, the factors constructed from dynamic variables *do not* change over time and, by themselves, are not dynamic.

4.4 Hypothesis H_1c

Factors significant to a new product's successful introduction are dynamic, not static. As more information becomes known to the firm over time, (both internal and external) these significant factors are perceived to evolve from a inadequate, incomplete, uncertain condition at the initial screen to a more adequate, more complete, more certain condition at the end of the first year of market entry with a change in their order and magnitude.

4.4.1 Introduction

Validation of hypothesis H_1c would demonstrate that unique linear predictive functions are possible at different data collection points in the new product development process. Consistent with seminal work (Calantone and Cooper 1979; Cooper 1979b, 1981; Cooper and de Brentani's 1984; de Brentani 1986; Zirger and Maidique 1990), factor scores produced to test H_1b above were saved as SPSS variables. These were used to construct one linear regression function at T_0 and another at T_1. Pearson's R (R), R Squared (R^2), Adjusted R Squared (Adj. R^2), Standard error of the model (Std Err), F value (F) and its significance with degrees of freedom (df) were compared by time period to determine if the function evolved between the initial screen and one year post launch.

4.4.2 Linear Regression model construction findings at T_0

The results of the linear regression at the initial screen is seen in Table 4-6a.

Table 4-6a: Linear regression at T_0 - the deterministic model.

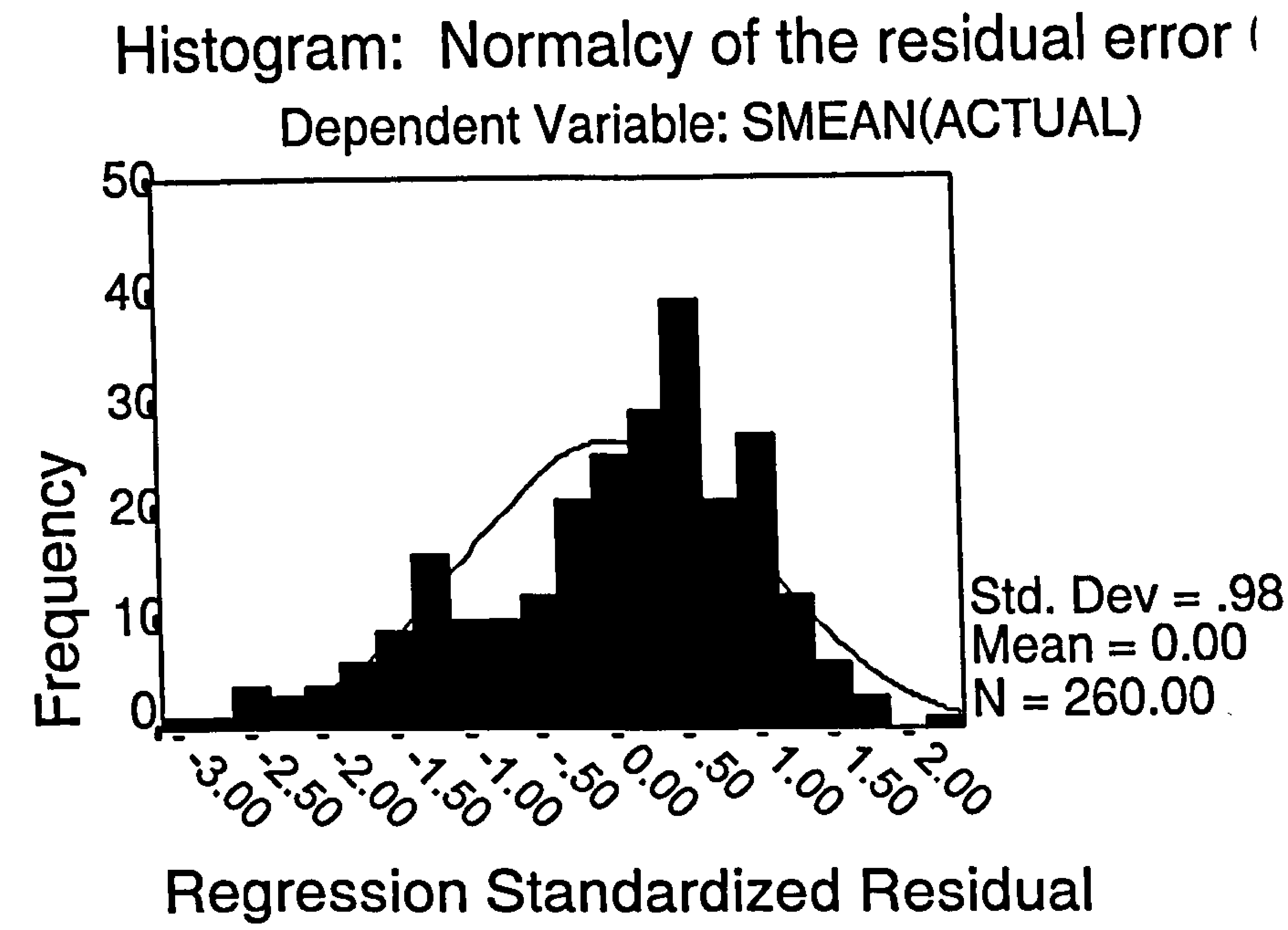
R=.56589, R^2=.32023, Adj. R^2=.29857, F =14.78065 at .0000 with 8df Standard error = 2.58869 accuracy = 81.15384%			
Key factors or dimensions (factor name)	*Reg. Coef*	*F value*	*Variables loading on factor*
NPD history of failure F 17	1.114580	48.01	In the last 3 years in this product market we have had ______Failure % (negative)
Strategic reaction capability F2	.700422	18.96	Our firm developed clear strategies to deal with deficiencies in the Final Product Our firm developed clear strategies to deal with deficiencies in the Nature of the Project Our firm developed clear strategies to deal with difficulties inherent in this market Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry We spent a long time on the market research for this product
New to the firm, didn't fit in F4	-.644947	16.08	We had never made or sold products to satisfy this type of customer need or use before The competitors we face in the market were totally new to our company The potential customers for this product were totally new to our company The product class or type of product itself was totally new to our company The product "fit in" with a family of products we already had on the market
NPD history of kills and success F16	.586054	13.27	In the last 3 years in this product market we have had ______Kills % (negative) ______Success %
Alertness to threat of competitive retaliation F7	.437518	7.40	Expected *magnitude* of competitive retaliation was an important consideration in this market entry decision Expected *speed* of competitive retaliation was an important consideration in this market entry decision Expected retaliation
Late market entry F14	-.410086	6.50	We entered the market somewhere between its maturity and decline We entered the market in its late growth stage
Overall project/company resource compatibility F3	.326788	4.13	Our company's sales force &/or distribution resources & skills were more than adequate for this project Our company's marketing research skills & people were more than adequate for this project Our company's management skills were more than adequate for this project Our company's advertising & promotion resources & skills were more than adequate for this project Our company's production resources or skills were more than adequate for this project Our company's financial resources were more than adequate for this project
Superior unique product meeting needs in large rapid growth market F6	.317466	3.90	Our product was clearly superior to competing products in terms of meeting customer needs Compared to competitive products (or whatever the customer was using) our product offered a number of unique features, attributes or benefits to the customer Potential customers had a great need for this class or type of product Our product permitted the customer to reduce his/her costs, when compared to what he/she was using Our product permitted the customer to do a job or do something that he/she could not do with what was available on the market The dollar size of the market (either existing or potential market) for this product was large
(Constant)	1.671875		

With R=.56589, R^2=.32023, Adj. R^2=.29857, F=14.78065 at .0000 with 8df and a standard error of 2.58869, the solution is inferior to NewProd generally[58]. The Adjusted R^2, the best estimate of the model's fit to new, similar populations, is lower than NewProd (Thesis=.32023/Cooper=.395). However, the solution's rigour is better with a lower standard error (Thesis=2.58869/Cooper=2.73), no outliers at 3 standard deviations from the mean[59] and a modest residual error (see Figure 4-6a)[60]. This lower error may be the result of a correction of Cooper's measurement timing

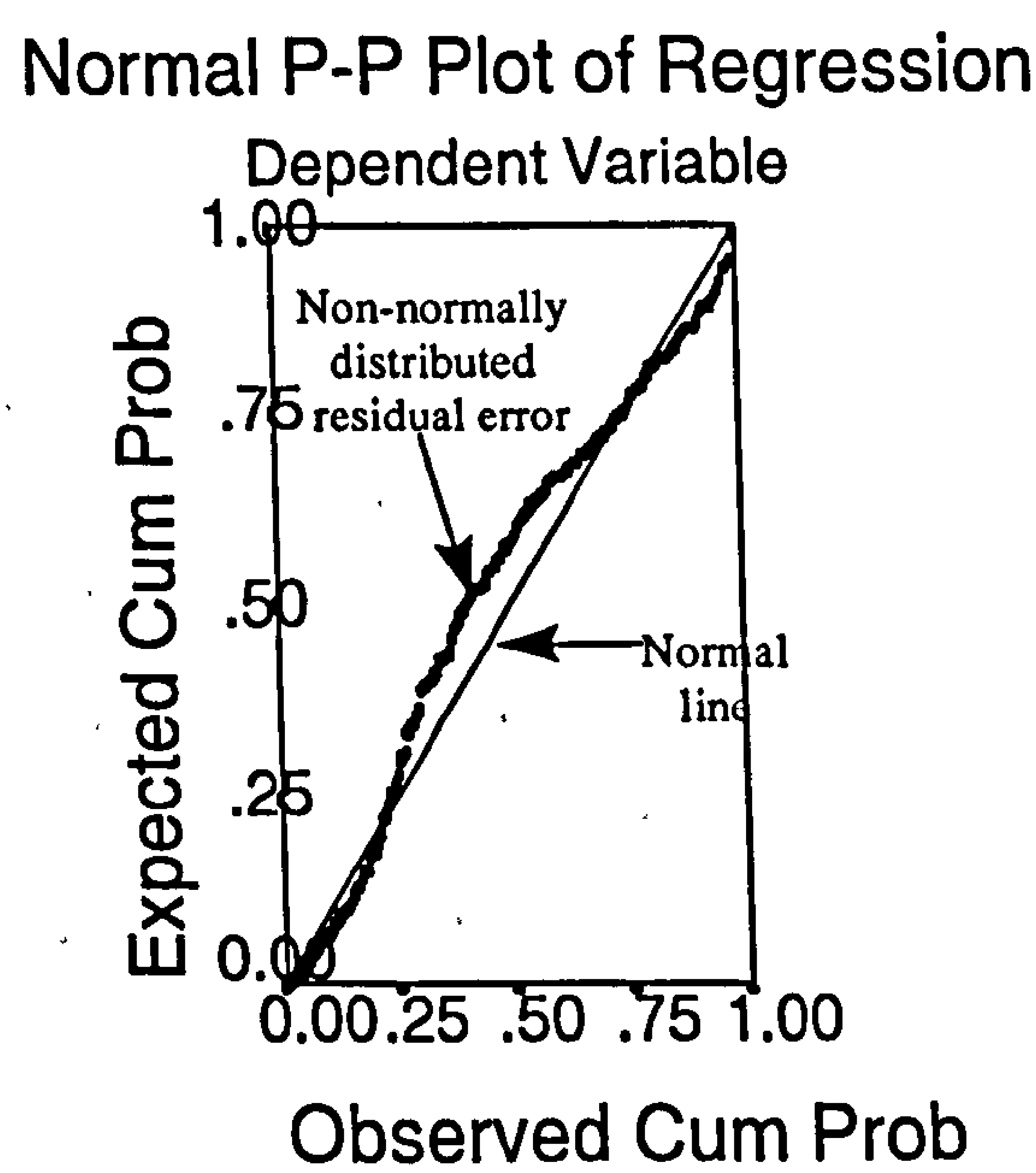
58 Cooper (1981) reports the following: R=.648074, R^2=.420, Adj. R^2=.395, F =16.83 with 8df and a standard error of 2.73.
59 outliers and residual error are not reported by Cooper.
60 ibid.

error (Crawford 1979, 1986; Cooper 1992) leading to improved dimensional construct validity. These measures suggest a relatively sound function given that, even when errors in the population are normal, errors in the sample residuals are only approximately normal (Norusis 1993).

Figure 4-6a: Error of the regression at T_0



Mean	.000
Std err	.158
Median	.521
Mode	-7.443
Std dev	2.548
Variance	6.494
Kurtosis	-.001
S E Kurt	.301
Skewness	-.675
S E Skew	.151
Range	13.504
Minimum	-7.443
Maximum	6.061



The sample was split into two randomly generated split-halves (n=130) with the model producing similar linear regression functions and validating statistics for each. Also, its outcome was compared to a discriminant analysis performed on the categorical variable success/failure (S=1, F=0). This yielded a Wilks lambda statistic of .745771, similar factor selection and similar factor order. These results indicate that the T_0 model is reasonably robust.

4.4.3 Dimensions of success at T_0

The dimensions of success at T_0 are similar, but more informationally apropos to an early initial screening decision, than either NewProd or Stanford. Five of the eight dimensions are new to NPD initial screen forecasting models. All dimensions except success, failure and kill history are based on early speculative perceptions. This gives the model a deterministic bias suggesting that what is past and certain is more powerful early on, than what is intended and only hopeful i.e. hindsight is 20:20 but the good intentions are not.

The T_0 model yields the certain "product market history of failure" as the most important dimension preventing future success. With a coefficient of 1.11458, a negative factor loading at -.87497 and an F value of 48.01, the dimension is new to NPD forecasting model construction and a very significant detractor. Its importance is consistent with Cooper and Calantone's (1979) conclusion that the same mistakes may be repeated over and over. With early information speculative at best, a cycle of failure colouring early NPD efforts makes sense. Past product market history is certain and is the experience (Abell and Hammond 1979; Booz, Allen and Hamilton 1982; Boston Consulting Group 1972) benchmark from which all learning and strategic planning begins.

"Strategic reaction capability", also new to NPD forecasting models, follows. This is logical also since learning from experience and planning a new way is critical to success. "New to the firm, didn't fit in" has been found significant before but only in ninth (Cooper 1979b) and fifth (Cooper 1981) position. Its greater importance here stresses that the negative ramifications of new customers, competitors and products must be considered and overcome by rapid learning in the time remaining before launch. Measurement timing error may be the cause of its lower position in NewProd and is treated in section 4.6.

The next three dimensions are new to NPD forecasting models. "Product market history of kills and success" compliments failure history and supports the importance of the experience effect (Abell and Hammond 1979; Booz, Allen and Hamilton 1982; Boston Consulting Group 1972) to success. The dimension indicates that early on, one's next success is related to past success and inversely proportional to past kills.

"Alertness to threat of competitive retaliation" is new and not the same negative dimension found by others. It contradicts Cooper (1979, 1984a) and Cooper and Kleinschmidt's (1987b) findings that marketplace variables and competitiveness dimensions are not related to success. Rather, in agreement with Song and Parry (1994), early success is very much related to perceived magnitude and speed of retaliation. And "late market entry", the last new dimension at T_0, warns that being too late hinders success.

The last two factors in the T_0 model, "overall project/company resource compatibility" and "superior unique product" are among the most often reported dimension of success (Montoya-Weiss and Calantone 1994). They have been found second and first most important by Cooper (1981), fourth and third by Zirger and Maidique (1990) and second and fourth by Cooper and de Brentani (1984). This work's comparatively low ranking for both at the T_0 stage suggests possible measurement timing error in seminal work.

Table 4-6c compares order results to both Cooper models (1979b, 1981), Zirger and Maidique's discriminant analysis model (1990) and Cooper and de Brentani's linear regression model (1984). The shaded areas match similar dimensional findings.

4.4.4 Linear Regression model construction findings at T_1

Table 4-6b demonstrates a 10 factor model more valid than NewProd. R improves to .68961 versus NewProd's .648074, R^2 to .47556 versus .420, Adj. R^2 to .45450 versus .395, F to 22.57937 at .0000 versus 16.83 and standard error to 2.28289 versus 2.73. Again, split-half analysis and discriminant analysis produced very similar results.

Table 4-6b: Linear regression at T_1 - the stochastic model.

R=.68961, R^2=.47556, Adj. R^2=.45450, F =22.57937 at .0000 with 10df Standard error = 2.28289 accuracy = 83.84615%

Key factors or dimensions (factor name)	*Reg. Coef*	*F value*	*Variables loading on factor*
Strategic reaction capability F2	1.096848	59.78	Our firm developed clear strategies to deal with deficiencies in the Final Product Our firm developed clear strategies to deal with deficiencies in the Nature of the Project Our firm developed clear strategies to deal with difficulties inherent in this market Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry Our firm developed clear strategies to deal with deficiencies/problems in the area of Newness/Innovation Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements We spent a long time on the market research for this product
NPD history of failure F15	1.050744	54.86	In the last 3 years in this product market we have had ____ Failure % (negative) The product which entered the market was significantly different than that approved at the initial screen
Superior product in large rapid growth market F3	.800692	31.87	Our product was clearly superior to competing products in terms of meeting customer needs Compared to competitive products (or whatever the customer was using) our product offered a number of unique features, attributes or benefits to the customer Our product permitted the customer to do a job or do something that he/she could not do

			with what was available on the market Our product was of higher quality - however quality is defined in this market - than competing products Potential customers had a great need for this class or type of product Our product permitted the customer to reduce his/her costs, when compared to what he/she was using The market for this product was growing very quickly The dollar size of the market (either existing or potential market) for this product was large
New to the firm, didn't fit in F5	-.717605	25.59	We had never made or sold products to satisfy this type of customer need or use before The competitors we face in the market were totally new to our company The product class or type of product itself was totally new to our company The potential customers for this product were totally new to our company The product "fit in" with a family of products we already had on the market
Relative high price of product F18	-.557748	15.46	Our product was priced considerably higher than competing products
NPD history of kills and success F14	-.542047	14.60	In the last 3 years in this product market we have had ______Kills % ______Success %
Marketing & management resource compatibility (synergy) F7	.399238	7.92	Our company's sales force &/or distribution resources & skills were more than adequate for this project Our company's advertising & promotion resources & skills were more than adequate for this project Our company's marketing research skills & people were more than adequate for this project Our company's management skills were more than adequate for this project
Alertness to threat of competitive retaliation F 8	.372806	6.91	Expected *speed* of competitive retaliation was an important consideration in this market entry decision Expected *magnitude* of competitive retaliation was an important consideration in this market entry decision Expected retaliation
Technological resource compatibility (synergy) F4	.302579	4.55	Our company's R&D skills & people were more than adequate for this project Our company's engineering skills & people were more than adequate for this project Our company's production resources or skills were more than adequate for this project The technical aspects - exactly how the technical problems will be solved - were very clear Our company's financial resources were more than adequate for this project The product specifications - exactly what the product will be - were very clear
1st in new, highly innovative market F6	.292228	4.24	We were the first to market this product New-to-the-world (a true innovation in the product marketplace listed above) Our product was highly innovative - totally new to the market We were not first to market this product; we followed close behind however (negative loading)
(Constant)	1.671875		

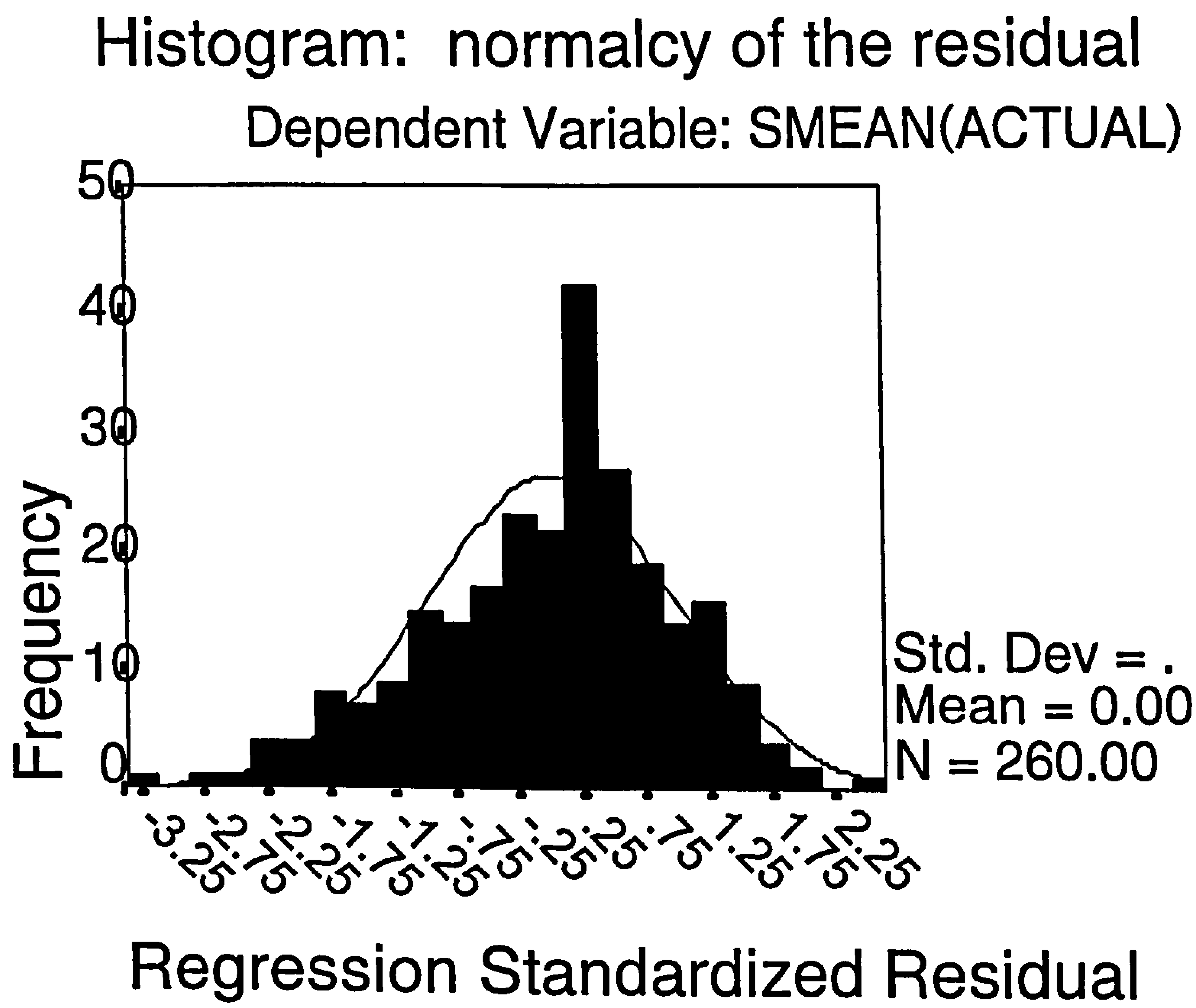
The Adjusted R^2 of .45450 versus NewProd's .42 implies better extrapolative ability to similar populations. The function's rigour is better than either NewProd or the T_0 model with even smaller standard error (Thesis at T_0 = 2.58869, Thesis at T_1 = 2.28289, Cooper = 2.73), one outlier at 3 standard deviations from the mean and a narrowing of the residual error (see Figure 4-6b)[61]. Logically, the residual error being largest in the middle indicates that marginal success/failure was most difficult to predict. This much improved solution may be confirming a coalescence of perceived process and environmental states of nature, along with less measurement timing error than found in longer retrospectives (Crawford 1979, 1986; Cooper 1992).

4.4.5 Dimensions of success at T_1

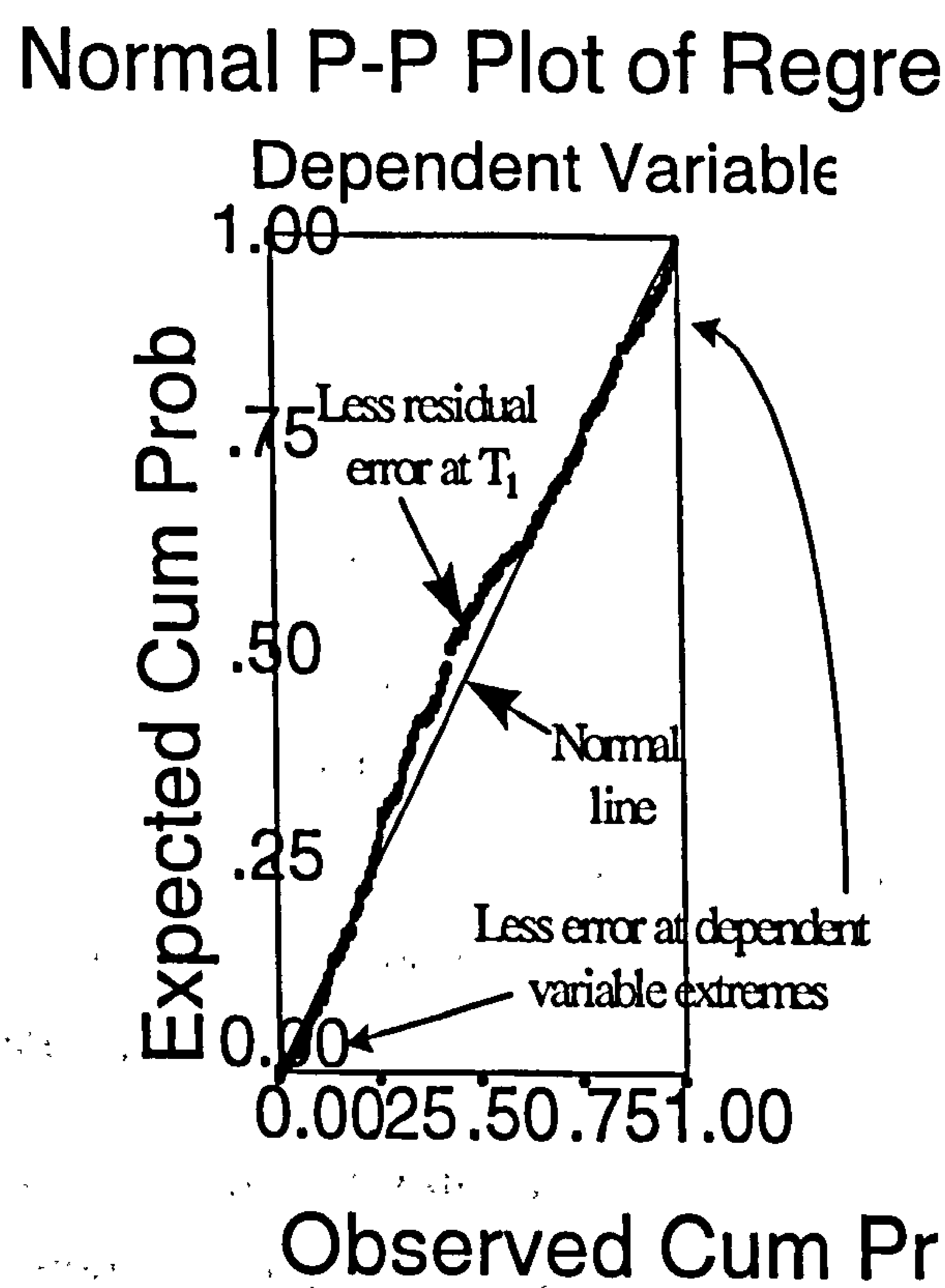
The model describes well, the evolved success environment at one year post launch. In general, dimension F values are higher than both NewProd and the T_0 model. This

61 illustrated by an improvement in residual error normalcy i.e. the gap between the normal line and the actual standardised residual narrows between T_0 and T_1 at both the middle and the extremes of the dependent variable.

Figure 4-6b: Error of the regression at T_1



Mean	.000
Std err	.139
Median	.327
Mode	-7.539
Std dev	2.238
Variance	5.010
Kurtosis	.151
S E Kurt	.301
Skewness	-.468
S E Skew	.151
Range	13.389
Minimum	-7.539
Maximum	5.851



may be the result of reduced measurement timing error permitting description of dimensions more appropriate at the one year post launch point than traditional 5 year retrospectives. "Product market history of failure" declines to second position at T_1, with "strategic reaction capability" rising to first place. Both F values rise, not surprisingly, as information becomes more certain over time. "Superior product in large rapid growth market" leaps from last place at T_0 to third place here. Its F value improves by a factor of 8. This, in combination with the increasing importance of delivering technical detail to early benefit protocol (see factor construction at both T_0 and T_1) validates the importance of launching a superior product. The impact of the dimension's new combination of market growth and size constructs suggests that these issues are unclear at T_0. This suggests over attention by NewProd vis-à-vis the dimension's true importance at the initial screen.

"New to the firm" declines to fourth position compared to fifth position in NewProd, as the "newness" at T_0 is tempered by learning. "Relative high price of product", in fifth position, is a new factor at T_1 and consistent with its sixth place position in the original NewProd (1979b). However, its lack of significance at T_0 questions its value at the initial screen in Cooper's discriminant analysis. Product market "history of kills and success" declines to sixth position in sympathy with failure history. This confirms its diminishing deterministic effect over time. Clearly, "what you do" becomes more important than "what you've done". In seventh position, "Marketing and management resource compatibility" splits from the "overall project/company resource compatibility" dimension of T_0. The appearance of "Technological resource compatibility", absent at T_0, confirms the dimension's split and indicates that close team communication, so important at T_0, becomes less important post launch. Again, temporal validity of established models comes into question.

Finally, "alertness to threat of competitive retaliation" and "1st in new, highly innovative market" complete the model. "Alertness" falls in importance, reasonably, as more "intelligence information" is gathered from the "battle". And "1st in new highly innovative market", new to initial screening forecasting models, becomes declarative vis-à-vis required level of innovativeness.

Importantly, it is obvious that the T_1 model is much closer in construction to the NewProd and Stanford models. This is probably the result of internal construct validity problems in their models, cause by measurement timing error and survivor bias. These are discussed in section 4.6.4.4.

Table 4-6c: Comparison of Thesis v screening forecasting literature Black cells = new to initial screening forecasting models; shaded and cross-hatched cells compare similar factors between models.

H_1c (T_0) Lin. Reg.	*H_1c (T_1) Lin. Reg.*	*Cooper 1979b Disc. Anal.*	*Cooper 1981 Lin. Reg.*	*Zirger & Maidique 1990 Disc. Anal.*	*Cooper & de Brentani 1984 Lin. Reg.*
History of failure	*Strategic reaction capability*	Product uniqueness, & superiority	Product superiority, quality & uniqueness	Excellence in R&D organisation	Financial potential
Strategic reaction capability	*NPD history of failure*	Market knowledge & marketing proficiency	Overall project/co resource compatibility	Superior technical performance	Corporate synergy
New to the firm, didn't fit in	Superior product in large rapid growth market	Technological resource compatibility	Market need, growth & size	Product value	Technological & production synergy
NPD history of kills & success	New to the firm, didn't fit in	Market dynamism (frequency of new product introductions)	Economic advantage of product to end user	Synergy with existing competencies	Product differential advantage
Alertness to threat of competitive retaliation	[illegible]	Market need, growth & size	Newness to the firm	Management support	Product life
Late market entry	*NPD history of kills & success*	Relative[illegible] product [illegible]	Technological resource compatibility	[illegible]	Market maintenance strategy
Overall project/company resource compatibility		[illegible]	Market competitiveness	Weak competitive environment	Size of market
Superior unique product meeting needs in large rapid growth market	*Alertness to threat of competitive retaliation*	Marketing competitiveness (& customer satisfaction)	Product scope	Large & growing market	Diversification strategy
	Technological resource compatibility (synergy)	Newness to the firm			Domestic market
	1^{st} in new, highly innovative market	Strength of marketing communications & launch effort			
		Source of idea/investment magnitude			

4.4.6 Factor/Model difference

Factor differences easiest to identify are those significant in one model and not in the other. The only absolute example of this is "relative high price of product", found only in the T_1 model. However, some dimensions change from immature at T_0 to "mature" at T_1. For example "late market entry" warns of failure at T_0 but "1^{st} in new, highly innovative market" declares innovativeness requirements for success at T_1. This is consistent with Nijssen, Arbouw and Commandeur (1995) that introduction of a late new product can have a negative effect and that timely introduction of a product, under specific conditions, is important. This evolution of character, however, has never been established empirically in an NPD forecasting context.

Another example of dimension evolution involves the general "overall synergy" factor at T_0 maturing into two functionally distinct factors, "marketing and management synergy " and "technological synergy" at T_1. New to the field, this could be extremely consequential. It suggests conditions and limitations are appropriate to communication and information exchange between departments (Calantone, Di Benedetto and Haggblom 1995; Hise, O'Neal, Parasuraman and McNeal 1990; Moenart, Souder, De Meyer and Deschoolmeester 1994; Rochford and Rudelius 1992; Souder 1988; Souder and Chakrabarti 1978, 1980).

The simple comparisons above are quite clear. However, the determination of statistical differences between "common" factors appearing to measure the same dimension is methodologically complicated. For example, factors significant in both the T_0 and T_1 models include "history of failure", "strategic reaction capability", "history of kills and success", "alertness to threat of competitive retaliation" and "superior product". Aside from noting variable loading and order differences, aggregate paired-samples t-tests whilst useful, are impossible due to normalisation. However, when sorted by success/failure, factors do exhibit variance.

The use of a paired-samples t-test in Table 4-7 illustrates common factor distribution mean differences as they evolve from T_0 to T_1. It indicates that for successes, "history of failure", "new to the firm", "history of kills and successes" and "competitive alertness" decline in importance absolutely (but not statistically) over time. This argues for acceptance of the null form. Conversely, strategy[62] and superior product increase at statistically significant levels over time. This indicates "common" factors can be significantly different over time, argues for acceptance of H_1c and supports the importance of the rise of these factors by model over time.

Table 4-7 also indicates that for failed cases, "history of failure", "new to the firm" and "competitive alertness" rise absolutely over time as "history of kills and successes" rises significantly. Kill magnitudinal difference in the opposite direction from successes, is illustrative[63]. Moving in the opposite direction also, the positive advantages of "strategy" and "superior product" to success cases are lost to failures at statistically significant levels. Again, this evidence supports the argument for "common" factor difference, advocates acceptance of H_1c and supports temporal dimension conclusions.

[62] at $p=.08$.

[63] the dimension at T_1 has a negative regression coefficient. The kill variable has a positive loading factor of .92170. Because successes have a smaller, negative loading factor of -.78354, when multiplied by the negative regression coefficient, the success effect is positive and the kill effect is negative. Therefore, an increase the factors magnitude over time produces a negative effect overall.

Table 4-7: "Common" factor distribution means by success/failure.

Factor	Success					Failure				
	T0 Factor Mean	*T1 Factor Mean*	*Diff.*	*Sig.*	*up/dn*	*T0 Factor Mean*	*T1 Factor Mean*	*Diff.*	*Sig.*	*dir.*
History - Failure	.2099	.1738	-.0361	.405	⇓	-.5689	-.4719	.0979	.189	⇑
Strategy	***.1073***	***.1918***	***-.0845***	***.082***	⇑	***-.2913***	***-.5207***	***.2294***	***.012***	⇓
New	-.1123	-.1312	.0189	.563	⇓	.3048	.3560	-.0512	.235	⇑
History - Kill/Succ	.1069	-.1022	-.2071	.150	⇓	***-.2901***	***.2720***	***.5622***	***.016***	⇑
Alertness	.0954	.0605	.0349	.434	⇓	-.2588	-.1641	-.0947	.168	⇑
Superior Product	***.0560***	***.1914***	***.1354***	***.018***	⇑	***-.1520***	***-.5196***	***-.3676***	***.008***	⇓

Differences in the model factors are confirmed again by observing dimension order and significance ratios. The two largest differences in regression coefficients and F values are "strategy" and "superior product" (see Table 4-8, bold italics). The leap in coefficient and F ratio for "superior product in large growing market" suggests the factor is considerably more valid and important at T_1. Again, this intimates measurement timing error in NewProd.

Though appearing to measure the same dimension, these changes in common factor relative standing and validity indicate the T_1 model is different in construction from the T_0 model and much improved over time. This supports acceptance of H_1c.

Table 4-8: Aggregate difference in coefficient order and significance.

Factors	*T0 Reg. Coef*	*T0 F value*	*T1 Reg. Coef*	*T1 F value*	*Ratio F1 to F0*	*Ratio T1 Reg. Coeff. to T0*
NPD history of failure	1.114580	48.01	1.050744	54.86	1.142679	0.942726
Strategic reaction capability	***.700422***	***18.96***	***1.096848***	***59.78***	***3.152954***	***1.565982***
New to the firm, didn't fit in	-.644947	16.08	-.717605	25.59	1.591418	1.112657
NPD history of kills and success	.586054	13.27	-.542047	14.60	1.100226	0.92491
Alertness to threat of competitive retaliation	.437518	7.40	.372806	6.91	0.933784	0.852093
Superior unique product meeting needs in large rapid growth market	***.317466***	***3.90***	***.800692***	***31.87***	***8.171795***	***2.522135***

4.4.7 Other differences

Mahalanobis' distance measures how much a case's value on the independent variables differs from the average of all cases. With an average saved variable Mahalanobis distribution of 7.9692 at T_0 and 9.9615 at T_1, the t-value of -6.76 at .0000 suggests that a significant difference does exists in the independent variable distributions underlying each model. Similar significance is attributed to leverage values (Mahalanobis' distance divided by n-1; Norusis 1993). This also confirms acceptance of H_1a.

Finally, residual variation in a regression model expresses the portion of the total variability in the dependent variable that cannot be attributed to, or explained by, the regression. Having a mean of 0 and a standard deviation of 1, they cannot be tested for difference in the aggregate, but they can be tested when sorted by success/failure.

Table 4-9: Model residuals by success/failure

	Success means				*Failure means*			
	T0	*T1*	*Difference*	*Sig.*	*T0*	*T1*	*Difference*	*Sig.*
Residual	1.1320	.8633	.2687	.001	-3.0726	-2.3433	-.7293	.000

Table 4-9 demonstrates the T_1 model as more impressive than the T_0 model. More variation is explained (less residual error) by the T_1 function in both success and failure cases. Opposite NewProd (Cooper 1981), the model is more rigorous when predicting successes than failures at either T_0 or T_1. These also support acceptance of H_1c.

4.4.8 Conclusion

The functions at T_0 and at T_1, whilst not completely unique, are dissimilar. The striking difference in model validating statistics suggests the T_1 model is more rigorous. Increases in coefficient F value, reduction in model error and higher R, R^2 and Adjusted R^2 statistics support this difference. It is superior in all aspects to the T_0 model and improves upon the NewProd linear regression. As compared to T_0, the T_1 model reveals more significant factors (10 versus 8) which are also more valid overall (rising F values), unique to the time period ("high price; 1st in" versus "late entry") and more mature ("overall project compatibility" splitting into "marketing/management synergy" and "technological synergy"). Distribution differences exist in "common factors" also.

The T_0 dimensions reflect an early deterministic bias based on the certainty of history and the static "a priori" characteristic of early information. The T_1 dimensions exhibit more stochastic characteristics based on posterior probabilities and revised conditions as information becomes known over time. The T_1 function emphasises a conditional, stochastic "what if" character, rather than the T_0 function's determinism. Whilst more complex, it is a more valid predictor of the future *if the dimension constructs are achieved at T_1*. Based on conditional probabilities, its dimensional priorities evolve from what was known certainly at T_0 (the influence of history in first and fourth position) to what must be achieved vis-à-vis strategy and superior product at T_1. This seems, in large part, to be a conditional process of learning and implementing the past history lessons.

These intuitive, observable and empirical differences argue for the acceptance of H_1c and the rejection of the null form. Many dimensions of success, as perceived by managers, are demonstrated to evolve. Over time, the functions become more adequate, certain and disturbingly, more like NewProd. Over time, more variation is explained as less residual error is produced by both success and failure case distributions. Therefore, this research accepts the alternate form of the hypothesis and rejects the null form that the models are equal. Factors important to a product's successful introduction *do* change over time.

4.5 Hypothesis H_1d

As the factors contributing to a new product's success evolve, the resulting new product screening model's predictive proficiency evolves also.

4.5.1 Introduction

This hypothesis follows logically from H_1c and suggests that as the T_0 model evolves in form to T_1, its predictive accuracy rises. As demonstrated above, the T_0 model is observably different and inferior to the T_1 model. Using each function to predict success/failure for 260 cases, the T_0 model is 81.15384% accurate compared to the 83.84615% accuracy at T_1. This observation alone argues for acceptance of the alternate hypothesis that their accuracy rates do differ. However, the difference in absolute value of the increase is small. This begs the use of a paired-samples t-test to measure the statistical significance of the difference.

4.5.2 Paired-samples t-test findings

Table 4-10 illustrates a paired-samples t-test of the prediction and model residual saved as SPSS variables at each time period. The statistically significant difference in both prediction and residual by success/failure argues for rejection of the null form that the predictions are equal over time.

Table 4-11 illustrates accuracy outcome by type of model outcome. All possibilities include:

1. actual success ⇒ predicted success = a model success
2. actual failure ⇒ predicted failure = a model success
3. actual success ⇒ predicted failure = a model failure (and)
4. actual failure ⇒ predicted success = a model failure.

The results demonstrate a statistically different prediction mean distribution in category 1, 2 and 4. For example, in category #1, (cases where success was predicted and there was an actual success at both T_0 and T_1), the 69.6% rate at T_0 was statistically different from the 68.5% rate at T_1. The poor result in category #3 is probably due to a comparison of only 4 cases fitting this profile. This clear statistical differences in prediction by category argues further for acceptance of H_1d and rejection of the null form that the predictions by each model are equal.

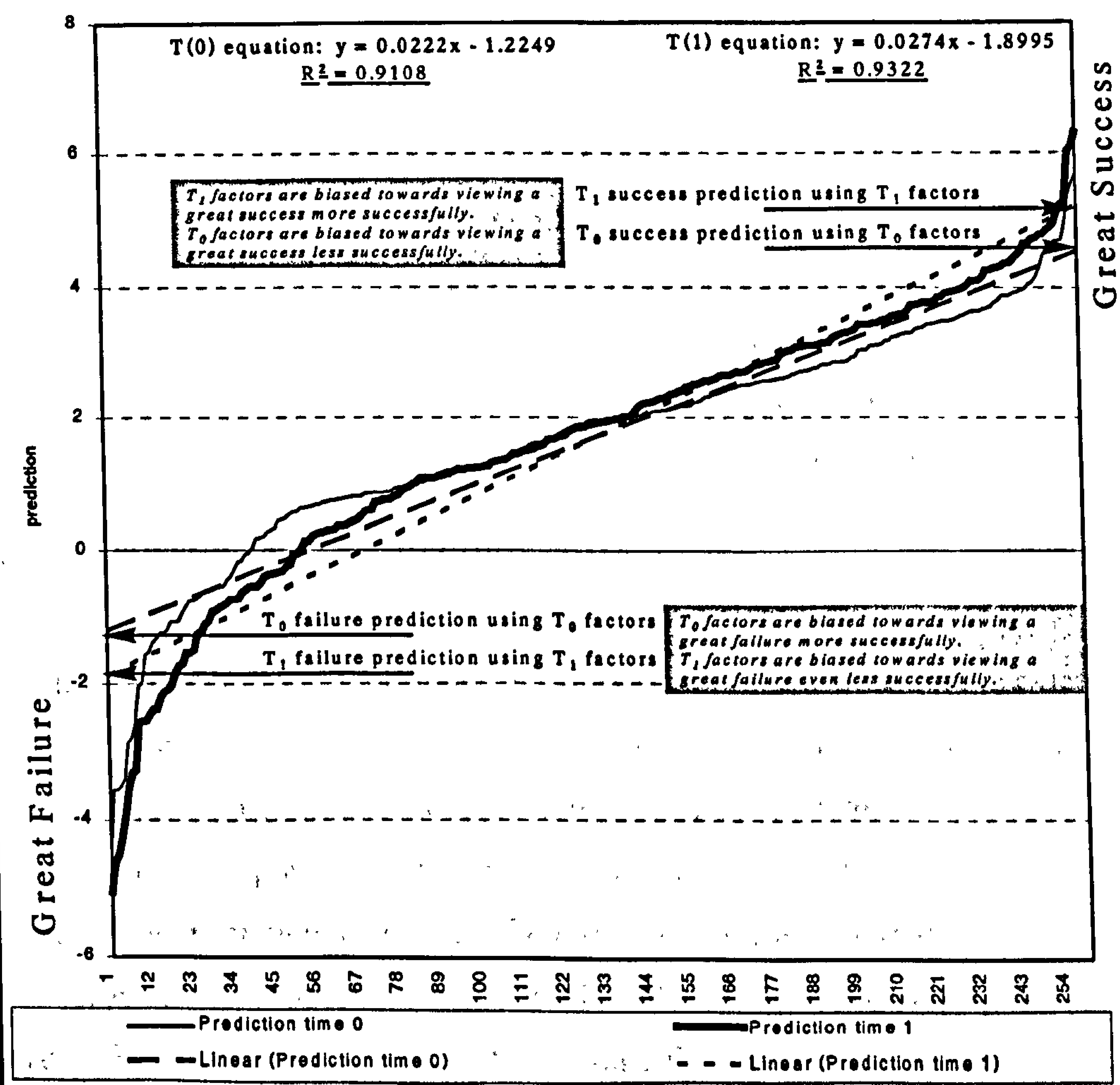
Table 4-10: Model prediction rate and residual means by success/failure

	Success means				Failure means			
	T0	*T1*	Difference	Sig.	*T0*	*T1*	Difference	Sig.
Prediction	2.2190	2.4877	-.2687	.001	.1869	-.5424	.7293	.000
Residual	1.1320	.8633	.2687	.001	-3.0726	-2.3433	-.7293	.000

Table 4-11: Model prediction mean comparison by category. **Significant statistical differences in *bold italics*. *Better model by time period is shaded***

Time	Category #1 Actual=S Predicted=S	Category #2 Actual=F Predicted=F	Category #3 Actual=S Predicted=F	Category #4 Actual=F Predicted=S
T_0	***mean = 2.4381*** ***69.6% n=181*** t=-4.57 at .000 with 172 df	mean = -1.6200 11.5% n=30	***mean = -1.3770*** ***3.5% n=9*** t=-.16 at .885 with 3 df	mean = 1.5734 15.4% n=40
T_1	mean = 2.7811 68.5% n=178	***mean = -2.3266*** ***15.4% n=40*** t=-2.85 at .009 with 24 df	mean = -1.4469 4.6% n=12	***mean = 1.1669*** ***11.5% n=30*** t=3.10 at .005 with 24 df

Figure 4-7: Linear regression of the prediction



Two simple bivariate regression equations of the aggregate predictions were plotted (see Figure 4-7) and strengthen these arguments graphically. These functions indicate that at T_0, the equation for the bivariate regression forming the line ($y = 0.0222x - 1.2249$) has a lesser slope than the equivalent equation at T_1 ($y = 0.0274x - 1.8995$). They intersect at approximately case 130, the mean of the common dependent variable (1.67). These lines have different and improving R^2 values (.9108 v .9322 respectively), an indication of improved prediction variation explanation over time. Also, the lines yield different prediction biases depending on which set of factors is used. The T_0 prediction underestimates the potential gravity of great losses and underestimates the potential for great success. This is logical and supports the difficulty of using early, speculative data (Albala 1975; Cooper and Kleinschmidt 1987b, 1990; Souder 1978). The T_1 function, because of clearer data, fits the extremes better (see Figure 4-6a versus 4-6b) and predicts great successes and great failure more accurately. This visual gap argues for the acceptance of H_1d.

4.5.3 Conclusion

Absolute accuracy improvement demonstrated in the $T_0 \Rightarrow T_1$ functional evolution argues for the acceptance of H_1d. Also, statistically significant differences in mean predictions and residuals and mean predictions by model category of success supports this argument. Further, the different and improving simple regression lines resulting in an expected cost of error bias gap supports acceptance of the alternate hypothesis. Therefore, this research accepts the alternative form of hypothesis H_1d. As the factors contributing to a new product's success evolve, model predictive accuracy evolves also. The null form maintaining that the models are equally accurate is thus rejected.

4.6 Discussion of H_1a through H_1d

4.6.1 General implications

Accepting three of four hypotheses has important ramifications on the existing body of work, as well as the future of screening research activity. Observing that 26 variables are significant to success at both T_0 and T_1 validates Cooper and Kleinschmidt's hypothesised finding (H_7) that *new product success is positively related to the proficiency of the up-front or pre-development activities of the new product process* (Cooper and Kleinschmidt 1987b). However, changes demonstrated beyond the initial screen agree with (Albala 1975) and suggest that process activities should be based ultimately, on the significance of information, difficulty of attainment and its relative value over time. Changes agree also with those suggesting that, whilst the greatest difference between successful and unsuccessful projects may be up-front, these do not guarantee success (Cooper 1988) but only help to avoid pitfalls (Cooper 1980b, 1990; Cooper and Kleinschmidt 1994). Some of these pitfalls and proactive activities are temporal and shown here to come later, not sooner. Further, some characteristics of successful entry are uncovered only in their relationship to strategy. Innovation and barriers to entry are examples.

Virtually all variables constructing factors significant in the NewProd linear regression model (1981) were validated as important here (see Table 4-12a). This resulted in synthesis of knowledge requested (Montoya-Weiss and Calantone 1994). Also, many new variables (see Table 4-2 in ***bold italics***) and factors (see Table 4-12b) were found important at T_0 and/or T_1, thus validating calls for multi-disciplinary integration (Wind and Mahajan 1988) and temporal justification (Montoya-Weiss and Calantone 1994). These discoveries strengthen requests for more dynamic models (Wind and Mahajan 1988) and support the drive towards third generation conditional processes (Cooper 1994b).

Table 4-12a: Synthesis of this work versus NewProd. **(A √ means Thesis results confirmed Cooper's (1981) linear regression construct findings[64])**

Cooper, Robert G. An empirically derived new product project selection model. *IEEE Transactions on Engineering Management* EM-28:54-61 (1981)			
SP=found in Thesis as "Superior Product dimension" *TR=found in Thesis as "Technological Resource dimension"* *1st = found in Thesis as "1st in new, highly innovative market dimension"* *HP= found in Thesis as "Relative high price dimension"*		*Found significant in Thesis at:*	
Key factors or dimensions	***Variables loading on factor***	***T_0***	***T_1***
Product superiority, quality and uniqueness	highly innovative, new to mkt.		√1*
	product has unique features for user	√	√
	product is superior to competing products	√	√
	product reduces customers' costs	√	√
	product does unique task for user	√	√
	product is higher quality than competitors	√	√
Overall project/co resource compatibility	adequate financial resources	√	√TR
	compatible R&D resources		√TR
	compatible engineering skills		√TR
	necessary marketing research skills	√	√
	needed managerial skills	√	√
	compatible production resources	√	√TR
	compatible sales force/distribution resources	√	√
	adequate advertising/promo skills	√	√
Market need, growth and size	high need level by customers for product type	√ SP	√ SP
	large market ($ volume)	√ SP	√ SP
	high growth market		√ SP
Economic advantage of product to end user	product reduces customers' costs	√SP	√SP
	product is priced lower than competing products		√HP
Newness to the firm	new customers to firm	√	√
	new product class to firm	√	√
	new customer need to firm	√	√
	new production process to firm		not tested
	new product technology to firm		not tested
	new sales force/distribution to firm		not tested
	new advertising/promotion to firm		not tested

64 "not tested" indicates that they were eliminated by Cooper as he reduced the data set from 77 variables over time to the "Cooper 30".

	new competition to firm	√	√
Technological resource compatibility	compatible R&D resources & skills for project compatible engineering skills & resources		√TR √TR
Market competitiveness	highly competitive market intense price competition in market many competitors many new product introduced into market changing user needs	√	not tested √ √ √
Product customness/specialisation	a market-derived new product idea a custom product a mass market for product		not tested not tested not tested

Table 4-12b: Found significant in Thesis but not in Cooper 1981 i.e. new variables

NPD history of failure	In the last 3 years in this product market we have had _____ Failure %	√	√
Strategic reaction capability	Our firm developed clear strategies to deal with deficiencies in the Final Product Our firm developed clear strategies to deal with deficiencies in the Nature of the Project Our firm developed clear strategies to deal with difficulties inherent in this market Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry We spent a long time on the market research for this product Our firm developed clear strategies to deal with deficiencies/problems in the area of Newness/Innovation	√ √ √ √ √	√ √ √ √ √ √
NPD history of kills and success	In the last 3 years in this product market we have had _____ Kills % _____ Success %	√	√
New to the firm, didn't fit in	The product "fit in" with a family of products we already had on the market	√	√
Alertness to threat of competitive retaliation	Expected *magnitude* of competitive retaliation was an important consideration in this market entry decision Expected *speed* of competitive retaliation was an important consideration in this market entry decision Expected retaliation	√ √ √	√ √ √
Late market entry	We entered the market somewhere between its maturity and decline We entered the market in its late growth stage	√ √	
Technological resource compatibility	The technical aspects - exactly how the technical problems will be solved - were very clear The product specifications - exactly what the product will be - were very clear		√ √
1st in new highly innovative mkt.	New-to-the-world (a true innovation in the product marketplace listed above) We were not first to market this product; we followed close behind however (negative loading)		√ √

The unfolding conditional nature of the NPD process, demonstrated in the acceptance of these hypotheses, suggests monomorphic deterministic models do lead to temporal contradictions (Albala 1975; Grossman and Gupta 1974; Ronkainen 1985) when applied to stochastic processes. As such, these models may be inadequate to practitioner needs. Whilst they are useful for bringing together eclectic groups in an evaluation session (Cooper 1992), practitioner under-utilisation in stochastic forecasting situations is understandable. Acceptance of H_1a, H_1c and H_1d stands as one empirical footing in the foundation necessary to build more relative, dynamic models, needed to justify recommended conditional third generation processes (Cooper 1994b).

4.6.2 Specific variable implications

The acceptance of H_1a, H_1c and H_1d implies some alteration of understanding is needed. This is true concerning the role of product/project, marketplace, strategic reaction, newness/innovation, barriers to entry and resource variables.

4.6.2.1 Product/project variables

The change demonstrated in significance and magnitude of product/project variables suggests re-examination is in order.

I. Regularly cited as the most important factor of success, "superior product's" construct evolution is instructive. The T_0 factor focusing on meeting customer needs better than competition (see Table 4-3) is supplemented at T_1 by statements measuring customer defined quality in a fast growing market. Only by time T_1 is customer feedback accounted for. The possibility that customers are unable to define quality at the initial screen is supported by the "market research" variable being significant only at T_1 and its significant increase over time for success cases. Its upward evolution suggests that "market research" must continue through one year post launch. Its lack of significance at the initial screen, whilst unclear, suggests temporal limitations on research spending may be appropriate. Supporting this, "product specifications were very clear" is significant at T_1 only. This is consistent with Crawford's (1984) idea of screening stage protocol being loosely defined in terms of benefits, not technical specifications, to be produced.

II. Failed cases deteriorated in "our product was clearly superior to competing products in terms of meeting customer needs". This validates the emphases placed on these attributes by NewProd. And it warns that intra-process and post launch monitoring is necessary. Allowing relative superiority to decline during the process or after commercialisation is a straight path to entry failure. Due to competitive constructs in the T_1 dimension, the importance of monitoring competitive activity is validated as important again.

III. No success case product quality measurement increased significantly over time. "Strategy vis-à-vis the final product" was the only related variable to increase. This hints at the importance of a dynamic strategy in dealing with an evolving superior product whose requisite ultimate quality is unknown at the initial screen. More critical than simply producing one's initial screening image of a "superior product" (Cooper and Kleinschmidt's 1990), this "later rather then sooner" bias awaiting strategic feedback may be a clue to practitioner lack of up-front activity.

4.6.2.2 Marketplace variables

Significant evolution in marketplace variables suggests they are more important than Cooper has indicated.

I. Dynamic markets can actually facilitate success. They shouldn't be avoided by those prepared. Contradicting Cooper (1979b, 1980b), success cases experienced statistically significant increases in "amount of change", "fast production method changes", "rapid R&D advancements", "fast competitive introductions", "fast rate of technological change" and "dynamic market situations" (see Figure 4-3). In the aggregate, "number of competitors" was significant at T_0 but not T_1, as success cases saw a significant increase from T_0 to T_1 but failure cases didn't. This suggests that today successful firms move to attractive, dynamic markets and thereafter, thrive on the competition. Avoidance recommended by Cooper and Stanford is conditionally misguided.

II. "High need level by customers for the product in a large market ($ volume)" is common to success cases over time (see table 4-3). This validates both NewProd and Stanford's conclusions. However, "growth potential" is significant only at T_1. This implies forecasts at the initial screen may be premature, inaccurate or both. Contrarily, failed cases display statistically significant declines in "customer need", "size of market", "growth", "order of entry", "length of PLC" and "market strategic alternatives" (see Figure 4-4).

III. Clearly, product market characteristics such as order of entry, PLC and contribution margin are more important than thought previously.

- "Late to enter" is significant at both T_0 and T_1. This supports its importance to both managers (Maidique and Zirger 1984) and scholars (Ansoff and Stewart 1967; Booz, Allen and Hamilton 1982; Hopkins and Bailey 1971; Lambkin 1988; Lilien and Yoon 1990; Robinson and Fornell 1985; Robinson, Fornell and Sullivan 1992; Urban, Carter, Gaskin and Mucha 1986). The appearance of 1st to market at T_1 casts additional suspicion on luke warm statements concerning order's influence in the NPD process (Cooper and Kleinschmidt 1993).
- Length of PLC, significant at T_1, supports Cooper and de Brentani's (1984) finding of PLC length as an important initial screening dimension. Whilst thought important generally (Ansoff and Stewart 1967; Buzzell 1966; Catry and Chevalier 1974; Day 1981; Dodge and Rink 1978; Doyle 1976; Gordon, Calantone and di Benedetto 1991; Kotler 1994; Luck 1972; Levitt 1965, 1966; Michael 1977; Rink and Swan 1979; Tellis and Crawford 1981; Thorelli and Burnett 1981; Utterback and Abernathy 1975; and Wasson 1978), this is the first validation of the variable's importance in NPD success/failure modelling. Its appearance at T_1 only may suggest that this is another characteristic of success which cannot be measured precisely at the initial screen. Finally, in harmony with entry order and PLC and supporting Maidique and Zirger (1984) and others (Ansoff and Stewart 1967; Cooper 1975; Hopkins 1980)[65], financial contribution margin is an important consideration in new product development. Financial risk assessment as part of a new product project evaluation has been confirmed as important by practitioners (Calantone, Di Benedetto and Haggblom 1995; Cardozo and Smith 1983; Page 1993). It should be integrated into process model construction.

It is quite apparent that temporal constraints placed on marketplace variables remove the averaging effects of aggregate analyses. Removing the handicaps of measurement timing error and survivor bias helps clarify their relationship to entry success. The exogenous variable "time" must be viewed as a process catalyst/moderator.

65 Professor John Klus at the Engineering School of the University of Wisconsin, Madison, USA has found contribution margin one of many important improvements to the NewProd model.

4.6.2.3 Strategic reaction variables

Demonstrating the ability to react to external and internal developments significant to success in an NPD context is quite significant.

I. Five of the six strategy constructs were important at both T_0 and T_1. This indicates that planning and strategic reactive ability is critical initially and remains so through one year post launch. Statistically significant increases are seen in aggregate case project strategy (see Figure 4-2) and successful case product, project, barrier and newness strategies (see Figure 4-3). This supports those arguing the importance of overcoming unexpected problems, leveraging opportunities and maintaining a successful equilibrium (Abell and Hammond 1979; Kotler 1994; Porter 1991). Further, it confirms success to be a result of initial strategy, strategic market interaction (Cooper and Kleinschmidt 1987b; Crawford 1986) and the compounding of external and internal variable groups (Calantone and Di Benedetto 1990) over time. However, "holding enough resources back to react strategically" may help explain why only 7.1% of NPD process expenditures are spent on up front activities (Cooper and Kleinschmidt 1988).

II. The isolated significance of "clear strategies to deal with newness/innovation" at T_1 (see Table 4-3) suggests that developing strategies to deal with newness is difficult and possibly premature, at the initial screen. The diminution of carte blanche support for omni-present strategic activity may smack of heresy. However, practitioners may understand that developing a useful and effective innovation strategy requires market feedback on one's innovativeness versus the competition. This may be unavailable until closer to launch.

4.6.2.4 Innovation

Innovativeness is another characteristic which seems more important to NPD success than forecasting model developers have indicated. Static methods may hide a richer understanding of the phenomena which surfaces when variables are not painted broadly over long periods of time.

I. Finding new-to-the-world levels of innovativeness significant to success supports Cooper's belief that innovativeness is a moderating variable (Cooper 1979a, 1979b, 1980a, 1980b; Cooper and Kleinschmidt 1993). It is also consistent with innovativeness as an important characteristic describing success/failure scenario (Calantone and Cooper's 1981) such as "innovative mousetrap, not better" and "innovative high-tech". Though only one newness variable, "a repositioning", was significant at both time periods, two were significant at T_1 only ("new-to-the-world" and "addition to an existing product line"). This temporal high end bias suggests that to be successful, higher order innovative projects must be positioned in light of more certain, market feedback closer to launch. This finding supports calls for reassessment of innovativeness (Kleinschmidt and Cooper 1991) as an ingredient of success and validates requests for examination of antecedent temporal stability (Montoya-Weiss and Calantone 1994). Clearly, what is "innovative" is a function of customer perception rather than what management thinks at the initial screen (Cooper and Kleinschmidt's 1990).

II. Absolutely higher T_0 innovativeness levels for success cases suggests innovators may be generally more successful. Logically, the characteristic decreases over time (see Figure 4-2, 4-3 and 4-4) for both successes and failures. With negative decreases more severe for failure cases, its importance as a descriptor of successful projects (Davidson 1976; Marquis 1969; Rothwell 1976) is validated. Successful teams seem to introduce more innovative products and/or position their entries to "stay newer longer".

The ability to develop innovative strategies to manage an evolving superior product is characteristic of successes only. This work confirms more recent suggestions (Cooper 1994b; Cooper and de Brentani 1991) that innovative products, in spite of their perceived risks and pitfalls, should be pursued.

4.6.2.5 Barriers to entry

Barriers to entry have never been tested in a NPD success/failure context. Results suggest their significance in new product development is important early and remains so over time.

I. Implicit in the concept of barriers to entry is that they are barriers *before entry*. However, because success cases increased significantly in their ability to deal with barriers strategically over time, entry barriers deserve continued consideration at least through the T_1 period.

II. As T_1 approached, success cases (see Figure 4-3) had clear and significant increases in appreciation for competitive retaliatory efforts, importance of government policy, improved access to distribution channels and customer switching costs. This supports their importance as suggested by Bain (1956), Karakaya and Stahl (1989) and Porter (1980, 1985). Contrarily, failed cases showed neither an increase nor a decrease in any barrier to entry.

These external considerations, despite their under-representation in the NewProd and Stanford models, advise vigilance in monitoring and reacting to barriers through the post launch period. Rather than disagreeing with NewProd's emphases on controllable over uncontrollable variables, the importance of barriers shown here suggests that attention to their magnitude over time allows some strategic control over their impact.

4.6.2.6 Resource variables

Resource variables are validated here as very important to a favourable outcome.

I. Adequate resource levels are confirmed as necessary to success (Abell and Hammond 1979; Ansoff and Stewart 1967; Booz, Allen and Hamilton 1982; Calantone and Cooper 1979; Calantone and Di Benedetto 1988, 1990, 1993; Cooper and Kleinschmidt 1987a, 1987b, 1988, 1993; Cooper 1975, 1976, 1979a, 1980b, 1983, 1994b; Lambkin 1988; Lambkin and Day 1989; Maidique and Zirger 1984; Robinson, Fornell and Sullivan 1992; Rothwell 1972; Rubenstein, Chakrabarti, O'Keefe, Soulder and Young 1976; Utterback, Allen, Hollomon and Sirbu 1976; Wensley 1982) with most remaining significant over time.

II. The temporal nature of resource allocation is new to the field and instructive. For failed cases R&D, engineering, marketing research, management, sales/distribution, advertising, production and financial resources decline significantly over time. This diminution supports those suggesting one must monitor environments (Abell and Hammond 1979; Kotler 1994; Porter 1991) and match them with resources accordingly. Interestingly, whilst success case resource levels declined over time (see Figure 4-3), this decrease was far less than for failed cases. Also, "advertising and promotion resources and skills" becomes significant at T_1 only. This difference is important to prioritisation issues (Cooper 1994b). Delaying advertising expenditure is consistent with Calantone, Di Benedetto and Haggblom's (1995) finding that 67.2% of managers believed advertising to be most beneficial at the early stages of introduction (Horsky and Simon 1983).

These findings validate the importance of resources to success. But they also indicate that temporal resource management needs greater scholarly attention.

4.6.3 Specific dimensional implications

The evolution of dimensions from uncertain and prescriptive at the initial screen to more certain and descriptive following the screen is logical and consistent with those believing early information is volatile (Albala 1975; Cooper and Kleinschmidt 1987b, 1990; Souder 1978). Scholars delivering only prescriptive advice to managers practising in dynamic, downstream, conditional environments is somewhat naive and possibly dangerous. Answering Montoya-Weiss and Calantone's (1994) question, "best practices" do change over time!

4.6.3.1 *Product market history of failure*

Calantone and Cooper (1977), Cooper (1975) and Hopkins and Bailey (1971) were correct. A definite pattern of project failure does exist. Evidence is quite decisive in confirming that the same mistakes are regularly made over and over again (Calantone and Cooper 1979).

Because early information on the future state of controllable variables affecting outcome is quite speculative, certain, deterministic dimensions such as "a failure history" seem to have a disproportionate early influence on success. But this influence declines over time.

I. "Failure history" is new to the literature as a success/failure model dimension. The T_0 failure history dimension is certain with all else except "kill and success history" speculative. Failure history declines to second position at T_1, due probably to downstream learning and plan execution. The dimension mimics natural selection (Darwin 1859) with multigenerational influences affecting industrial "reproductive success". This is consistent with Meyer and Utterback's (1993) advice that individual products are the offspring of multigenerational product platforms with successor platforms the result of a firm's underlying core capabilities. In the absence of a bold break with the past, such "hereditary traits" may be buried in corporate culture to promote stabilisation within the population's ecology (Hannan and Freeman 1977; Lambkin 1988; Lambkin and Day 1989). This may lead to quite "natural" deterministic early tendencies. These may be hidden by time, changing organisational structures and key personnel transition (O'Connor 1994). Thus, this dimension may also tap other phenomena previously unmeasured such as corporate culture, incompetence, office politics, decision making bias (risk prone versus risk averse) and learning ability not measured in the synergy dimension.

II. "Nurturing" activities can override "nature", depending on product market condition and appropriate dimensional selection, emphases and implementation. Though deterministic failure can lead to more failure (Calantone and Cooper 1979), the dimension's decline over time is optimistic for practitioners. It confirms that a failed "nature" can be overcome by organisational learning (Kiechel 1990; Mumford 1992; Nonaka 1988, 1991; Shrivastava 1988; Shrivastava and Souder 1987), experience (Abell and Hammond 1979; Booz, Allen and Hamilton 1982; Boston Consulting Group 1972; Buzzell and Gale 1987; Cooper and de Brentani 1984; Cooper and Kleinschmidt 1987b; Crawford 1980, 1994; Lambkin 1988; Lilien and Yoon 1990; Peters and Waterman 1982; Schmalensee 1982) and strategic plan implementation.

Measuring only one product generation fails to account for phenomena not found in single-generation synergy measures. With simple historical bivariate regression and extrapolation one of the most common techniques used in business forecasting, omission of this dimension in seminal models is an oversight. Clearly, it represents an almost perfect "null scenario/do nothing" deterministic model[66]. As such, it may be preferable and more parsimonious to other seminal dimensions which are simply "convenient representations" of available experience and knowledge (Calantone and De Benedetto 1990).

4.6.3.2 Strategic reaction capability

This dimension, implied previously in statements of controllable variable importance (Cooper 1979a, 1981; Zirger and Maidique 1990), is demonstrated here for the first time in a project level forecasting model.

I. Whilst strategy has been shown related to performance (Buzzell and Gale 1987), this phenomena has not been demonstrated in a screening model reactive context until now. At its simplest, the dimension confirms that strategic typologies are relevant to NPD success (Cooper 1984a, 1984b, 1985b). However, until now, project level strategy dynamics have not been linked empirically to implementing the desired, forecasted situation (Abell and Hammond 1979). This research's observation of equilibrium alignment (Kotler 1994) at work does this, thus satisfying requests for model examination under dynamic conditions (Wind and Mahajan 1988) with dimensions qualified temporally (Montoya-Weiss and

66 A deterministic mathematical model can be expressed as $Y=B_0 + B_1X_1$ i.e. no error component. Given any value for X the value of Y can be determined with precision. A stochastic model contains one or more random components that lead to errors in prediction and is written as $Y=B_0 + B_1X_1 + e$ (epsilon/error; Webster 1992). Being a "null scenario/do nothing" dimension, it suggests the probable outcome if one does nothing different than what is "usual".

Calantone 1994). Further, illustrating the dimension's reactant linking characteristics to all other remaining dimensional states of nature over time confirms that superior performance is a longitudinal attainment of superior market position over time (Porter 1991).

II. Inferior early information at T_0 handicaps strategy, positioning it as inferior to deterministic "failure history". However, unfolding and more certain downstream information enables the strategically adroit. This is demonstrated by the dimension's improving influence on the model. Linking experience with optimising all remaining dimensions is conceptually accordant with new product strategy linking the NPD process to company objectives (Booz Allen and Hamilton 1982).

Observing strategic adjustment of innovativeness, barrier, resource, project, product and market related problems confirms that success is not determined from initial strategy alone but by dealing with the interaction of process and environment change (Cooper and Kleinschmidt 1987b; Crawford 1986). This may be the most important contribution of this work.

4.6.3.3 Superior product

These findings do not diminish seminal efforts but validate and enhance understanding of how superior products become superior over time.

I. Superior product's importance in both the T_0 and T_1 models validates Cooper and Kleinschmidt's hypothesis (H_1) that *new product success is positively related to product advantage* and (H_2) that *new product success is positively related to market potential for the new product* (Cooper and Kleinschmidt 1987b). Further, it supports three hypotheses accepted by Zirger and Maidique (1990):

- H_4: *a product providing a significant value (performance to cost) to the customer is positively related to successful products and negatively related to failures,*
- H_5: *a technically superior product is positively related to successful outcomes and negatively related to failures* (and)
- H_8: *markets that are large and growing are positively related to successful outcomes and negatively related to failures.*

II. Superior product's last place ranking at T_0 may be a clue to understanding why superior products still fail. Endorsing Calantone, di Benedetto and Divine's (1993) finding that simply having good product quality alone is not enough, the T_0 deterministic "success, failure and kill history" dimensions stand as arbiters of all controllable dimensions - including superior product. Whilst supporting those suggesting the dimensions ultimate importance (Bennett and Cooper 1981, 1984; Booz, Allen and Hamilton 1982; Calantone and Cooper 1981; Cooper 1979b, 1980b, 1981, 1985a, 1990b; Cooper and de Brentani 1991; Cooper and Kleinschmidt 1986, 1987a, 1987b, 1990, 1993; de Brentani 1986; Maidique and Zirger 1984; Zirger and Maidique 1990), it advises that failing to improve the next generation's product by first learning from past problems and emulating past success consigns even a superior product to failure. This disquieting limitation on the dimension's carte-blanche endorsement is consistent with practitioner experience. Products defined precisely, early and incorrectly, condemn teams to labour under false assumptions of superiority, with the truth known too late and only after launch (Cooper and Kleinschmidt 1990).

III. Customer cost reduction, utility and competitive quality features are added to the factor at T_1 (see factor in both Table 4-5a and Table 4-5b) as the superior product dimension evolves in importance. This validates the positive consequence of delivering stated protocol (Ansoff and Stewart 1967; Crawford 1980, 1984, 1986, 1994; Cooper 1992; Cooper and Kleinschmidt 1994; Maidique and Zirger 1984; Rothwell 1972; Pinto and Pinto 1990; Utterback 1974) from desired benefits to precise, technical features (Crawford 1984). Its importance supports Cooper and Kleinschmidt's hypothesis (H_6) that *new product success is positively related to project definition or protocol-how well defined the project strategy is prior to product development* (Cooper and Kleinschmidt 1987b) as well as others (Calantone, Di Benedetto and Haggblom 1995; Cooper 1988; Cooper and Kleinschmidt 1987a, 1987c; Crawford 1984, 1994; Kleinschmidt and Cooper 1991). Its evolution from speculative benefit to feature delivery may illustrate how rapid learning (Day and Wensley 1988; Slater and Narver 1995) is used by successful teams to develop a superior product in stages. With technical features uncertain initially and where accelerated market and technological learning is possible (Day 1994), teams should not kill products too early, simply because they lack concrete advantages at the screen (Crawford 1984).

Beyond these explanations of the dimension's assent, speculation of measurement timing error in NewProd and Stanford is discussed in section 4.6.4.3.

4.6.3.4 Newness to the firm

Findings here confirm the negative impact of this dimension on success.

I. Consistent with Abette and Stuart (1988), Calantone and Cooper (1979), Cooper (1979b, 1980b, 1981), Kleinschmidt and Cooper (1991) and Roberts and Berry (1983), the dimension suggests that the team should "stick to their knitting" (Peters and Waterman 1982). Warning not to go too far afield from proven abilities, it validates a "short pass" strategy (Kleinschmidt and Cooper 1991).

II. At T_1 the dimension falls back one place. This temporal validation is new to the field and suggests fresh approaches to the short versus long pass problem are possible. The deterministic effects of never having made or distributed products to different customers and against new competitors, whilst dangerous initially, diminish over time. Probably the result of an average 855 days of learning, the decreasing impact of "newness" validates a "long pass" strategy, but only in conjunction with learning and the appropriate strategic mix of other important dimensions over time.

III. At T_1 "superior product" moves ahead of "newness" in sympathy with "strategy's" increased importance. Taken together these suggest that though "new to the firm" products, customers and competition are foreboding initially, over time the introduction of a superior new product evolving in conjunction with a reasoned, new product strategy (Crawford 1986) is <u>more</u> important. Negative implications of a failed history and "newness" can be overcome with the right mix of rapid learning (Day 1994; Day and Wensley 1988; Slater and Narver 1995), superior product development and strategic positioning.

In addition to confirming much from seminal literature, these discoveries add the optimism of a learning organisational culture (Kiechel 1990; Mumford 1992; Shrivastava 1988; Shrivastava and Souder 1987; Slater and Narver 1995). This and the synergy issue should not be seen glibly as "short pass versus long pass". Rather, it should be viewed as optimising the value of superior products, even if they are new to the firm, by overcoming newness via accelerated learning.

4.6.3.5 Resource requirements and synergy

This dimension substantiates much from seminal literature.

I. The dimension is represented at both T_0 and T_1 and validates Cooper and Kleinschmidt's hypothesis (H_4) that *new product success is positively related to market synergy or fit - the ability of the project to build from the firm's existing marketing resources* and (H_5) that *new product success is positively related to technological synergy or fit-the ability of the project to build from the firm's existing development and production resources* (Cooper and Kleinschmidt 1987b). It also validates Zirger and Maidique's hypothesis (H_6) that *products that build upon the firm's existing market, technology and product competencies are positively related to successes and negatively related to failures* (Zirger and Maidique 1990).

II. The dimension's lower ranking at both time periods supports synergy's more recent, lesser role on project outcomes (Cooper and Kleinschmidt 1987c). Importantly, this may be due to using a measurement period ending at one year post launch, before process related efficiencies (Abernathy and Utterback 1978; Utterback 1981, 1982 Utterback and Abernathy 1975; Calantone, Di Benedetto and Meloche 1988; de Bresson and Townsend 1981) can be realised. Nonetheless, synergy is validated as important (Ansoff 1965; Calantone and Cooper 1981; Cooper 1979a, 1979b, 1981, 1985a, 1990; Cooper and de Brentani 1984; Cooper and Kleinschmidt 1986, 1987a; de Brentani 1986; Kulvik 1977; Lambkin 1988; Link 1987; Nystrom and Edvardsson 1977; Rothwell 1972; Zirger and Maidique 1990).

III. Its dissolution over time into separate synergistic dimensions by function is provocative. The dimension separates into management/marketing versus technical functions. This synergistic temporal maturation is new to the field and may indicate that whilst functional co-ordination is important (Ansoff and Stewart 1967; Crawford 1980, 1984, 1986, 1994; Cooper 1992; Cooper and Kleinschmidt 1994; Maidique and Zirger 1984; Rothwell 1972; Pinto and Pinto 1990; Utterback 1974), it may have timing limitations (Montoya-Weiss and Calantone 1994). Seemingly troublesome when all performance indicators in NPD point to the need for function harmony, it is consistent with Hart and Baker's ideas on multiple convergent process models (Hart and Baker 1994). Interestingly, the "technological resource adequacy" variable is not critical to success at T_0 but only at T_1. This again validates Crawford's thinking that projects should not be rejected if the technological specifications cannot be met at the screen; as long as they can be met by launch. New to the field and inconsistent with both Cooper works (1979b, 1981), Cooper and de Brentani (1984) and Zirger and Maidique (1990), temporal instability indicates that the functional walls broken down successfully at the initial screening are actually reconstructed by successful teams over time.

Beyond this explanation of the dimension's maturation, measurement timing error in seminal models may average two dimensions into one.

4.6.3.6 Relative high price of the product

This dimension suggests that a price too high in the first year will have negative ramifications on success.

I. This is consistent with early cross-sectional findings related to failure typologies (Calantone and Cooper 1979). Significant at T_1 only, its fifth place position is consistent with the original NewProd discriminant analysis (Cooper 1979b) and the constructs of the negative competitive dimension in the follow-up linear regression (Cooper 1981). At T_0, when product features and required pricing are part of a nebulous early environment, it is reasonable that pricing should not be rigid. Rationally, pricing strategy evolves with the downstream learning, competitive analysis and the T_1 superior product construct developments over time.

II. Though low price strategy has been found ineffective in the chemical industry (1994) and a poor discriminator of success (Cooper and Kleinschmidt 1987a), the dimension detracts from success in the first year of launch. It indicates possibly, that low price strategy is more appropriate in today's dynamic environment than "skimming". This is supported by success case ability to succeed in dynamic environments (see Figure 4-3) and today's shorter life cycles (Griffin 1993; Qualls, Olshavsky and Michaels 1981). Faster diffusion rates (Liberman and Montgomery's 1988) may effectively reduce the time allowed for skimming to be effective. As such, price competitiveness may become an even more important discriminator in the future, as margins erode even earlier because of more dynamic environments.

4.6.3.7 Product market history of success and kills

This dimension is new and represents the remainder of the "history dimension".

I. The only empirical work examining the kill issues is Cooper and Kleinschmidt (1990). This was done to rectify methodological problems[67]. Asking "what separates kills from successes?" and "what distinguishes kills from failures?" they found nothing compelling, thus preserving earlier conclusions concerning success/failure. This dimension only concludes that kills are inversely proportional to successes at both T_0 and T_1 and does not support or dispute their "failures = kills" hypothesis.

II. The dimension is as paradoxical as Cooper and Kleinschmidt's finding that management kills synergistic projects (1990). It does not suggest companies should be overly active in new introductions (Booz, Allen and Hamilton 1982) simply to gain experience. Rather, it suggests that kills are an opportunity cost keeping the team from successful learning experiences. As they dissipate valuable time and resources, kills may dilute what's left to critically inadequate levels.

67 previous works overlook kills entirely.

III. Successful experience (Booz, Allen and Hamilton 1982; Boston Consulting Group 1972) in marketing, production and technology should lead to more success (Cooper and Kleinschmidt 1987b). Though intuitively obvious, this could be a "natural" function of individual products being the offspring of product platforms that are enhanced over time from designs of longer duration and broader scope (Meyer and Utterback 1993). This dimension is in harmony with organic natural selection theory (Darwin 1859). Success leading to success is important because it has never been demonstrated empirically in a forecasting context. As with history of failure, this deterministic dimension becomes less important over time. This suggests that even teams graced with the comparative advantage of a predisposition to success, yield ultimately, to its diminishing returns. It suggests further, that excessive killing of projects "on the bubble" based on early evidence only, may not only waste resource but prove unwise based on evolving conditional developments.

4.6.3.8 Alertness to the threat of competition

Contradicting Cooper (1979, 1984a) and in agreement with Parry and Song (1994), early success is very much related to perceived magnitude and speed of retaliation. Characteristics of competition deserve a prominent, positive role in initial screening models.

I. The alertness dimension does not disagree that competition can be a detriment to success. However, this *favourable* dimension measures the assessment of potential magnitude and speed of competitive retaliation. As measured here it is supportive of Cooper and Kleinschmidt's *rejection* of their hypothesis (H_3) that *new product success is negatively related to the level of competitiveness in the new product's market* (Cooper and Kleinschmidt 1987b). And it disagrees with those recommending the unconditional avoidance of highly competitive markets (Cooper 1979b, 1980b, 1981; Zirger and Maidique 1990). The dimension also denies Zirger and Maidique's finding (H_7) that *weak competitive environments are positively related to product successes and negatively related to failures* (Zirger and Maidique 1990) but is consistent again with Cooper and Kleinschmidt's (1990) determination, that kills and failures are both introduced in markets where competitive concentration was lower.

II. The dimension's positive regression coefficient connotes a substantial difference from NewProd and Stanford's negative competitive dimension. This factor supports competition being *recognised* as important by NPD managers (Maidique an Zirger 1984). It is in complete accord with the importance of competitive assessment (Bain 1956; Booz, Allen and Hamilton 1982; Cooper 1975; Cochran and Thompson 1964; Cooper and Kleinschmidt 1987a; 1987b; Hopkins and Bailey 1971; Lambkin and Day 1989; Lazo 1965; Link 1987; Porter 1980, 1985, 1991) and it does not imply avoidance.

III. Alertness is not at odds with Calantone and Cooper's (1979) failure scenario of "competitive brick wall". It is in harmony with the same work's "the environmentally ignorant" scenario. The dimension is optimistic and fundamental to taking appropriate action. It suggests that competition, whilst material to entry, can be handled with proper research, assessment, planning and strategic reaction. Recognising that successful firms learn from history, it suggests a realistic assessment of the competitive environment and then dealing with it strategically. This is one explanation why Cooper and Kleinschmidt regularly find competitiveness fails to impact on NPD success (Cooper and Kleinschmidt 1993). Another is offered by the authors themselves to wit "*One possible reason why market environment characteristics appear so low on the list of success ingredients, is that products facing highly negative markets were likely scrubbed much earlier in their development*" (Cooper and Kleinschmidt 1987a p222). It is possible that they failed to measure the importance of alertness to competition due to management's "alertness" and subsequent killing of projects judged poor competitively. Thus they may have given the "go" to those with strategic plans in place and/or the reactive ability to overcome the competitive disadvantage.

By measuring before survivour bias can diminish this dimension's effect, this factor confirms the importance of competitive assessment on entry success.

4.6.3.9 Order of entry/innovativeness

In opposition to NewProd and Stanford, entry order and innovation level are important to success.

I. These dimensions disagree strongly with the original NewProd finding that "*... although product uniqueness (first to market) is an important dimension describing new product projects (factor analysis results), it is not a determinant of success or failure" (Cooper 1979b, p102).* The T_0 "late entry" dimension is in sixth place and its complement "1st in" falls to tenth place at T_1. Though neither has been found very significant in any other NPD forecasting work, they both support the feelings of practitioners (Maidique and Zirger 1984) if not NPD modelers. This additional reality check may be yet another reason for practitioner avoidance.

II. The dimension's evolution from a moderate to low level determinant is new to the field. It is consistent with Cooper and Kleinschmidt's chemical industry conclusion (1993) that order of entry is only slightly important to success, as success rates decrease with later entry. It agrees also with Booz, Allen and Hamilton (1982), Hopkins and Bailey (1971), Lambkin (1988), Lilien and Yoon (1990), Robinson and Fornell (1985), Robinson, Fornell and Sullivan (1992) and Urban, Carter, Gaskin and Mucha (1986). Its importance here should provoke discussion of why the NewProd and Stanford models do not find order/innovation important. The dimension's relative absence in both models is probably a result of measurement timing error and survivour bias (Kerin, Varadarajan, and Peterson 1992; Mitchell 1991) in five year retrospectives imprecisely benchmarked.

III. At T_0 the dimension emphasises "do not be late". At T_1, by adding new-to-the-world constructs, it becomes more conditional by suggesting one attempt to "be 1st into the product market with a new-to-the-world entry". The caution expressed in the T_0 dimension is consistent with improper timing being judged a hindrance to success (Cochran and Thompson 1964; Hopkins 1980). As it evolves over time it supports innovativeness as an important characteristic for new products (Davidson 1976; Gerstenfeld 1976; Kulvik 1977; Marquis 1969; Myers and Marquis 1969; Rothwell 1972, 1974, 1976; Utterback, Allen, Hollomon and Sirbu 1976). The drop in the factor's importance may suggest that diffusion is occurring more rapidly, lessening the effects of learning-based, entry order advantage (Liberman and Montgomery 1988).

Though not powerful, this dimension is quite significant and free of "survivor bias" (Crawford 1979; Kerin, Varadarajan and Peterson 1992; Mitchell 1991) clouding other studies. It supports those believing that innovative products can do well, by not being "caught in the middle" (Aker and Day 1986; Kleinschmidt and Cooper 1991; Porter 1980, 1985). Being relatively free of measurement timing error than either NewProd or Stanford, it is more sound in its advice for the one year post launch period.

4.6.4 Model usage

The models at T_0 and T_1 are different absolutely and in potential application. Albala (1975) suggests that NPD process activities should be based, ultimately, on the significance of information, its difficulty of attainment and its relative value over time. "No use" by practitioners may represent seminal model up-front inadequacies represented visually in Figure 4-7. These are demonstrated here by differences in validity, accuracy and deterministic versus stochastic information requirements. These differences have important implications on model worth to the team.

4.6.4.1 Validity and accuracy

Significant difference in model validity over time is demonstrated by the improvement in R, R^2, Adj. R^2, F and Standard error (see Table 4-13). In all cases the statistics demonstrate a more valid, robust model as information concerning stochastic environmental dimensions becomes more certain over time.

Table 4-13: Differences in model validity

	T0	*T1*	*difference*
r	.56589	.68961	+.12372
R^2	.32023	.47556	+.15533
Adj. R^2	.29857	.45450	+.15593
F	14.78065 at .0000 with 8df	22.57937 at .0000 with 10df	+7.79872
Std Error	2.58869	2.28289	-.3058
# dimensions	8	10	+2
accuracy	81.15384%	83.84615%	+2.69231%
residual (success)	1.1320	.8633	-.2687
residual (failure)	-3.0726	-2.3433	-.7293
Mahalanobis	7.9692	9.9615	+1.9923

The validity difference is augmented by a small but statistically significant increase in accuracy. The importance of the difference is sustained by the large reduction in residual error of the prediction and visual error gap in the bivariate regression (see Figure 4-7). This suggests the T_1 model deserves greater confidence as information evolution reduces perceived ECE (expected cost of error) and increases EVII (expected value of imperfect information). This does not suggest however, that all teams should use the T_1 model. That is a measure of model worth - a calculation unique to every team. This is fundamental to understanding probable reasons for practitioner avoidance of front-end activities.

4.6.4.2 A pure deterministic versus pure stochastic example

In some measure models are either deterministic or stochastic. Deterministic models presume decision making under certainty and suggest "what's best?" by maximising or minimising an objective function. These are exemplified by NewProd, Stanford and this work's T_0 aggregate model. All prescribe what should be done to achieve success using early dimensional probability distributions. Contrarily, stochastic models are concerned with decision making under probabilistic risk. They ask instead, "what if" (Burns and Austin 1985) and are based on downstream conditional dimensional distributions. This work's T_1 model, evolving based on underlying antecedent evolution, is a good example.

Overemphasising expensive, speculative, up-front deterministic forecasting activities, knowing that evolutionary change is imminent, may be off-putting to practitioners. The reasonableness of this proposition is demonstrated by the comparisons in Table 4-14a through Table 4-14d. In Table 4-14a and 4-14b two pure deterministic models are based on past product market history of success, failure and kills *only*. They contain little if any information error and exemplify a "null (no change)" scenario. Contrarily, the stochastic models in Table 4-14c and 4-14d are based on all other dimensions except history. These exemplify the "maximum possible change" scenario with commensurate forecasting error potential.

As seen in Table 4-14a and Table 4-14b, the deterministic models become less certain over time, F values and accuracy fall and standard error rises. Clearly, both history factors experience diminishing returns. Absent probabilistic dimensions, validating statistics are unimpressive and the prediction rates fall over time. However, they are far better than chance alone and suggest historical intuition as a reason why seminal models are under-utilised.

Table 4-14a: T_0 pure deterministic model with only product market history

R = .40741, R^2 = .16598, Adj. R^2 =.15949, Std. Err. = 2.83374, F = 25.57319 at .0000 % *accuracy = 76.9%*	
Key factors or dimensions (factor name)	**Reg. Coef.**
History of failure	1.114580
History of kills and success	.586054
constant	1.671875

Table 4-14b: T_1 pure deterministic model with only product market history

R = .38251, R^2 = .14632, Adj. R^2 = .13967, Std. Err. = 2.86695 F = 22.02413 at .0000 *accuracy = 74.2%*	
Key factors or dimensions (factor name)	**Reg. Coef.**
History of failure	1.050744
History of kills and success	-.542047
constant	1.671875

Practitioners may ask "why bother" and in effect subscribe to "insufficient reason criterion"[68]. This would be true, especially if they have limited forecasting ability to predict the future states of T_1 dimensions. Here, a "history only" choice of acting intuitively based on what one does well, is sensible for those with a successful track record. They would not be inclined to change procedures. On the other hand, intelligent teams with a bad track record would try something else as failure diminishes in importance over time.

Table 4-14c: T_0 pure stochastic model with no product market history

R = .36404, R^2 = .13253, Adj. R^2 = .11892, Std. Err. = 2.90132 F = 9.73934 at .0000 accuracy = *75%*	
Key factors or dimensions (factor name)	**Reg. Coef.**
Strategic reaction capability F2	.700422
New to the firm, didn't fit in F4	-.644947
Alertness to threat of competitive retaliation F7	.437518
Late market entry F14	-.410086
(Constant)	1.67187

Table 4-14d: T_1 pure stochastic model with no product market history

R= .55743, R^2 = .31072, Adj. R^2 = .29438, Std. Err. = 2.59642, F = 19.00863 at .0000 accuracy = *80.4%*	
Key factors or dimensions (factor name)	**Reg. Coef.**
Strategic reaction capability F2	1.096848
Superior product in large rapid growth market F3	.800692
Relative high price of product F18	-.557748
New to the firm, didn't fit in F5	-.717605
Marketing & management resource compatibility (synergy) F7	.399238
Alertness to threat of competitive retaliation F 8	.372806
(Constant)	1.671875

For the pure stochastic models in Table 4-14c and Table 4-14d the reverse is true. The T_1 version is more valid and accurate than the T_0 version. Constructed entirely of conditional dimensions, *but requiring accurate prediction and dimensional execution,* the models are more complex, have higher accuracy rates and a lower standard error over time. These pure stochastic models are appealing for all teams with the ability to predict and deliver dynamic dimensions more certainly and those with a significant failed history needing extensive change (or no history in the product market at all).

4.6.4.3 $T_0 \Rightarrow T_1$ evolution and worth

Like the example immediately above, this work's demonstration of model evolution has significant implications on model worth to and choice by the team.

4.6.4.3.1 Evolution

The $T_0 \Rightarrow T_1$ metamorphosis demonstrates a deterministic to stochastic evolution in bias. At T_1, controllable dimensions become more important to success, confirming the findings of Cooper (1980b) and Cooper and Kleinschmidt (1987a, 1993). Absolutely certain "failure, kill and success" dimensions decline in importance as probabilistic dimensions rise ("strategic reaction capability", "superior product") or

[68] This is the most subjective decision making criteria and focuses on personal knowledge of the problem and its environment. Marquis Pierre Simon de Laplace, the father of "insufficient reason", argued that admitting that you have no idea of underlying probability governing the states of nature means they are all equally likely to occur (Burns and Austin 1985).

are selected for the first time ("1st in new, highly innovative market", "technological resource synergy"). The probability for prediction error rises as illustrated by the large, statistically significant 1.9923 point Mahalanobis' distance (see APPENDIX B) change over time.

4.6.4.3.2 Worth

Clearly, model choice is proprietary and related to team resources, ability and tolerance for risk. Its worth is a function of the decision's expected monetary value, expected opportunity loss, value of perfect information, value of imperfect information and/or management's attitude towards risk[69] (Burns and Austin 1985). These characteristics are unique to each team, de Brentani's defence of universal models notwithstanding (de Brentani 1986).

Like the extreme examples in Table 4-14 above, each model's informational requirements affect its worth based on team ability and inclination towards risk. The deterministic T_0 model is 81.2% accurate and uses only eight dimensions. Initial use is justified by its clarity, simplicity and unswerving prescription. It should be appealing to those with poor forecasting and/or limited reactive ability. Though more accurate and valid, the T_1 model can lead to larger expected cost of error depending on team forecasting ability and probability of dimensional attainment. In either case, after the project is "off the ground", evolving data richness, parallel decreases in expected cost of error and team forecasting skill advises the T_1 model for simulative/diagnostic purposes. Thus, choice optimises the expected value of imperfect information (a function of forecasting ability) by allowing action and redirection based on "cheaper" information from more certain conditions over time.

4.6.4.4 T_0, T_1 and NewProd

The aggregate models differ primarily because of the reduction of measurement timing error. This is manifest in "superior product", "order of entry/level of innovativeness" and "synergy" dimensional evolution changing the model's structure over time. As such, the T_1 model moves away from the T_0 model as its dimensions, validity and accuracy reflect the NewProd model quite closely. This suggests probable measurement timing error in the field's most respected model when it claims to represent the environment known at the initial screen.

The dimensions recommended for use at the initial screen by NewProd do not represent those properly known or most appropriate at that time. This is disquieting

[69] maximin, maximax, minimax regret and de Laplace insufficient reason.

and sustains those warning of problems associated with field validity (Montoya-Weiss and Calantone 1994), long retrospectives (Crawford 1979) and survivor bias (Kerin, Varadarajan and Peterson 1992; Mitchell 1991). However, it is consistent with Cooper's own admission that NewProd may actually measure average dimensions as they "turn out" based on strategic reaction long after launch (Cooper 1992). Being heavy with measurement timing error, NewProd is inappropriate for temporal dimensional prescription, especially at the initial screen.

Chapter Five - Analyses and findings (H_2, H_3 and H_4)

5.1 Introduction

Chapter 5 tests hypotheses H_2, H_3 and H_4 utilising the methodologies delineated in Chapter three. To test H_2, the metrically scaled variable "life_exp"[70] was divided into three approximately equal categories of short, medium and long PiLC. A linear regression function was constructed for each category at each time period. To test H_3, "1st in new, highly innovative market" (factor 5 at T_0 and factor 6 T_1), was used to categorise cases. A linear regression function was then constructed for each category, at each time period. Acceptance or rejection of H_2 and H_3 was made based on differences in model validity, dimension selection and prediction accuracy among categories, across time periods and compared to the aggregate models. To test H_4, a paired-samples t-test was used to examine strategic variable increases or decreases as they affected success/failure.

5.2 Hypothesis H_2

Factors significant in contributing to a new product's successful introduction are perceived to vary as a function of the length of the product's introductory life cycle.

5.2.1 Introduction

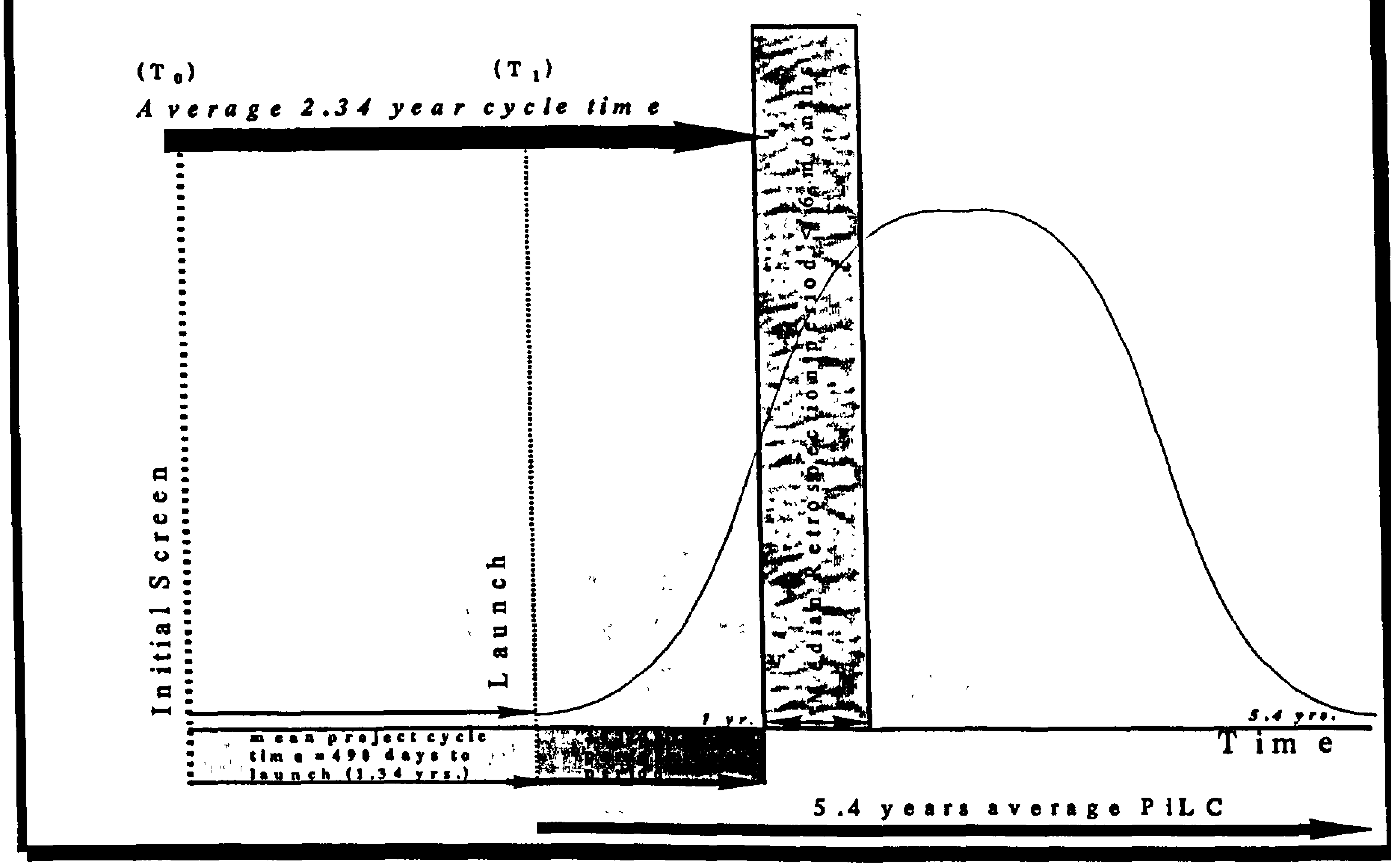
H_2 tests whether success factors are perceived to change if the product's PiLC is estimated to be short, medium or long. The "life_exp" variable was not normally distributed (see Figure 3-4). Categorisation was approximate with short defined as 0-3 years (n = 71), medium as 3.001-4.999 years (n = 76) and long as 5 years and longer (n = 57). Acceptance of H_2 was based on observable differences among categories and between time periods. Duncan's multiple range test was used to determine "common" factor distribution differences. Prediction and residual error distribution differences were tested by category and supplemented by paired-samples t-tests of the factor and prediction distributions over time.

The average cycle time (see speed to market, APPENDIX B) was 490 days. Thus the average retrospective period was 855 days (490 days to launch + a 365 day launch period = 2.34 years; see Figure 5-1). Over half the sample reported product development cycle times of one year or less with 2/3rds under 1.25 years. The median anniversary performance measurement date was less than six months from the median

70 the life_exp variable was obtained from the question: "The product's life expectancy in original form before modifications was: #_____Yrs.#_____Mos".

response date. This means that the average project was screened, produced and evaluated in under three years. NewProd's average would be much longer based on a five year retrospective without a 1 year maximum benchmark date. Thus, the much shorter retrospective encouraged less measurement timing error and better represented market failure phenomena overlooked in other work due to survivor bias.

Figure 5-1: PiLC cycle time and retrospective period



5.2.2 PiLC conditioned model at T_0

Table 5-1a offers the results of the three conditional linear regression procedures at T_0.

Table 5-1a: Linear regression conditioned by PiLC at T_0.

p = PiLC model prediction; a = aggregate factors predicting success after sorting by category

Aggregate at T_0: R=.56589, R^2=.32023, Adj. R_2=.29857, F =14.78065 at .0000 with 8df Standard error = 2.58869 prediction accuracy rate = 81.2 %				
PiLC % correct p= PiLC model a= Agg. model	*Factor*	*Description*	*Regression Coefficient*	*Model Fit*
SHORT: 0-3 yrs. p=71.8% *correct* a=71.8% *correct*	F6 Constant	Superior unique product, meeting needs in large rapid growth market	.913093 1.58491	R=.29718, R^2=.08832, Adj. R^2= .07510, StdErr=3.14585, F=6.68410, Sig=.0118, 1df
MEDIUM >3&<=5 yrs. p=80.3% *correct* a=86.8% *correct*	F17 F2 F16 Constant	NPD history of failure Strategic reaction capability NPD history of kills and success	1.382622 .954682 .947944 1.986872	R=.61923, R^2=.38345, Adj. R^2=.35776, StdErr=2.49795, F=14.92635, Sig=.0000, 3df
LONG >5 yrs. p=78.9% *correct* a=80.7% *correct*	F17 F2 F16 F4 Constant	NPD history of failure Strategic reaction capability NPD history of kills and success New to the firm, didn't fit in	1.150245 1.141745 .807148 -.767273 1.56471	R=.69685, R^2=.48560, Adj. R^2=.44603, StdErr=2.42112, F=12.27196, Sig=.0000, 4df

Figure 5-2a: P_iLC Histogram of residual error-T(0)

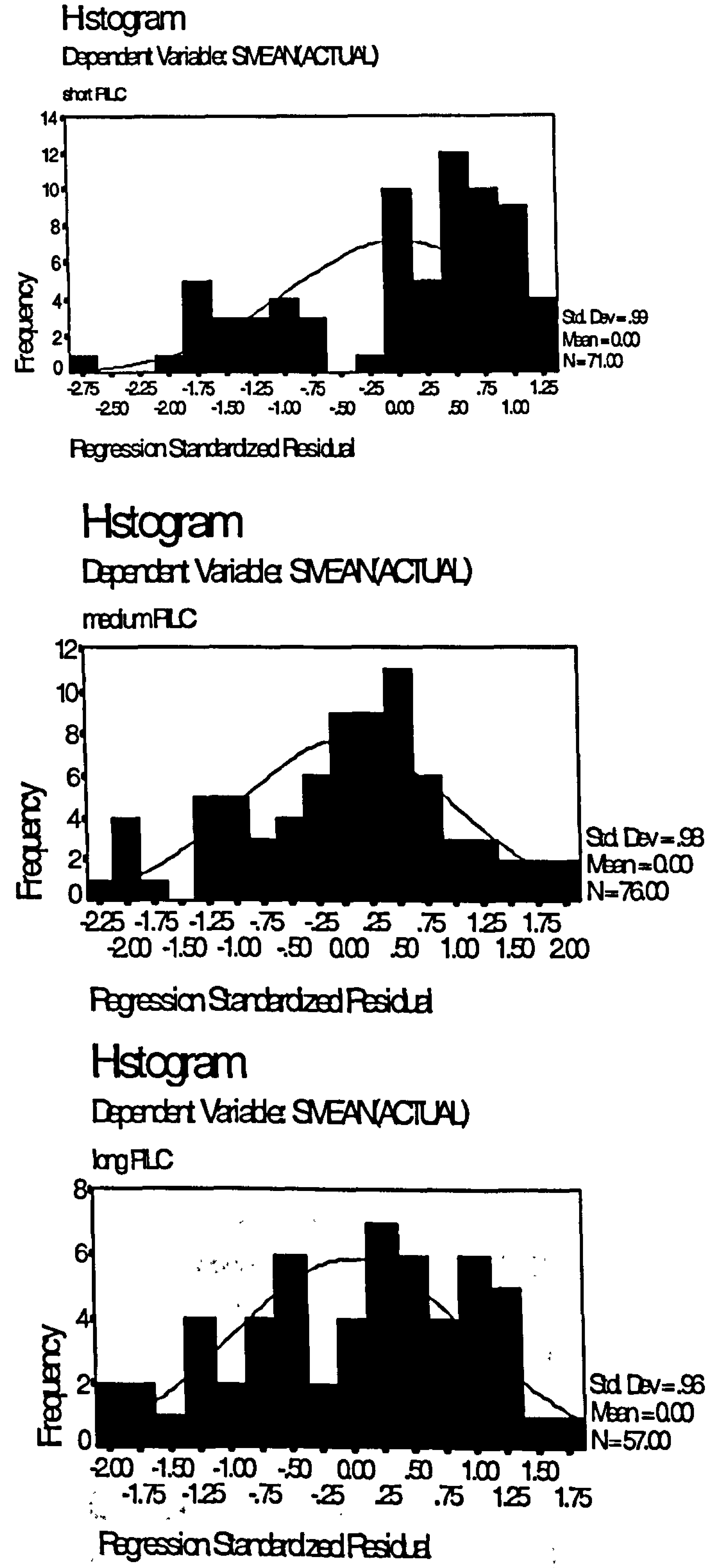


Figure 5-2b: Normalcy of residual error

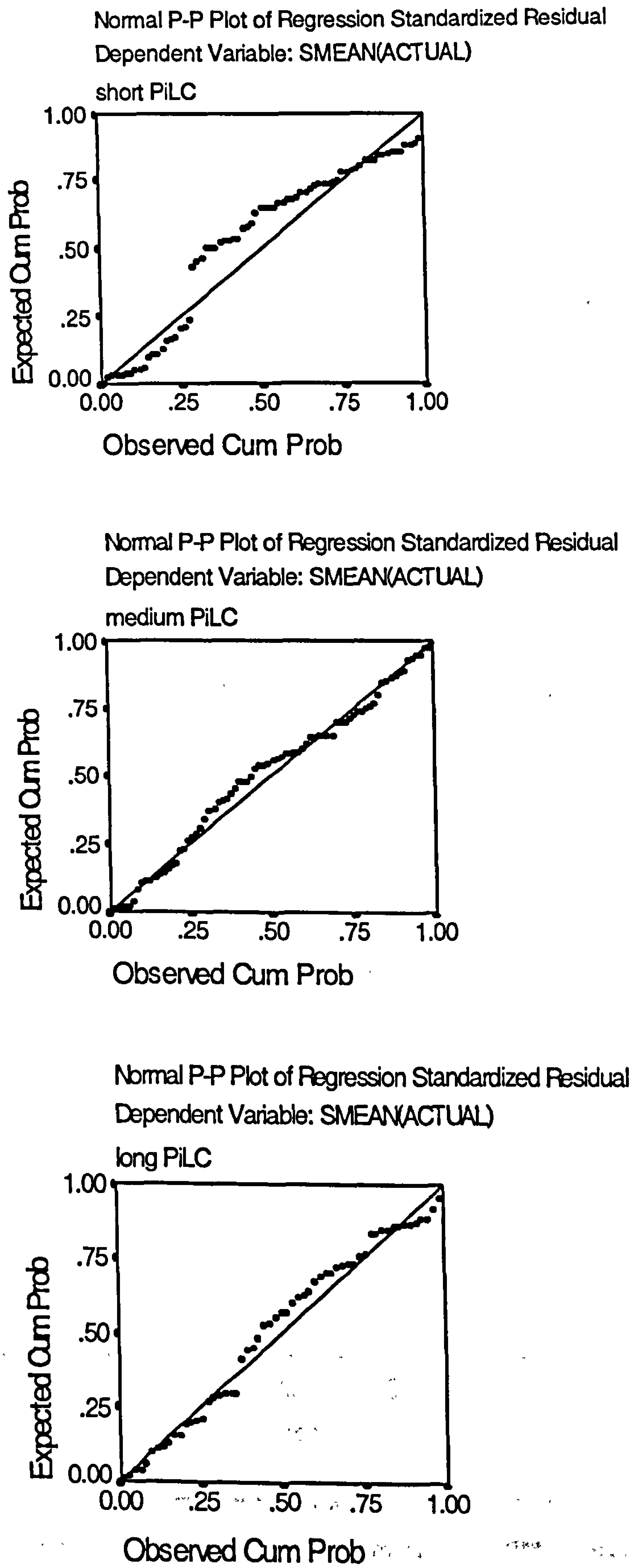
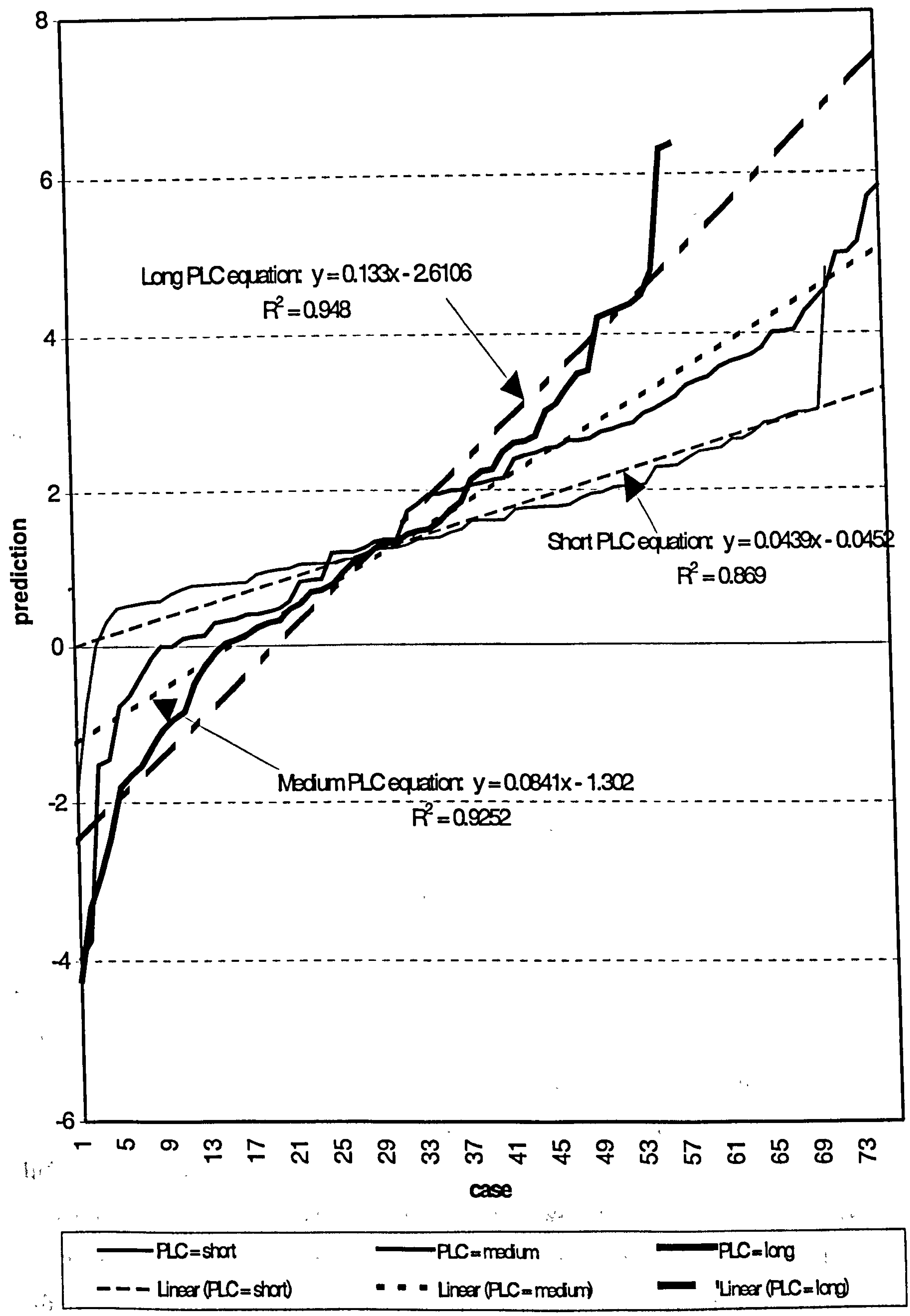


Figure 5-1a LINEAR REGRESSION PLC MODEL PREDICTION (T0)



Differences are observed in model construction, validity and accuracy among categories and compared to the aggregate model at T_0. There are less dimensions overall but these are fairly consistent between medium and long categories. Though the short model is poor, the medium and long model are more valid than the aggregate at T_0. This suggests that conditional models are preferable to an aggregate when medium and long PiLC can be predicted with accuracy. These differences support the acceptance of H_2, as PiLC is sustained as a moderator (Cooper 1979b, 1981, 1984a; Montoya-Weiss and Calantone 1994) of success at the initial screen. Medium and long accuracy rates of 80.3% and 80.7% are only slightly inferior to the aggregate model's 81.2% at T_0 and NewProd's 84.1%. The rising bivariate R^2 values (see Figure 5-1a) and increasing normalcy (see Figure 5-2a and Figure 5-2b) over time sustains PiLC's role as a forecast enabler (Day 1981). At T_0, "history of failure", "strategic reaction capability" and "history of kills and successes" dominate, with "new to the firm" a detractor in the long function. Obvious model differences argue for acceptance of H_2.

5.2.2.1 Factor difference at T_0

Duncan's multiple range test was used to determine which "common" factors had statistically different distributions within each time period at $p < .05$. Three environmental factors were significantly different from each other by category but none was significant in the linear regression at T_0 (see Table 5-2a). Suggesting differences in environments but not outcome argues for acceptance of the null from.

Table 5-2a: Duncan Multiple Range Analysis by PiLC at T_0 (no factors significant in the PiLC linear regression model)

Factor At T_0	*sign at < .05*	*short mean*	*medium mean*	*long mean*
F2: Dynamic change in fast growing market	short ≠ long	.2738	.0420	-.0975
F10: Exogenous timing variables	short ≠ long	.2453	.0204	-.2483
F18: Government/capital barriers	short ≠ medium long ≠ medium	.1428	-.2876	.0669

5.2.2.2 Prediction differences at T_0

Duncan's multiple range test was used to uncover significant differences in prediction for both the sorted aggregate models and the three PiLC models. For the sorted aggregate model, no group prediction or residual error distributions were significantly different from each other at the p=.05 level. Therefore, using the aggregate factors sorted by PiLC category to predict success/failure would not produce statistically different results. However, the three PiLC predictions demonstrate significant difference between medium and long model means at p=.05. This indicates that one should use different models at the initial screen subject to whether the product market had a medium or long PiLC. These differences in accuracy are significant, interesting and support the acceptance of H_2.

5.2.3 PiLC conditioned model at T_1

Table 5-1b exhibits the results of the three conditional linear regression procedures at T_1.

Table 5-1b: Linear regression conditioned by *PiLC* at T_1

p = PiLC model prediction; a = aggregate factors predicting success after sorting by category. Bold italics= not in aggregate models

Aggregate at T_1: R=.68961, R^2=.47556, Adj. R_2=.45450, F =22.57937 at .0000 with 10df Standard error = 2.28289 prediction accuracy rate = 83.8 %				
PiLC ***p= PiLC model*** ***a= Agg. Model***	*Factor*	*Description*	*Regression Coefficient*	*Model Fit*
SHORT: ***0-3 yrs.*** p=90.1% *correct* a=84.5% *correct*	F15 F2 F3	NPD history of failure Strategic reaction capability Superior product in large rapid growth market	1.639324 1.522217 1.218584	R=.77053, R^2=.59371, Adj. R^2=.54857, StdErr= 2.19779, F= 13.15189, Sig=.0000, 7df
	F10 F7 F4 F1 Constant	***Intense market competitiveness*** Marketing & management resource compatibility (synergy) Technological resource compatibility (synergy) ***Dynamic change***	***-1.013218*** .953863 .930960 ***.658222*** 1.368538	
MEDIUM >3&<=5 yrs. p=81.6% *correct* a=86.8% *correct*	F15 F2 F14 F11 Constant	NPD history of failure Strategic reaction capability NPD history of kills and success ***Satisfied customer with dominant competitor***	1.289708 1.032534 -.770734 ***-.627633*** 1.906633	R=.64116, R^2=.41108, Adj. R^2=.37790, StdErr=2.45847, F=12.38996, Sig=.0000, 4df
LONG >5 yrs. p=86.0% *correct* a=82.5% *correct*	F2 F5 F15 F14 F3 Constant	Strategic reaction capability New to the firm, didn't fit in NPD history of failure NPD history of kills and success Superior product in large rapid growth market	1.275299 -1.014396 .976890 -.788625 .777590 1.304038	R=.73641, R^2=.54229, Adj. R^2=.49742, StdErr=2.30608, F=12.08508, Sig=.0000, 5df

By observation, each T_1 model varies from the aggregate and from each other to a greater degree than the T_0 models. All appear sound, with one outlier found in the short model only. Compared to the PiLC models at T_0, there are more and new significant dimensions but still less than the aggregate model or NewProd. Whilst all models deserve confidence, the short and long are superior to the aggregate and more valid than NewProd[71]. At 90.1% and 86% accuracy respectively, they are more accurate than the aggregate T_0 model (81.15384%), T_1 model (83.84615%) and NewProd (84.1%). Bivariate prediction lines (see Figure 5-1b) show R^2 values improving by length of PiLC, as the residual errors become more normally distributed. The soundness of the seven factor short PiLC model is clear-cut, with R = .77053, R^2 = .59371, Adjusted R^2 = .54857 and a StdErr of 2.19779. This strongly supports the significance of factors conditionally "enabled" by PiLC (Day 1981) including the negative "intense market competitiveness" and the *new to the field and*

[71] Except model F values due to smaller category sample sizes.

Figure 5-1b: LINEAR REGRESSION PLC MODEL PREDCTION (T1)

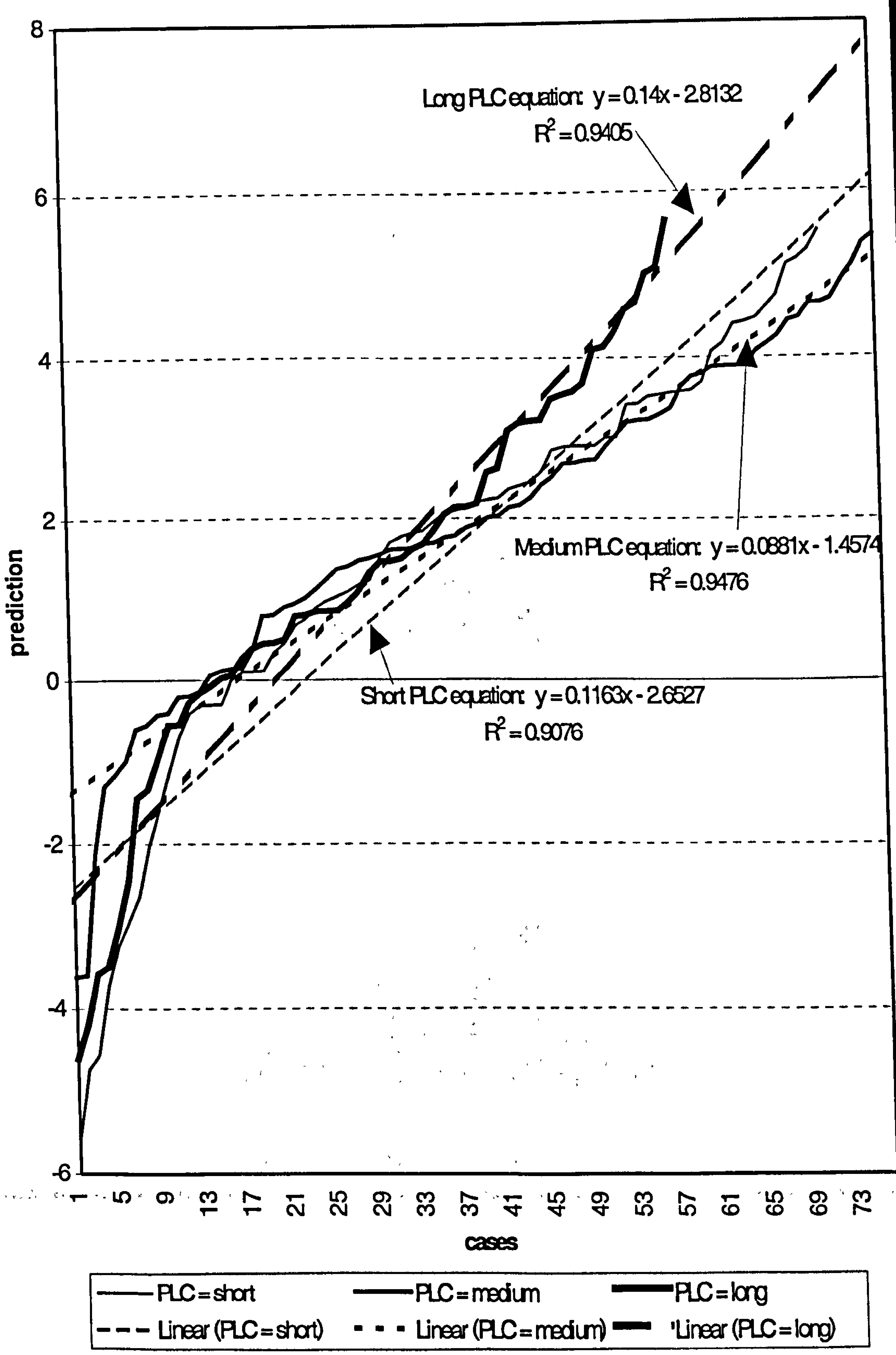
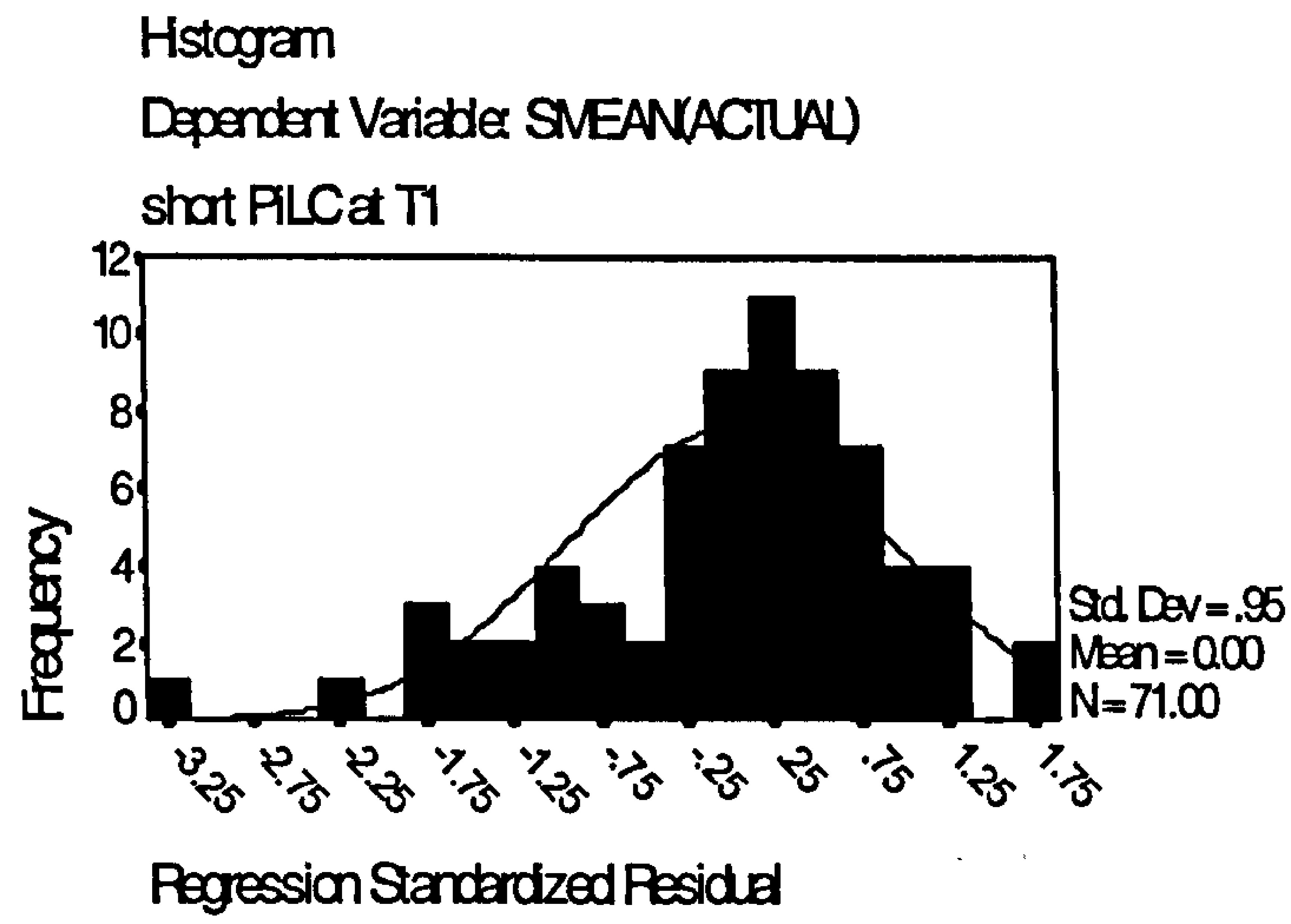
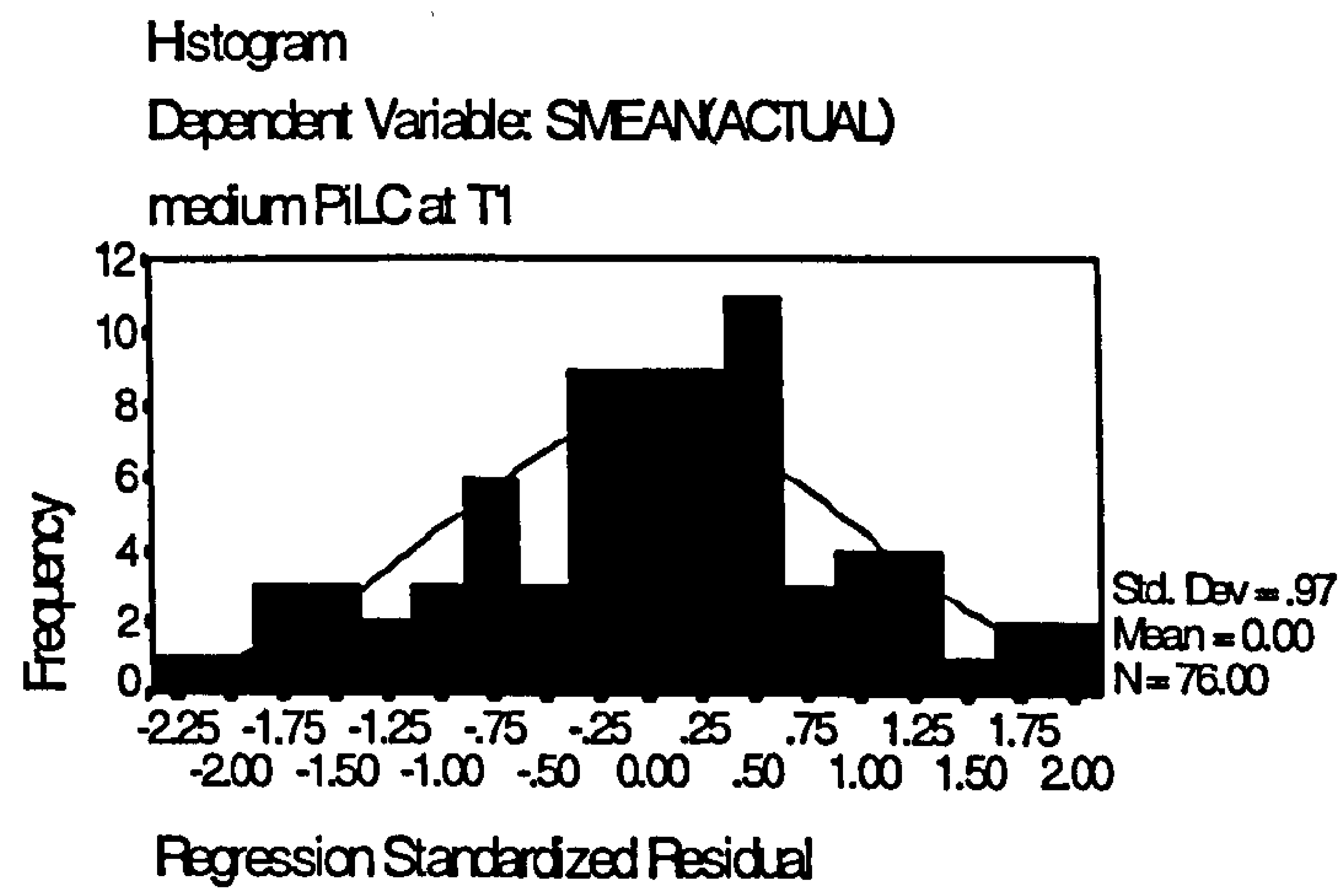


Figure 5-2c: P_iLC Histogram of residual error at T_1





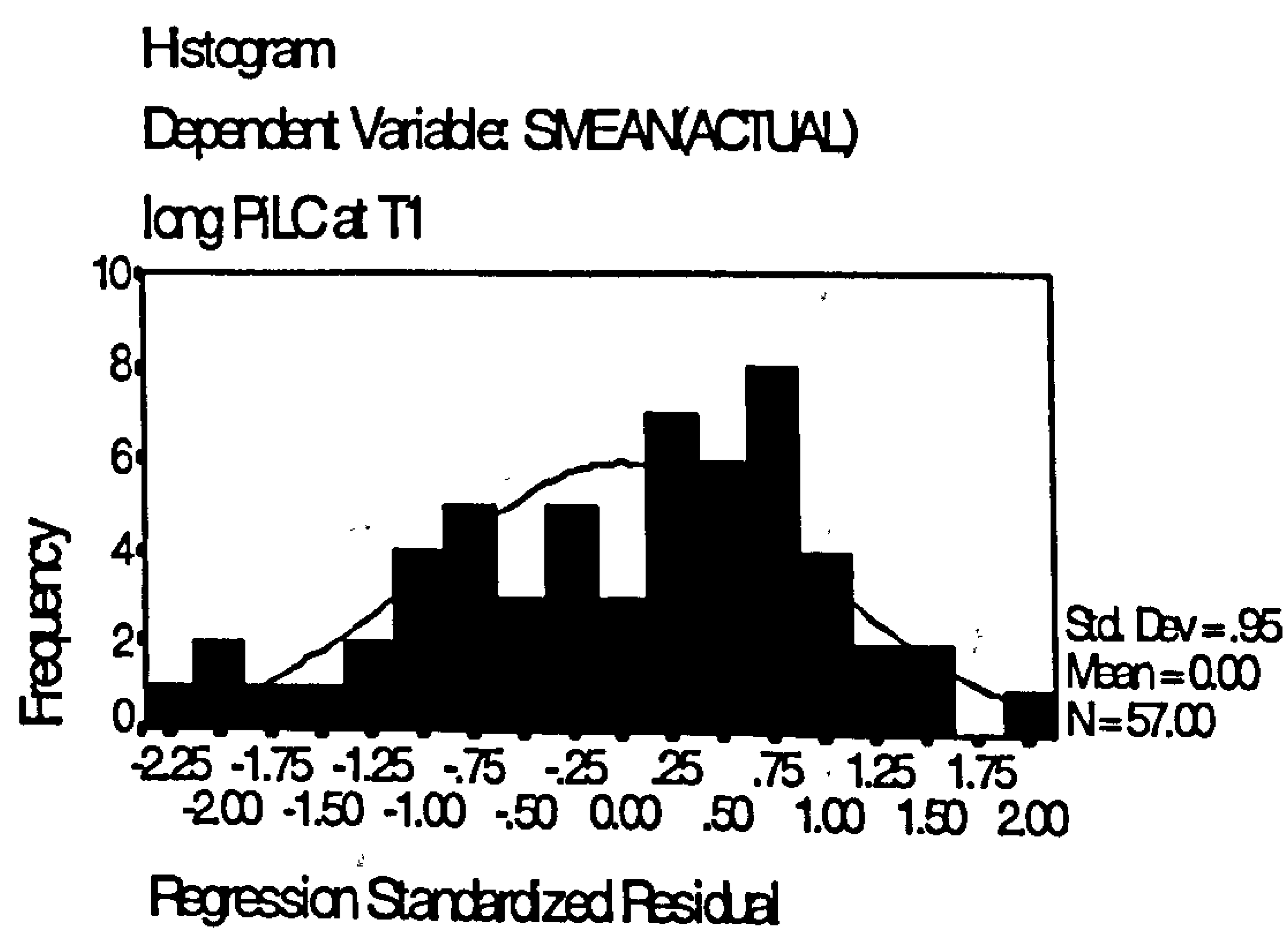
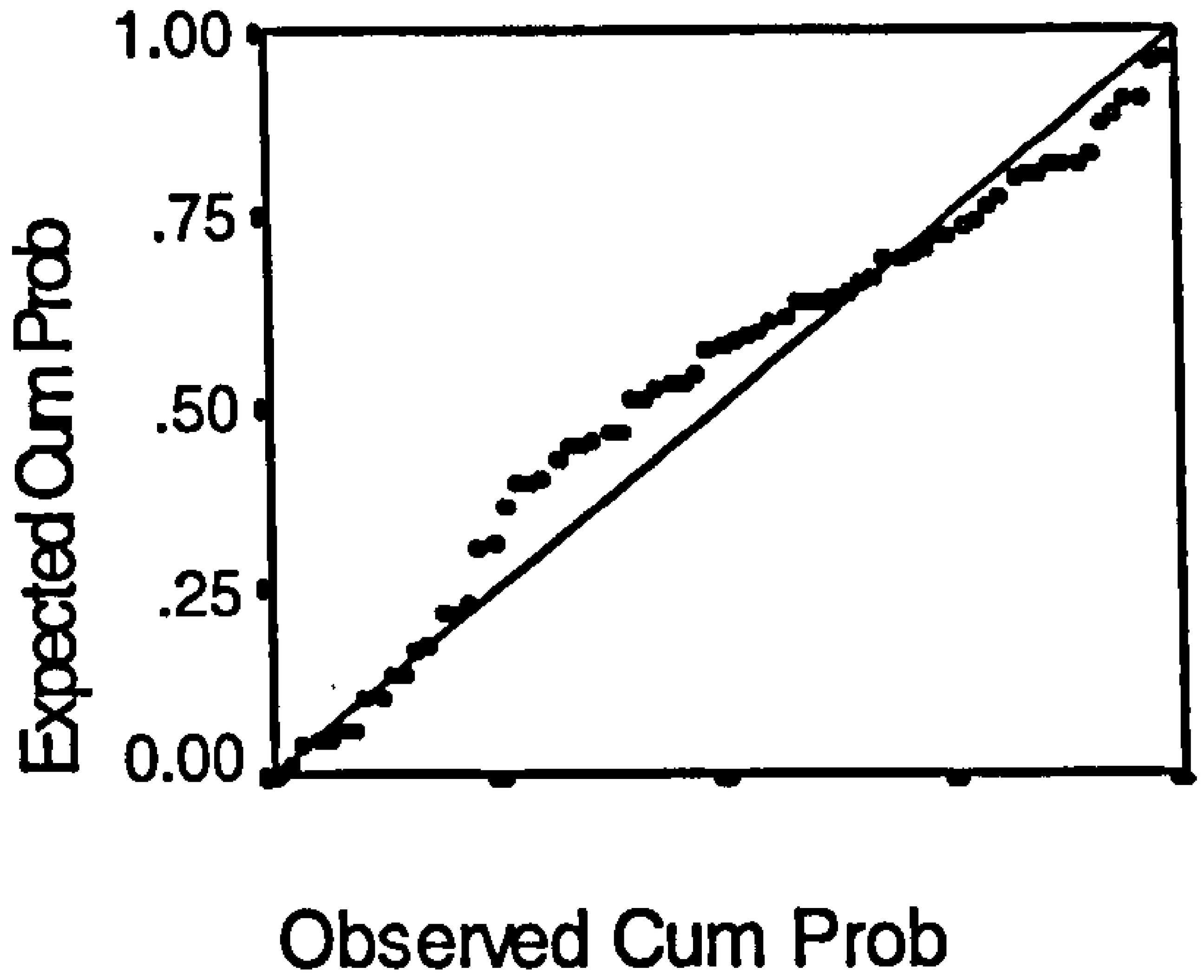
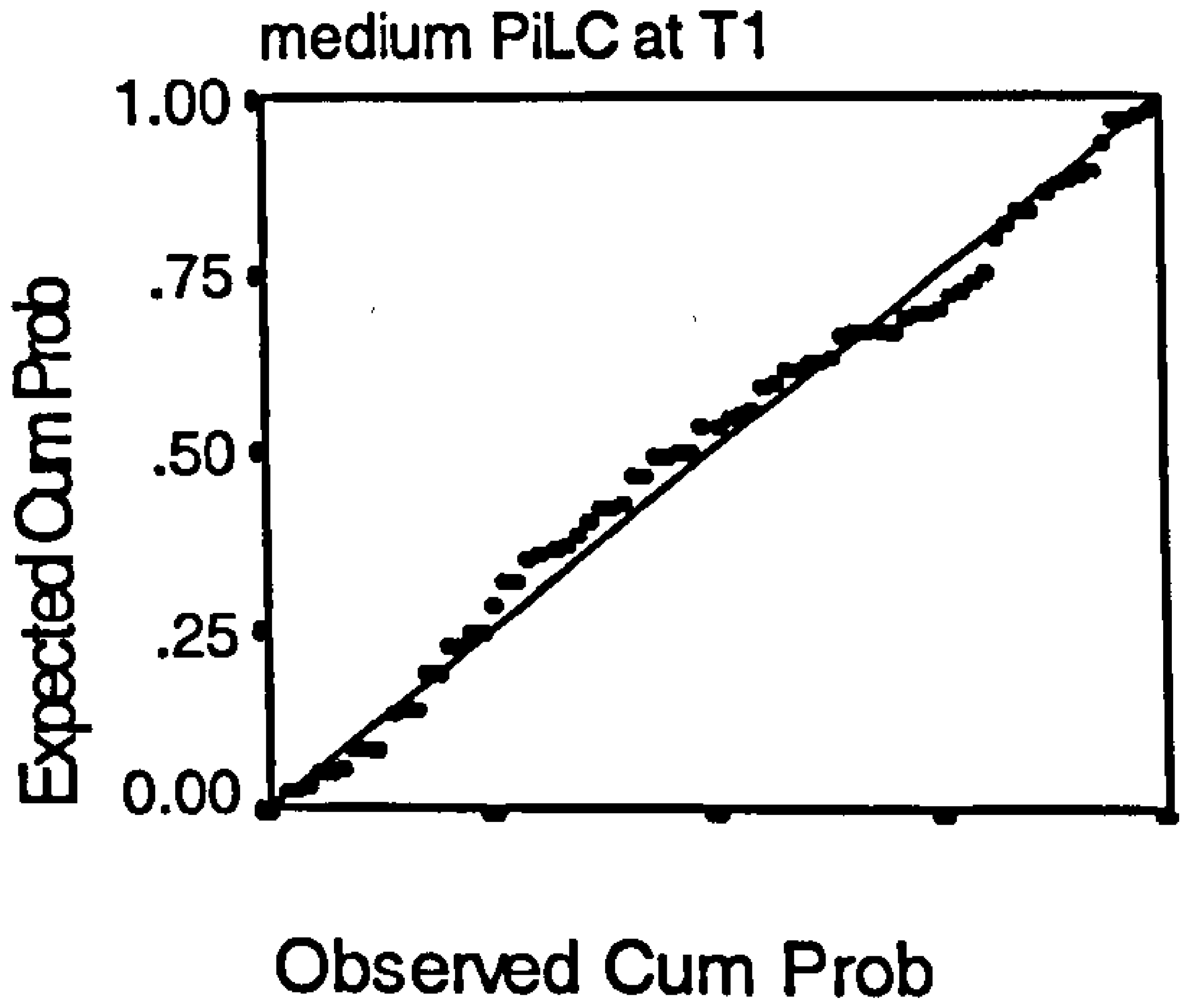


Figure 5-2d: Normalcy of residual error at T1 by PiLC

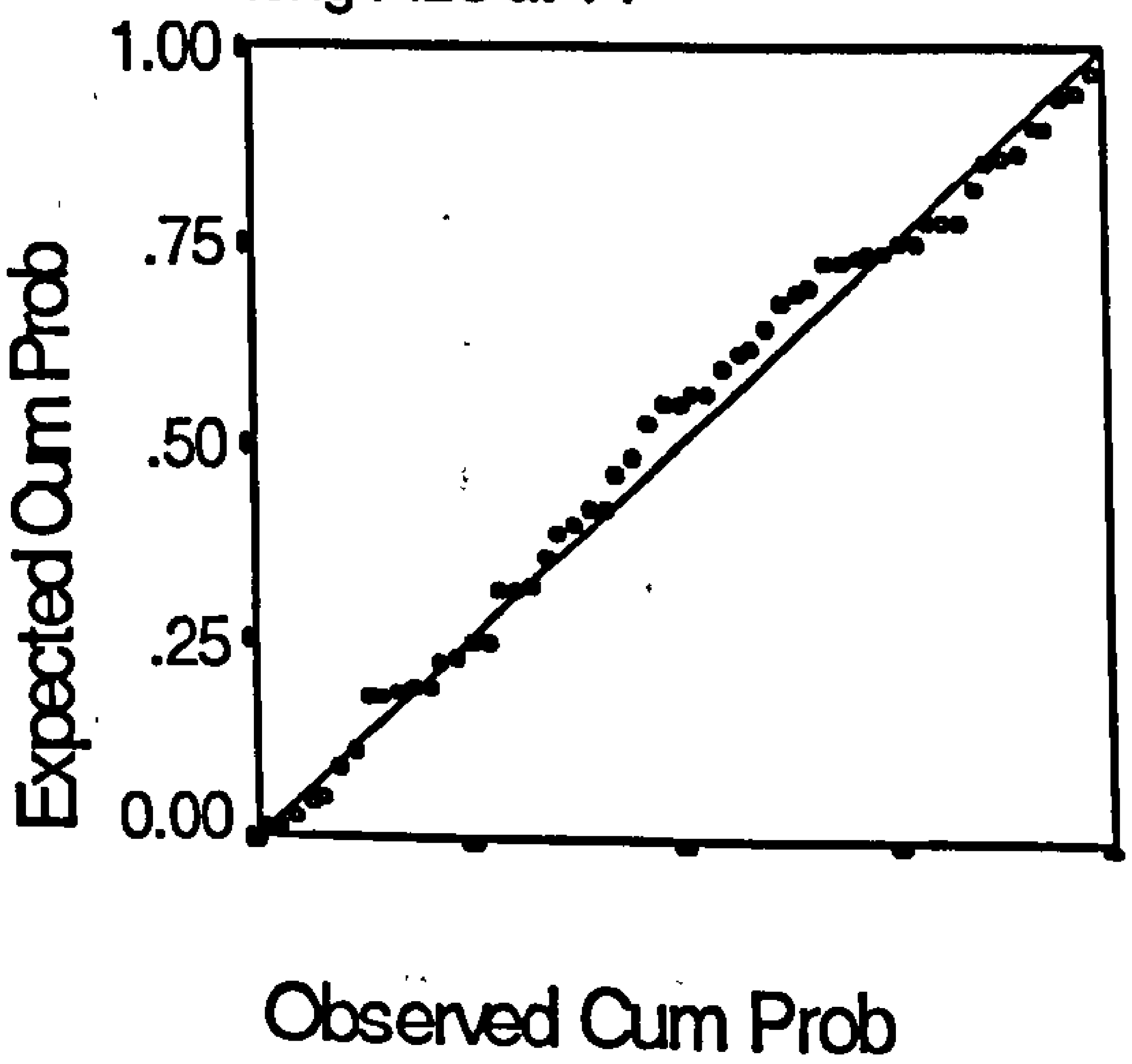
Normal P-P Plot of Regression Standardized Residual
Dependent Variable: SMEAN(ACTUAL)
short PiLC at T1



Normal P-P Plot of Regression Standardized Residual
Dependent Variable: SMEAN(ACTUAL)
medium PiLC at T1



Normal P-P Plot of Regression Standardized Residual
Dependent Variable: SMEAN(ACTUAL)
long PiLC at T1



positively signed "dynamic change". The acceptable medium model brings forth "satisfied customer with dominant competitor", a negative factor. With R = .73641, R^2 = .54229, Adjusted R^2 = .49742 and a standard error of 2.30608, the long model is also superior to both aggregates. Its validating statistics, with the exception of lower F values, are better than NewProd. Like the short model, the exceedingly high Adjusted R^2 statistic allows extrapolation to larger, similar product market populations. These striking differences also argue for acceptance of H_2.

5.2.3.1 Factor differences at T_1

Duncan's multiple range test yields statistically significant differences in six factors. F1, "dynamic change" and F11, "satisfied customer with dominant competitor" are significant in the linear regression PiLC models at T_1. "1st in" and "alertness" were significant to the aggregate models and "exogenous timing variables" and "government barriers" only environmentally different (see Table 5-2b). Difference based on PiLC suggests that issues are more complex than suggested by others (Cooper 1979b, 1981, de Brentani 1984, Zirger and Maidique 1990) and argues for acceptance of H_2.

Table 5-2b: Duncan Multiple Range Analysis by PiLC at T_1 *(bold italics = significant in linear regression by PiLC)*

Factor At T1	*sig. at < .05*	*short mean*	*medium mean*	*long mean*
F1: Dynamic change	***short ≠ medium*** ***short ≠ long***	***.3337***	***.0047***	***-.0983***
F6: 1st in new, highly innovative market	short ≠ medium	.1210	-.2402	.0161
F8: Alertness to threat of competitive retaliation	short ≠ long	.2329	.0369	-.1777
F9: Exogenous Timing Variables	short ≠ long	.1803	.0426	-.2764
F11: Satisfied customer with dominant competitor	***short ≠ long***	***-.2144***	***.0454***	***.2742***
F21: Government Barriers	long ≠ medium	.0220	-.2057	.3143

5.2.3.2 Prediction differences at T_1

Mean prediction distributions for the sorted aggregate models do not differ at the .05 level. Further, unlike the T_0 models, neither do the predictions differ by category. This argues for rejection of the hypothesis. However, important to practitioners, the short and long PiLC models at T_1 are better predictors actually, than either the aggregate model or NewProd and require far less information. Achieving higher levels of accuracy by estimating PiLC and then using the more parsimonious, more potent PiLC dimensions, is supportive of Levitt (1965, 1966).

5.2.4 Paired-samples t-test

Table 5-3 suggests that except for short failure cases, no PiLC categorical common factor distributions actually change over time. e.g. the "superior product" dimension for short PiLC successes at T_0 is the statistical equivalent of superior product at T_1, but the failure superior product dimension for short PiLC is different. Demonstrable at the .102 level, this provides weak evidence in support of H_2.

Table 5-3: Model of common factor comparison by success/failure over time ***Bold italics = significant at .1***

	Success means				Failure means				
Factor	*T0*	*T1*	*Diff*	*Sig.*		*T0*	*T1*	*Diff*	*Sig.*
SHORT n=51					***SHORT n=20***				
Superior product	.0644	.1438	.0794	.463		***-.3567***	***-.9866***	***-.6299***	***.102***
MED. n=57					***MED. n=19***				
History of Failure	.2683	.3187	.0504	.528		-.6807	-.6116	.0690	.633
Strategic reaction	.0782	.1645	-.0863	.311		-.6636	-.8015	.1380	.353
History of K&S	.1229	-.1110	-.2339	.375		-.3402	.2055	.5457	.206
LONG n=37					***LONG n=20***				
History of Failure	.0680	.0082	-.0598	.490		-.7467	-.5416	.2050	.183
Strategic reaction	.2655	.4046	-.1391	.281		-.4927	-.5491	.0565	.790
History of K&S	.1199	-.1065	-.2264	.393		-.3269	.3746	.7015	.151
New to Firm	-.2015	-.2270	.0255	.685		.5146	.5860	-.0713	***.435***

Table 5-4a, 5-4b and 5-4c depict change in categorical prediction over time. No predictions differ significantly in the aggregate. However, when sorted by success/failure, short PiLC predictions and complementary residuals do differ at p=.000 for both successes and failures. Similarly, long successes are different at p=.084. But medium case predictions and residuals are statistical equivalents for either success or failure.

Table 5-4a: Prediction means comparison by success/failure over time

	All cases prediction				*All case residual*			
	T0	*T1*	*Difference*	*Sig.*	*T0*	*T1*	*Difference*	*Sig.*
SHORT	1.8072	1.7854	.0218	.895	-.2718	-.2500	-.0218	.895
MEDIUM	1.6578	1.6353	.0225	.861	.2764	.2989	-.0225	.861
LONG	1.3393	1.4917	-.1523	.406	-.0937	-.2461	.1523	.406

Table 5-4b: Prediction means comparison by success/failure over time
(*bold italics* = significant at .05)

	Success means				*Failure means*			
	T0	*T1*	*Difference*	*Sig.*	*T0*	*T1*	*Difference*	*Sig.*
SHORT	***2.1502***	***2.6740***	***-.5238***	***.000***	***.9326***	***-.4804***	***1.4130***	***.000***
MEDIUM	2.2929	2.3941	-.1012	.457	-.2475	-.6412	.3938	.216
LONG	2.2327	2.6445	-.4118	.084	-.3134	-.6411	.3277	.234

Table 5-4c: Residual means comparison by success/failure over time
(*bold italics* = significant at .05)

	Success means				*Failure means*			
	T0	*T1*	*Difference*	*Sig.*	*T0*	*T1*	*Difference*	*Sig.*
SHORT	***1.2423***	***.7184***	***.5238***	***.000***	***-4.1326***	***-2.7196***	***-1.4130***	***.000***
MEDIUM	1.2685	1.1673	.1012	.457	-2.6999	-2.3061	-.3938	.216
LONG	1.1457	.7338	.4118	.084	-2.3866	-2.0589	-.3277	.234

The differences, especially between short PiLC success and failure cases, are supportive acceptance of H_2

5.2.5 Conclusion

PiLC categorisation by time period results in the dramatic reduction in the dimensions compared to the aggregate solutions or NewProd. Though tests yield mixed results, change occurs obviously, in factor selection by category both at T_0 and T_1. This argues for acceptance of H_2.

Further, two new and significant factors, "dynamic change" and "satisfied customer" are different statistically at T_1. Also, T_0 predictions are statistically different between medium and long models. These observable and empirically verifiable differences between the T_0 and T_1 PiLC models, along with obvious differences with aggregate models, argues for acceptance.

Categorisation by PiLC definitely differentiates the factors of success within and between time periods. Distinction, rather than similarity, is caused by this enabling dimension. Therefore, this Thesis accepts H_2, that success factors do vary as a function of the length of the product's introductory life cycle. The null form is thus rejected.

5.2.6 Discussion of H_2 findings

The operationalisation of PiLC avoided past problems whilst responding to calls for studying the moderating effect of selected variables on the NPD process (Cooper 1979b; Montoya-Weiss and Calantone 1994). With PLC as the catalyst, it also supported Day's (1981) enabling concept whilst producing fewer but more potent forecasting factors. However, though H_2 was accepted due to obvious gross model differences, small category sizes limits dimensional interpretation. Deep dimensional meaning in the discussion below is speculative and requires further study.

I. Accepting H_2 disputes those who disparage PiLC's usefulness in forming strategy (Dhalla and Yuspeh 1976; Lambkin and Day 1989; Thietart and Vivas 1984), thus validating its role as an enabling (Day 1981) and moderating (Cooper 1979b, 1981, 1984a) condition of success. Model and dimensions variance based on PiLC is consequential to both early and later strategy (Ansoff and Stewart 1967; Buzzell 1966; Catry and Chevalier 1974; Day 1981; Doyle 1976; Dodge and Rink 1978; Kotler 1980; Luck 1972; Michael 1977; Rink and Swan 1979; Tellis and Crawford 1981; Thorelli and Burnett 1981; Utterback and Abernathy 1975). Further, with short and long PiLC "exogenous timing variable" distributions statistically different at T_0, failure to account for product market cyclicality and seasonality characteristics vis-à-vis PiLC is a mistake.

II. Estimating product market PiLC (Levitt 1965, 1966) is important to creating parsimonious, accurate results and validates its importance as a framework for forecasting (Balachandran and Jain 1972; Cooke and Edmondson 1973; Kovac and Dague 1972; Parsons 1975). As PiLC lengthens, forecasting confidence and model error improves. This sheds light on PLC's importance in process time management (Cooper and de Brentani 1984). Validating its strategic role (Thorelli and Burnett 1981), PiLC models are more parsimonious than Cooper's eight (1981), nine (1992) or eleven dimensions (1979b) and Zirger and Maidique's (1990) eight dimensions. Combined with selected improvements in accuracy, less dimension investigation/activity should reduce cycle time as requested (Cooper 1994b, 1995; Millson, Raj and Wilemon 1992; Wind and Mahajan 1988). This should appeal to practitioners. Further, as time between innovations decreases (Bayus 1994), shorter PLC's may require even fewer screening dimensions, proclamations against taking shortcuts notwithstanding (Cooper 1988; Cooper and Kleinschmidt 1987b, 1988).

III. Multiple models that are easier to use (Albala 1975) may relate better to practitioners (Lilien 1975). Using more certain information germane to actual information availability states may be more appropriate in today's dynamic environments than static, deterministic methods. If PiLC is estimated, even less screening data may be required for "gate 1 or gate 2" gentle screens than previously thought (Cooper 1988, 1990a; Cooper and Kleinschmidt 1987b, 1991). This would allow more but gentler screens on a wider array of opportunities, thus optimising research resources.

IV. Model choice depends on the team's ability to accurately predict expected PiLC T_0 and T_1 dimensions and the expected value of imperfect information (EVII) based on the expected cost of errors (ECE). Model choice is appropriate only for those prepared to forecast all dimensions accurately and perform all activities required effectively and efficiently. Conditional PiLC models signal lower initial investment with project continuance based on probability of dimensional attainment. Requiring "just the right" information (like just-in-time inventory management; Meredith 1992) at exactly the right time would lower the ECE and increase EVII. This may improve ease of use, utilisation and success rates.

5.3 Hypothesis H_3

Factors significant in contributing to a new product's successful introduction vary as a function of its order of entry and related level of innovativeness.

5.3.1 Introduction

H_3 deals with changes important to success as the combination of entry order and relative level of innovation is controlled. To validate hypothesis H_3, Factor 5 at T_0 and Factor 6 at T_1 were divided into three almost equal categories and labelled 1st/high (n=86 at T_0; n=87 at T_1), middle/medium (n=88 at T_0; n=87 at T_1) and late/low (n=86 at T_0; n=86 at T_1). This was rigorous because the factor distribution at each time period approached normalcy and at both T_0 and T_1, exactly the same variables in exactly the same order with very similar loadings described the dimension "1st in new, highly innovative market". Linear regression was used again to construct models for these three categories at each time period. Factor 5 at T_0 and factor 6 at T_1 were excluded from the factor analysis. After noting obvious function differences, Duncan's multiple range test and a paired-samples t-test were used as in H_2 above, to verify factor differences within and between the time periods. Prediction

Figure 5-3a: ORDER Histogram of residual error at T_0

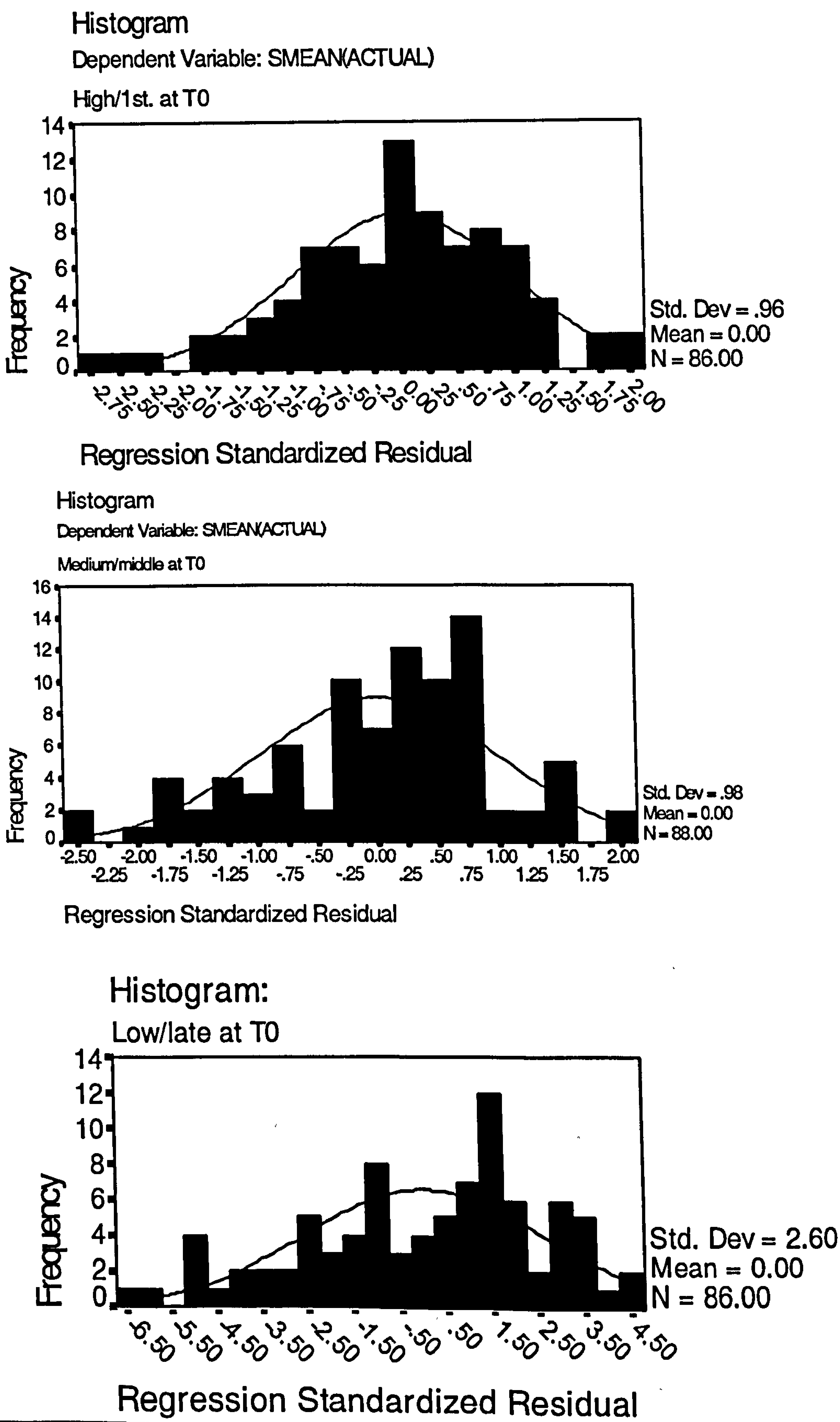


Figure 5-3b: Normalcy of residual error T(0)

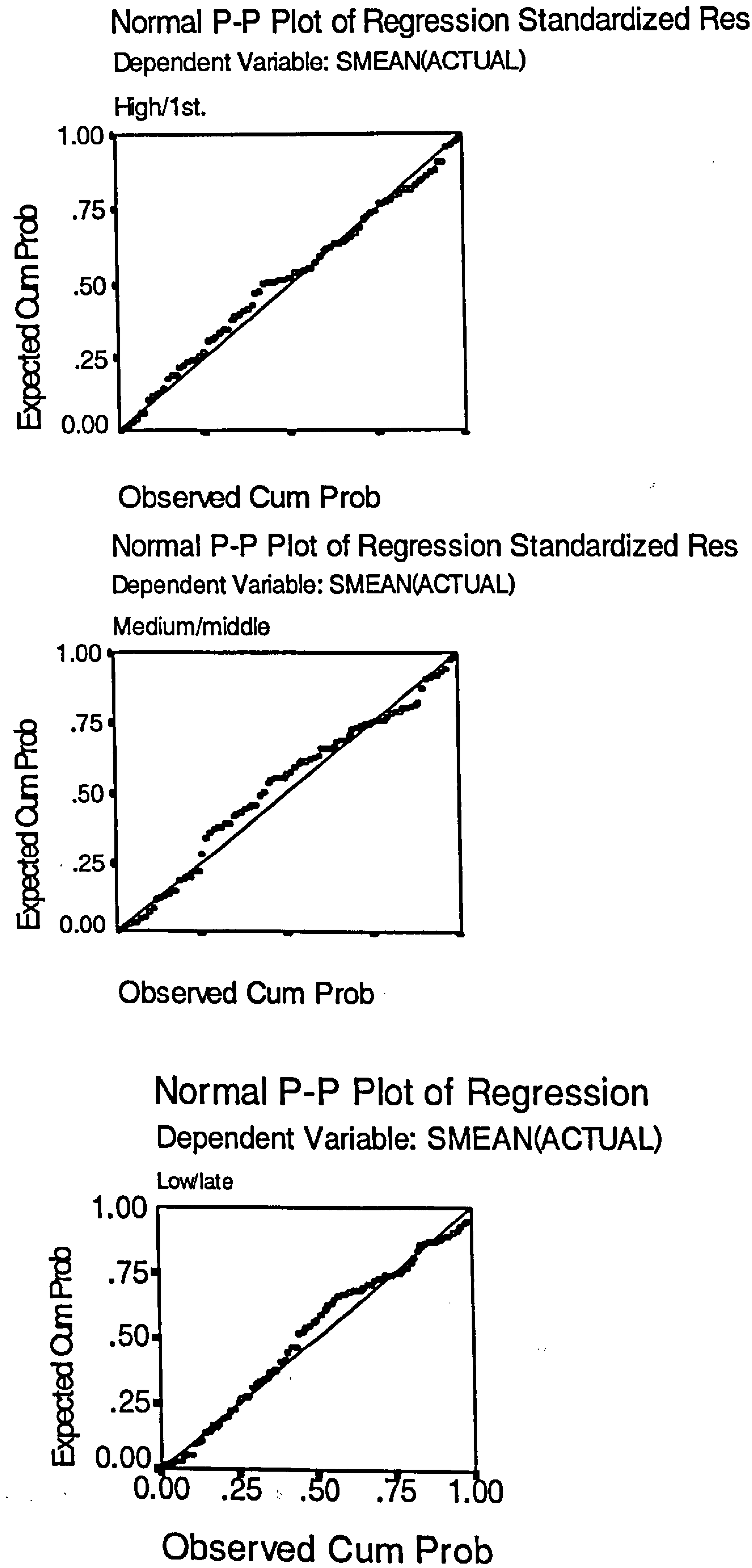


Figure 5-4a: LINEAR REGRESSION ORDER MODEL PREDICTION
T(0)

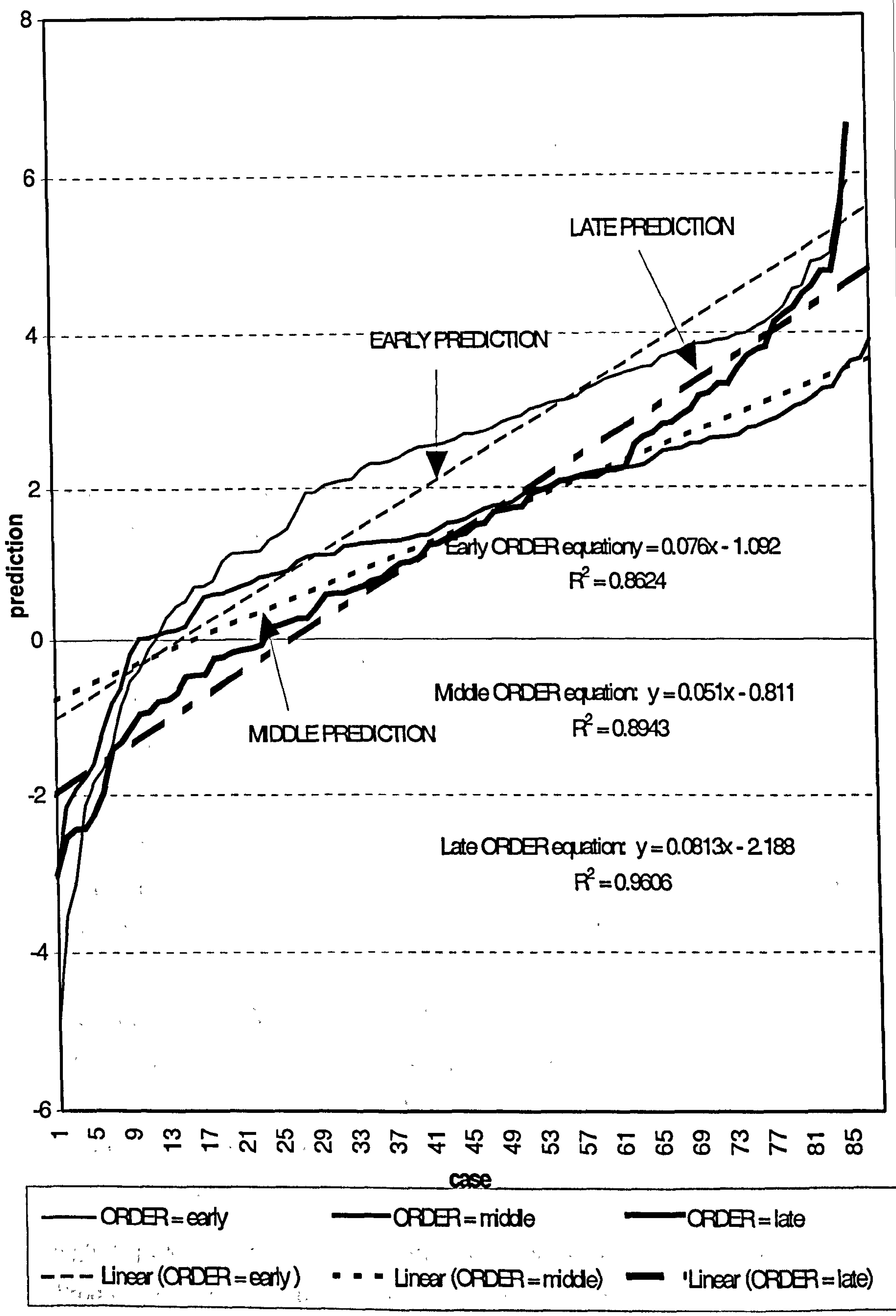


Table 5-5a: Linear regression conditioned by *order/innovation* at T_0

p = order/innovation prediction; a = aggregate factors predicting success after sorting by category ***BOLD italics = not in aggregate models***

Aggregate at T_0: R=.56589., R^2=.32023, Adj. R_2=.29857, F =14.78065 at .0000 with 8df, Std error = 2.58869 prediction accuracy rate = 81.2%

p=order/innovation model a= Agg. Model	*Factor*	*Description*	*Regression Coefficient*	*Model Fit*
1st high (Top 1/3 of factor) p=88.4 % a=87.2 %	F13	***Innovative strategy in highly competitive market***	***-1.522378***	R= .69861, R^2= 48806, Adj. R^2= .44211, StdErr= 2.18485, F= 10.62295, Sig=.0000, 7df
	F17	NPD history of failure	1.461672	
	F2	Strategic reaction capability	.794427	
	F4	New to the firm, didn't fit in	-.690323	
	F20	***Long life cycle high price/high quality strategy***	***-.527181***	
	F11	***Moderate innovation***	***.489349***	
	F7	Alertness to threat of competitive retaliation	.474390	
	Constant		1.836052	
Middle/medium (Middle 1/3 of factor) p=72.7% a=77.3 %	F2	Strategic reaction capability	1.021367	R=.45458, R^2=.20664, Adj. R^2=.17830, StdErr=2.74777, F=7.29289, Sig=.0002, 3df
	F17	NPD history of failure	.907352	
	F4	New to the firm, didn't fit in	-.646658	
	Constant		1.489603	
Late/low (Bottom 1/3 of factor) p=77.9 % a=79.1%	F17	NPD history of failure	1.290947	R=.60850, R^2=.37027, Adj. R^2=.33917, StdErr=2.65916, F=11.90672, Sig=.0000, 4df
	F16	NPD history of kills and success	1.238716	
	F9	***Satisfied, competitive market***	***-.854376***	
	F7	Alertness to threat of competitive retaliation	.765716	
	Constant		1.479023	

and residual error distribution differences were determined by success/failure category and by paired-samples t-tests between time periods.

5.3.2 Order/innovation conditioned model at T_0

Table 5-5a exhibits the results of the three conditional linear regression models at T_0. By observation, the three models vary in construction and validity from both the aggregate and each other. Like the PiLC conditioned models there are fewer but more powerful dimensions compared to either aggregate.

Figure 5-3a and figure 5-3b suggest the 1st/high function is superior to the others. However, figure 5-4a illustrates rising R^2 values of the bivariate predictions as order/innovation decreases. This is logical and suggests that the later one enters, the more predictive accuracy variation is explained by the model. However, caution is warranted since the predictive accuracy of the late/low model is significantly different from only the 1st/high. Conversely, the 1st/high model's wider predictive variation, suggests pioneering dimensions are more difficult to assess - and deliver. Logical again, being 1st with a new-to-the-world product based on speculative early information is not easy. But if possible, the dimensions are powerful in both prediction and effect.

The high Adjusted R^2 value of .4421 compared to the aggregate (.29857) and NewProd (.395) combine with the lowest Standard Error of any model in this work (2.18485). These indicate that extrapolation of 1st/high constructs to similar, larger populations is judicious. Featuring an 88.4% accuracy rate at the initial screen, planning to enter early with a new-to-the-world product whilst duplicating the seven dimensional states of nature should lead to exceptionally accurate forecasting results and produce high levels of success at one year post launch.

Though both the middle/medium and late/low models are inferior to NewProd, prediction accuracy and validity was higher than the aggregate model at T_0 overall. Abnormal residual error is noted for the poorly performing middle category (see Figure 5-3a), with the least amount of residual distortion exhibited by the 1st/high model (see Figure 5-3b). This suggests that being "caught in the middle" at T_0 may not be an attractive position (Aaker and Day 1986; Hannan and Freeman 1977; Kleinschmidt and Cooper 1991; Porter 1980, 1985). No outliers were found in any of the models.

The absence of "superior product" from any of the categories at T_0 is a very provocative result. It sustains the aggregate T_0 result that creating a truly superior product at the initial screen is difficult; especially when one must be first in and new-to-the-world. Its absence casts greater doubt concerning seminal measurement timing error in NewProd. Keeping in mind this work's "beginner bias" it suggests that: (1) when conditioned by entry and innovation, other factors take precedence; (2) entry success may differ from long lasting success and (3) to be successful initially, being early and innovative may be more important than being competitively superior and truly utilitarian.

Compared to the inadequate one dimension short T_0 PiLC model suggesting little besides superior product was important, this model's seven dimensions are a clear prescription as to what must be done to achieve the 88.4% accuracy rate <u>even without having a "superior product"</u>. New factors absent in the aggregate model include "innovative strategy in highly competitive market", "long life cycle high price/high quality strategy" and "moderate innovation". Taken together, the three new dimensions suggest that if one intends to be first with a new-to-the-world product, one should not spend time strategising about the problems of being innovative in a crowded field. Rather than wasting resources developing a high priced, high quality, long lived superior entry, one should put the innovation into play early. As discussed in section 5.3.6, these dimensions sustain beliefs concerning innovation charters, protocols (Crawford 1984, 1986, 1994) and robust designs (Urban and von Hipple 1988) which evolve over time in response to user input and in the context of planned families of up-rated products designs. Failing to get in the game may condemn the "truly superior, long lived, high priced product" to being "caught in the middle."[72]

The middle model is a less certain predictor. It suggests those actually "caught" can benefit by strategic product positioning to avoid failure (Hopkins 1980). It validates strategic choices affecting profitability and growth for market followers (Buzzell and Gale 1987; Lambkin 1988; Levitt 1965, 1966; Urban, Carter, Gaskin and Mucha 1986). It confirms that market pioneers, early followers and late entrants have different skill and resource profiles (Robinson, Fornell and Sullivan 1992) yielding comparative advantage different from, but not inferior to, earlier entrants (Abell and Hammond 1978). This should be welcome news to those requesting follower strategies (Kerin, Varadarajan and Peterson 1992; Liberman and Montgomery 1988).

With only four dimensions, the late/low model is similar in validity to NewProd's eleven and eight factor solutions yet it is 77.9% accurate. The dimensions overlap the aggregate model suggesting that if one fails to learn history lessons, strategic reaction and alertness are required to compensate for being late with mundane offerings. It suggests also, that if one is late and low in innovativeness, one must not enter a market satisfied with competitive products.

The new and different factor selection, combined with validity differences, argues for acceptance of H_3.

5.3.2.1 Factor difference at T_0

Duncan's multiple range test uncovered only one factor different by condition. Noted in Table 5-6a, "overall project/company resource compatibility" is not significant to the T_0 function and argues for rejection of H_3.

Table 5-6a: Duncan Multiple Range Analysis by ORDER at T_0

(italics means significant in linear regression by ORDER)

Factor at T_0	*significant at < .05*
F3: Overall project/company resource compatibility	early ≠ middle (and) middle ≠ late

5.3.2.2 Prediction differences at T_0

Duncan's multiple range test for sorted aggregate predictions suggests the 1[st]/high prediction mean distribution is statistically different from the middle/medium distribution. This cautions that using sorted aggregate factors changes predictive

72 An example of launching (prematurely) a less than perfect product was given recently by Lew Pacley, P6 (chip intended to replace the infamous, error prone Pentium) product manager for Intel Corp. In response to questions concerning heat, size and price, Mr. Pacley stated "The most important thing we can do is get the chip working and get it out". "The heat and size will drop in succeeding generations" (the implication being that the chip is only the first of many improved chips to follow in the design family. The first P6 chips will be followed by smaller, cooler, less expensive iterations from a new process not yet in place. The small amounts of less than superior product was launched to head off the competition from PowerPC based machines (PC Week 1995).

Figure 5-3c: ORDER Histogram of residual error at T_1

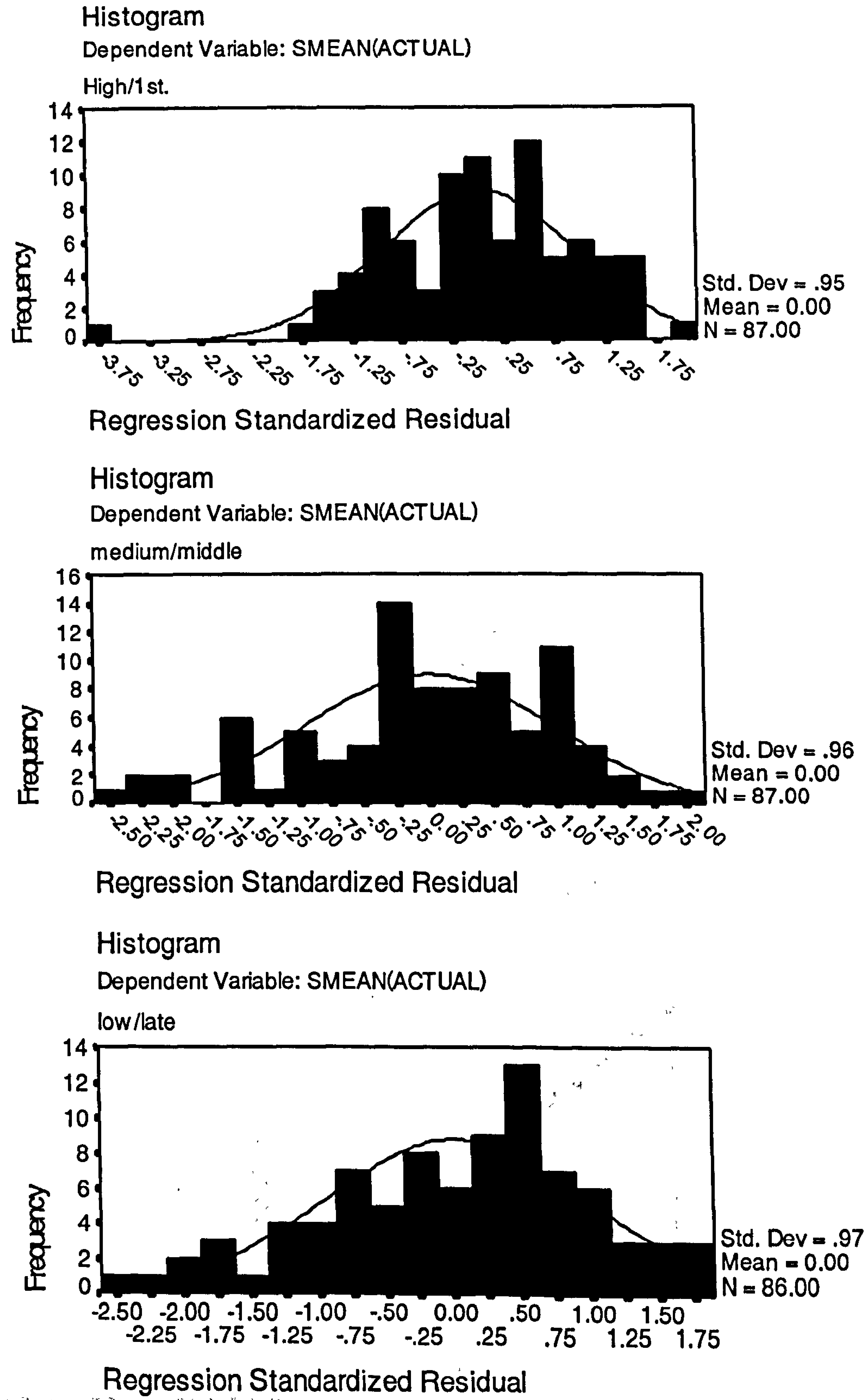


Figure 5-3d: Normalcy of residual error T(1)

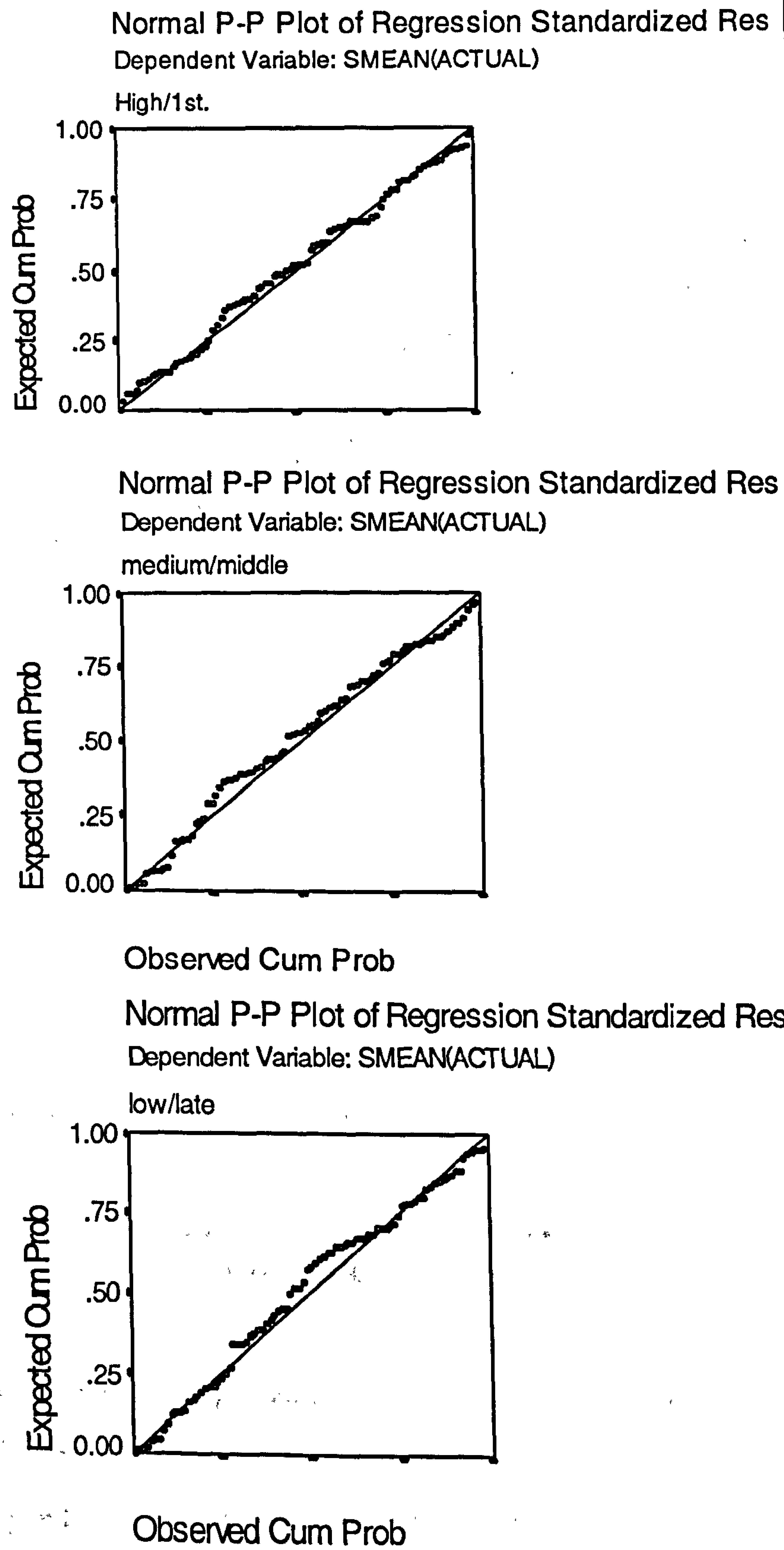
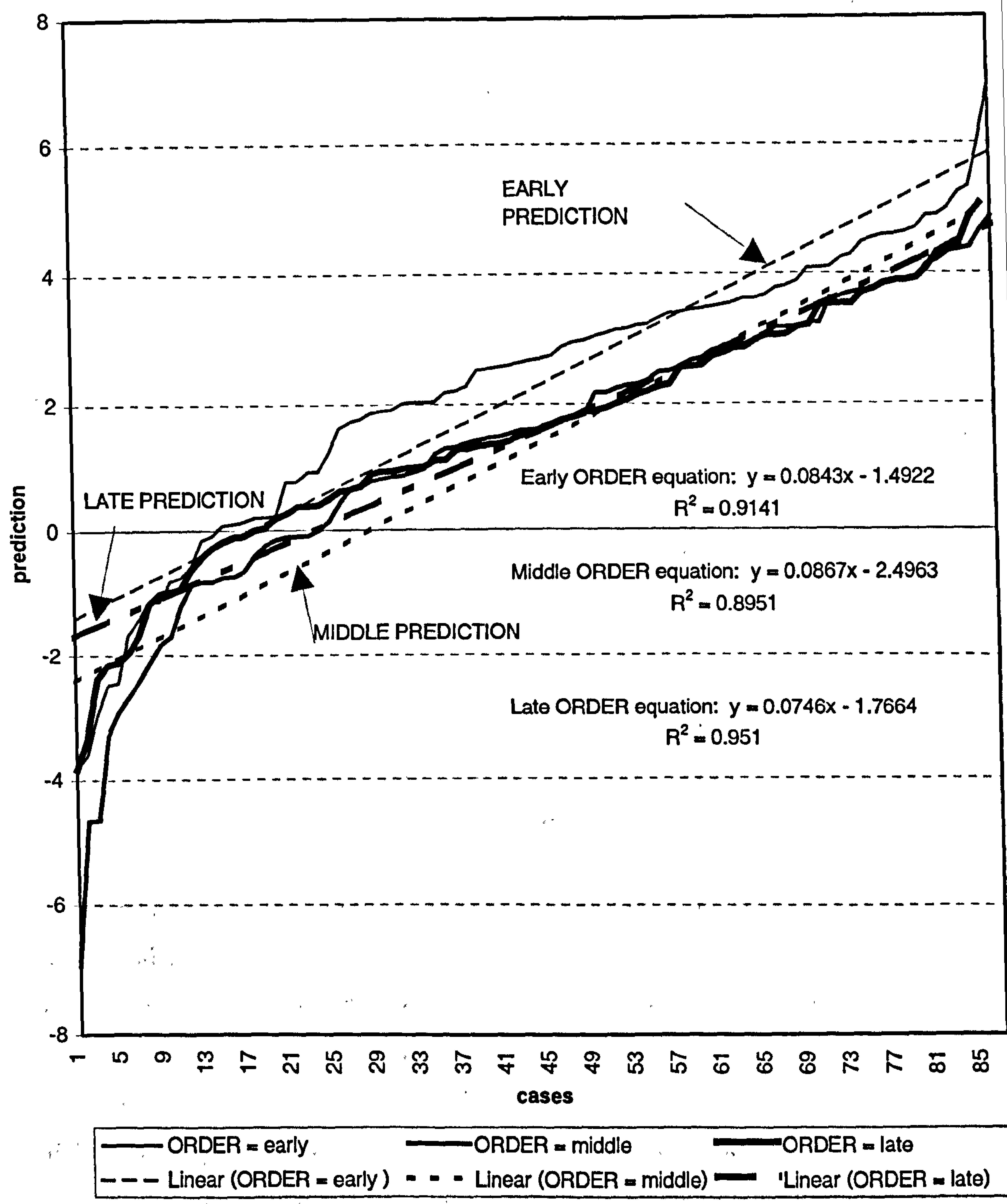


Figure 5-4b: LINEAR REGRESSION ORDER MODEL PREDICTIONS
T(1)



results, questions the wisdom of using aggregate "one size fits all" models such as NewProd or Stanford and argues for acceptance of H_3.

Represented graphically in Figure 5-4a, the early 1st/high prediction mean is statistically different from both the middle/medium and late/low means at the .05 level. This suggests strongly that if one is the pioneer, the 1st/high model and factors should be used to the exclusion of the middle/medium and late/low model. If one follows, either the middle/medium or the late/low model will yield statistically equivalent predictive mean distributions. These differences indicate that order/innovation is an enabling condition (Day 1981) of forecasting and dimension selection. This argues for acceptance of H_3.

5.3.3 Order/innovation conditioned model at T_1

Table 5-5b exhibits the results of the three conditional linear regression models at T_1.

Table 5-5b: Linear regression conditioned by *order/innovation* at T_1

p = order/innovation prediction; a = aggregate factors predicting success after sorting by category BOLD italics = not in aggregate models

Aggregate at T1: R=.68961, R^2=.47556, Adj. R_2=.45450, F =22.57937 at .0000 with df Std error = 2.28289 prediction accuracy rate = 83.8 %				
p=order/innovation model a= Agg. Model	***Factor***	***Description***	***Regression Coefficient***	***Model Fit***
1st/high: *(Top 1/3 of factor)* p=86.2 % a=87.4 %	F2	Strategic reaction capability	1.221241	R=.75437, R^2=.56908, Adj. R^2=.52488, StdErr=2.03578, F=12.87591, Sig=.0000, 8df
	F15	NPD history of failure	.832008	
	F7	Marketing & management resource compatibility (synergy)	.766623	
	F8	Alertness to threat of competitive retaliation	.667318	
	F3	Superior product in large rapid growth market	.607842	
	F5	New to the firm, didn't fit in	-.580374	
	F14	NPD history of kills and success	-.527212	
	F18	Relative high price of product	-.499475	
	Constant		1.980090	
Middle/medium *(Middle 1/3 of factor)* p=88.5 % a=86.2 %	F2	Strategic reaction capability	1.253960	R=.73505, R^2=.54030, Adj. R^2=.50582, StdErr=2.21350, F=15.67086, Sig=.000, 6df
	F3	Superior product in large rapid growth market	1.128727	
	F15	NPD history of failure	.871117	
	F18	Relative high price of product	-.742537	
	F5	New to the firm, didn't fit in	-.697598	
	F11	***Satisfied customer with dominant competitor***	***-.531555***	
	Constant		1.751458	
Late/low *(Bottom 1/3 of factor)* p=80.2 % a=77.9 %	F15	NPD history of failure	1.276861	R=.61038, R^2=.37257, Adj. R^2=.33335, StdErr=2.55363, F=9.50070, Sig=.0000, 5df
	F14	NPD history of kills and success	-.935726	
	F2	Strategic reaction capability	.858688	
	F3	Superior product in large rapid growth market	.822757	
	F5	New to the firm, didn't fit in	-.735710	
	Constant		1.245331	

Again by observation, the solutions are quite different from the aggregate model and from each other. Two of the three T_1 solutions are superior to the aggregate solution and more accurate and valid than NewProd. The 1st/high model, with an Adjusted R^2 of .52488 and accuracy of 86.2%, would be particularly applicable to similarly profiled populations. Rising dramatically from its T_0 position, the middle/medium model has an Adjusted R^2 of .50582 and is 88.5% accurate. The reason for this large rise in validity and accuracy is speculative, important and addressed in section 5.3.6 below. True of all conditional models, the number of success dimension is less than for the aggregates or NewProd. These differences argue for acceptance of H_3.

Overall, the residual error is distributed reasonably and commonly for all functions (see Figure 5-3c and 5-3d). This, in combination with the different but similar slopes of the bivariate prediction lines (see Figure 5-4b), argues for rejection of H_3. The predictions deviate from each other less than at T_0 (see Figure 5-4a). Like the T_0

predictions, the late/low model has the highest R^2. Caution is in order again since its accuracy is not statistically different from either of the others. With one outlier found for the 1st/high, the models are sound.

The 1st/high model is superior in validity and similar in accuracy to the short PiLC model. It is remarkable in its potential for extrapolation to large populations and it demonstrates strategies for pioneers capable of forecasting and implementing correctly, the eight dimensional states of nature at T_1. This again supports its use to alter the factors of success and if desired, change a deterministic history. Even more remarkable, the T_1 middle/medium solution's evolution, highlighted by the leap in importance of superior product, suggests that waiting to develop a better product with better strategic options can be a very successful strategy for some (Buzzell and Gale 1987; Lambkin 1988; Levitt 1965, 1966; Urban, Carter, Gaskin and Mucha 1986). Clearly, those "caught in the middle" (Aker and Day 1986; Kleinschmidt and Cooper 1991; Porter 1980, 1985) are not without opportunity. The late/low solution is quite similar to the late/low solution at T_0, with deterministic history dominating both. Being late with little innovativeness clearly limits one's strategic options. These dimensional differences support acceptance of H_3.

5.3.3.1 Factor difference at T_1

Duncan's multiple range test demonstrates that in the middle model, Factor 11 "Satisfied customer with dominant competitor", differed between 1st/high and late/low models (see Table 5-6b). This argues for acceptance of H_3.

Table 5-6b: Duncan Multiple Range Analysis by ORDER at T_1

(italics means significant in linear regression by ORDER)

Factor at T_1	*significant at < .05*
F11: Satisfied customer with dominant competitor	*early ≠ middle* *middle ≠ late*

5.3.3.2 Prediction differences at T_1

Duncan's multiple range test revealed a significant difference between 1st/high and middle/medium predictions at the .05 level in the sorted aggregate order/innovation models. These findings agree with the results for this test at T_0 and suggest that forecasts using the aggregate, NewProd or Stanford models may shroud prediction differences resulting from order/innovation conditional differences. The 1st/high order/innovation model prediction differed from both the middle/medium and the late/low distribution mean. The same as the T_0 result, this suggests again that for best results, the 1st/high model should be used by pioneers to the exclusion of the other two order/innovation models.

5.3.4 Paired-samples t-test

"Common" factors were tested for change between T_0 and T_1. Ranking at T_0 was used to categorise the cases. Table 5-7 indicates that no factors appearing to be similar over time are actually different in their distribution patterns at the p=.05 level. "New to the firm" for the 1st/high failed case distribution is statistically different over time at the .095 level. "Strategic reaction" for middle/medium failure cases is different at the .079 level. And "retaliation" for the 1st/high success cases is different at the .103 level. New to the firm and strategy being significant to the models suggests that "common" factors differ over time. This argues for acceptance of H_3.

Table 5-7: Model of common factor comparison by success/failure over time

	Success means				*Failure means*				
Factor	***To***	***T1***	***Diff***	***Sig.***		***To***	***T1***	***Diff***	***Sig.***
1st/high n=69					***1st/high n=17***				
History of failure	.2867	.2758	-.0109*	.870		-.5816	-.3395	.2421	.159
Strategic reaction	.2356	.2804	-.0448	.483		-.3726	-.6881	.3155	.222
New to the firm	-.0442	-.0819	.0377	.474		***.6901***	***.8662***	***-.1762***	***.095***
Retaliation	***.2358***	***.1120***	***.1238***	***.103***		-.5673	-.5534	-.0140	.943
Middle/medium n=63					***Middle/medium n=25***				
History of failure	.1509	.0730	-.0778	.330		-.5090	-.3787	.1303	.325
Strategic reaction	.0496	.1072	-.0576	.514		***-.4188***	***-.6466***	***.2278***	***.079***
New to the firm	-.1835	-.1855	.0020	.963		-.0124	.0334	-.0458	.559
Late/low n=58					***Late/low n=28***				
History of failure	.1827	.1620	-.0207	.800		-.6169	-.6354	-.0185	.859
History of K&S	.1704	-.1738	-.3442	.183		-.3294	.3236	.6530	.119

* - the absolute difference in the history dimension results from the factor's slightly different construction at T_1.

Table 5-8a examines model categorical prediction mean distributions over time. The middle/medium failure mean does vary over time. This indicates that prediction accuracy for failed cases can vary by model selection i.e. using the T_0 middle/medium model rather that its T_1 counterpart will give failed cases statistically different accuracy results.

Table 5-8a: Model prediction means comparison by success/failure over time *Bold italics = significant at p=.05*

	Success means				*Failure means*				
	To	***T1***	***Difference***	***Sig.***		***To***	***T1***	***Difference***	***Sig.***
1st/high n=56	2.8370	2.9359	-.0989	.493	1st/high n=13	-.5506	-.8426	.2920	.528
middle/ medium n=37	1.7237	2.0615	-.3378	.135	***middle/ medium n=16***	***.3248***	***-.5501***	***.8749***	***.032***
late/low n=47	2.2596	2.1953	.0644	.768	late/low n=21	-.2821	-.4550	.1729	.617

The residual error differences in Table 5-8b supports those in Table 5-8a and also demonstrates that residual error goes down over time. T_1 models are more valid and preferable all else being equal. Also, the middle/medium failure residual error, different at p=.032, supports the difference in the middle/medium prediction above. These prediction and residual error differences over time supports acceptance of H_3.

Table 5-8b: Model residual means comparison by success/failure over time ***Bold italics = significant at p=.05***

	Success means				*Failure means*				
	To	*T1*	*Difference*	*Sig.*		*To*	*T1*	*Difference*	*Sig.*
1st/high n=56	.6513	.5524	.0989	.493	1st/high n=13	-2.4494	-2.1574	-.2920	.528
middle/ medium n=37	1.2674	.9296	.3378	.135	**middle/ medium n=16**	**-3.3873**	**-2.5124**	**-.8749**	***.032***
late/low n=47	1.1872	1.2515	-.0644	.768	late/low n=21	-2.5751	-2.4021	-.1729	.617

5.3.5 Conclusion

These results demonstrate that when aggregate models are conditioned by order/innovation, model validity, significant factors and model accuracy differ by category. Controlling for order/innovation tends to reveal dimensional changes and new factors/variables having interesting ramifications vis-à-vis the aggregate model findings and seminal works. Some differences are also observed in "common" factors also. This argues for H_3 acceptance. Clearly, significant factors appear, disappear and change inherent properties over time. Therefore, the preponderance of evidence related to condition allows this research to accept hypothesis H_3. Factors significant in contributing to a new product's successful introduction *do* vary as a function of its order of entry and level of innovativeness. The null form is thus rejected.

5.3.6 Discussion of H3 findings

Accepting H_3 responded to requests for analysis by condition (Wind and Mahajan 1988). However, like the discussion of PiLC above, whilst obvious gross model differences exist here also, small category sizes limits dimensional interpretation to speculation.

I. Temporal qualification (Montoya-Weiss and Calantone 1994) and entry/innovativeness conditions alter aggregate success dimensions. Consistent with many (Lambkin 1988; Lilien and Yoon 1990; Robinson and Fornell 1985; Robinson, Fornell and Sullivan 1992; Urban, Carter, Gaskin and Mucha 1986) entry position does matter. Changes observed within categories as projects mature may reflect product⇒process innovation evolution (Abernathy and Utterback 1978; Ansoff 1965; Ansoff and Stewart 1967; Calantone, Di Benedetto and Meloche 1988; de Bresson and Townsend 1981; Utterback 1981, 1982; Utterback and Abernathy 1975). Suggesting entry and innovativeness have little impact (Cooper and Kleinschmidt 1987a; Cooper and Kleinschmidt 1993; Fershtman Mahajan and Muller 1990) is incomplete. Whilst "first in" advantages may be balanced by disadvantages (Cooper 1979b), the issue is more complex, with strategic choices affecting results for followers (Buzzell and Gale 1987; Lambkin 1988; Levitt 1965, 1966; Urban, Carter, Gaskin and Mucha 1986) based on different skill/resource profiles (Abell and Hammond 1978; Robinson, Fornell and Sullivan 1992).

II. Finding normative success strategies over time for followers (Liberman and Montgomery 1988) should be helpful to this vast majority of the market. Being high/first seems to compensate for having a less than "superior" pioneering introduction. Those yielding the pioneer role at T_0 are "caught in the middle" (Porter 1980; see Table 5-5a). The alarming, unreliable middle/medium model evolves to its T_1 equivalent. But here the team is finally "in the game" and pursuing the leader, with dimensions mapped precisely and reliably. This confirms that entry performance is a function of the moderation in the strategies of entrant categories (Lambkin 1988) and that entry position alone is not enough i.e. success is based on many factors (Kerin, Varadaragan and Peterson (1992); Lilien and Yoon 1990; Miller, Gartner and Wilson 1989). Logically, the 1st/high model evolves less as pioneers defend the status quo whilst followers play "catch up/leap frog" through T_1. "Superior product", missing for followers at T_0, "leap frogs" using strategic product positioning over time (Crawford 1984, 1986, 1994; Lambkin 1988; Levitt 1965, 1966; Urban and von Hipple 1988). Compared to superior product's fifth position for the 1st/high model and its insignificance in the late/low model, the "used apple policy" is validated as long as the team gets the second big bite and not the skimpy remains left to late entrants (Levitt 1965, 1966). The late/low entrant sees a more deterministic forecast with history dominating the dimension at both T_0 and T_1. Its lack of alternatives is seen by comparing failure history's role in the 1st/high model as only one of seven or eight dimensions in the T_0 and T_1 respectively. However, in the late/low model, history has disproportionate deterministic effects at both T_0 and T_1. Being "late with less" seems unforgiving, empowers past behaviour, limits creative response and makes developing competitive advantage troublesome.

III. Model choice is proprietary to team objectives, resources and forecasting/reactive abilities. Insignificant statistical differences in performance measurement distributions of 2.2133, 1.4585 and 1.3488 at T_0 and 2.2186, 1.3181 and 1.4767 at T_1, show 1st/high entrants more successful absolutely. However, lack of significance at $p=.05$ refutes Kleinschmidt and Cooper's (1991) poorly performing middle innovativeness category, at least through one year post launch. The issue of choice seems better stated as "which one of the six models relates better (Lilien 1975) to our strengths, weaknesses and objectives?" This is a function of: (1) ability to predict order accurately at T_0; (2) probability of successful dimension implementation by T_1 and (3) model expected value vis-à-vis strategic firm/project objectives (Booz, Allen and Hamilton 1982), abilities (Abell and Hammond 1979; Aaker and Day 1986; Ansoff and Stewart 1967; Calantone and Di Benedetto 1988; Lambkin 1988; Utterback, Allen, Hollomon and Sirbu 1976) and time remaining (Albala 1975; Ansoff and Stewart 1967; Baker 1974; Charles and Stedry 1966; Glotskey 1960; Rubenstein 1964). Relative to these criteria, any and all are useful if based on the situation. Success is more a function, not of entry order, but of the "strategic window" (Abell 1978) skills and resources presented to the firm at different times (Abell and Hammond 1979).

IV. "Innovative strategy in highly competitive market" is a new dimension to the field and a detractor from success for the T_0 1^{st}/high model. Competition at the higher end of the innovative spectra may be more critical to entry success than thought (Cooper and Kleinschmidt 1993) and supports firms killing mis-directed projects. The rise of "alertness to threat of competitive retaliation" to pioneers over time is logical given pioneers have no competition at T_0[73]. Over time they must increase their alertness decidedly. This confirms acknowledged undercounting of market competitive phenomena (Cooper and Kleinschmidt (1987a). The dimension's Newness/Innovation strategy construct, a detractor at T_0, enhances the 1^{st}/high T_1 "strategic reaction" dimension. Feedback is required from the market to determine levels of innovativeness. Innovative strategy's worth is dubious at T_0, but important at T_1 following feedback. This suggests again, that strategic effectiveness has temporal qualities.

V. "Long life cycle, high price/high quality strategy" is new to the field, detracts from success and suggests superior long lived products (Cooper and de Brentani 1984) are not required for a one year "foundation" success. In conjunction with "moderate innovation", these new dimensions may confirm that successful initial entries are only the first in a line of many incremental innovations to follow (Crawford 1986). With 90% of new products only moderately innovative (Booz, Allen and Hamilton 1982), robust design families (Rothwell and Gardiner 1988) sporting moderate, synergistic improvement, seem the foundations of long term product family (Meyer and Utterback 1993) success.

Testing H_3 responded to the inconsistency in the literature between those deeming order of entry important (Booz, Allen and Hamilton 1982; Hopkins and Bailey 1971; Lambkin 1988; Lilien and Yoon 1990; Robinson and Fornell 1985; Robinson, Fornell and Sullivan 1992; Urban, Carter, Gaskin and Mucha 1986) and those sceptical of its worth (Fershtman, Mahajan and Muller 1990; Kerin, Varadarajan and Peterson 1992; Miller, Gartner and Wilson 1989). It also provided new insight into the proper role of innovation in the success/failure dynamic (Davidson 1976; Gerstenfeld 1976; Kulvik 1977; Marquis 1969; Myers and Marquis 1969; Rothwell 1972, 1974, 1976; Utterback, Allen, Hollomon and Sirbu 1976). Clearly, the "one size fits all" approach (Cooper 1979b, 1981, 1992; Zirger and Maidique 1990) whilst prevalent and acceptable may not be best. de Brentani (1986) is imprecise in suggesting that general models are the equivalent of "custom" models because differences in outcomes are not supported. She is correct in that aggregate models can be applied to diverse sets of businesses. But models based on order/innovation can be more valid, accurate and less "information hungry". And though outcome based on different dimensions may be similar, models varying over time and conditionally by order/innovation may be a *very* important to practitioners. Consistent with Albala (1975), failure to recognise these differences leads to higher than expected cost of

[73] the aggregate model by construction methodology contains 2/3rds. medium/middle and low/late cases i.e. They *are* the competitive followers the pioneer is worrying about.

error, represented by unnecessary and premature speculative information accumulation and evaluation. Practitioner scepticism is warranted until more discriminating refined models are supplied.

5.4 Hypothesis H_4

Firms which develop precise initial strategies but react flexibly to deal with deficiencies in early assumptions of internal and external environments, are more successful than those that do not.

5.4.1 Introduction

Hypothesis H_4 suggests that successful firms deal better with initial strategies and strategic deficiencies than failures by modifying their response to suit the internal and external environments. Because there were differences in the "dynamic strategy" dimension's construction between time periods, comparison of three equal distributions was impossible. Instead, a paired-samples t-test was used to examine success/failure differences in common strategic variables over time. Acceptance of H_4 was based on the size and nature of variable change.

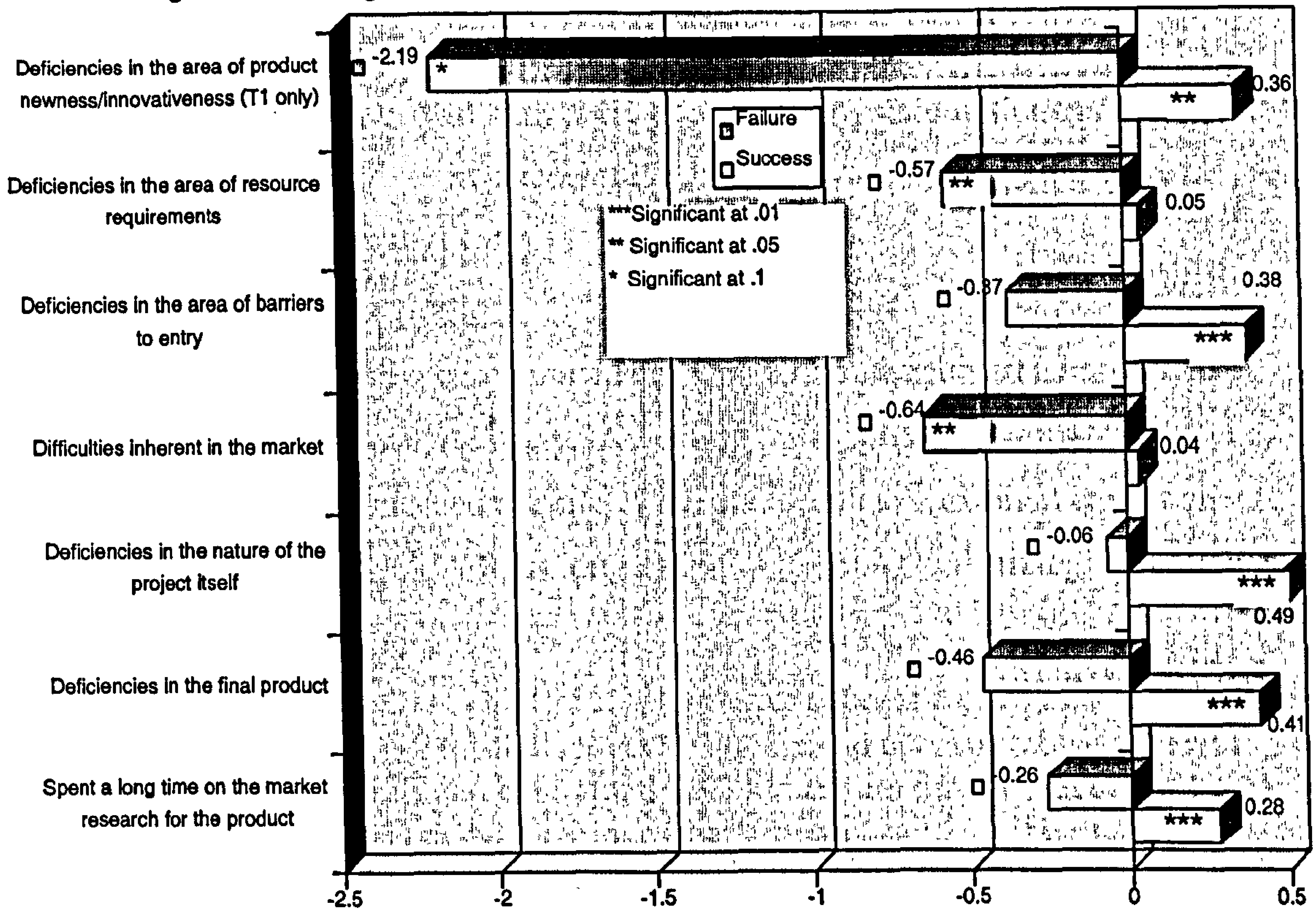
5.4.2 Analysis of strategic components

Table 5-9 and Figure 5-5 display the results, with significant differences noted at p=.001, .05 and .1 levels. All seven variables showed significant change by success and/or failure at the .10 level or better. This is not surprising given the factor's significance to the aggregate and conditioned models and its rise in rank over time for the aggregate model scenario.

Table 5-9: Strategic Reaction variable construct paired-samples t-test by success/failure

Developed clear strategies to deal with:		*Mean T_0*	*Mean T_1*	*Change between T_0 and T_1*	*t-score*	*Significance* ***= $p<.01$ ** = $p<.05$ * = $p<.1$
- deficiencies in the final product	Success	5.026	5.432	.41	3.16	***
	Failure	3.843	3.386	-.46	-1.6	
- deficiencies in the nature of the project itself	Success	4.253	4.747	.49	2.83	***
	Failure	3.371	3.314	-.06	-.18	
- difficulties inherent in the market	Success	5.458	5.495	.04	.27	
	Failure	3.586	2.943	-.64	-2.48	**
- deficiencies in the area of barriers to entry	Success	4.532	4.911	.38	2.71	***
	Failure	3.414	3.043	-.37	-1.5	
- deficiencies in the area of resource requirements	Success	4.600	4.653	.05	.38	
	Failure	3.743	3.171	-.57	-2.34	**
- deficiencies/problems in the area of product newness/innovativeness +	Success	5.311	5.668	.36	2.18	**
	Failure	4.857	2.671	-2.19	-1.65	*
- spent a long time on the market research for the product	Success	3.405	3.690	.28	2.48	***
	Failure	3.100	2.843	-.26	-1.52	
+ = variable loaded on factor based on T_1 data set but not T_0 data set	N.B. a minus sign implies a reduction in capability as judged by managers					

Figure 5-9: Strategic reaction comparsion between success and failure cases



The largest overall variable change was in "strategy to deal with deficiencies/problems in the area of newness/innovation". Whilst success cases increased their strategic readiness to deal with newness/innovation matters over time, failure cases decreased dramatically in this ability. In addition, success cases rose significantly in their ability to deal with deficiencies in the area of "barriers to entry", "nature of the project", "final product" and the amount of time spent on the product's "market research". Following the precipitous decline in "newness/innovation readiness", failures declined significantly also in their ability to implement strategies to deal with problems in the area of "resource requirements" and "the market". These strong results support acceptance of H_4.

5.4.3 Conclusion

Observing the importance and change in statistical significance of the "strategic reaction" factor over time in the aggregate, the PiLC and the order/innovation models, argues for acceptance of H_4; even without tests conducted here. The evidence is abundant that a dynamic strategy (Porter 1991) plays a critical part in success, through one year post launch. Isolating each construct and observing perceived adaptation to internal and external environments only sustains an obvious conclusion. Every dimension construct changed statistically over time for either successes or failures. Therefore, consistent with Abell and Hammond (1979), Booz, Allen and

Hamilton (1982), Buzzell and Gale (1987) and Porter (1980, 1985, 1991), this work must conclude that firms which develop precise initial strategies but react to downstream information to deal with deficiencies in early assumptions of internal and external environments, *are* more successful than those that do not. This research accepts H_4 and rejects the null form.

5.4.4 Discussion of H_4 findings

This work's microscopic approach elucidates Cooper's rather broad admonitions concerning control over one's destiny. Adjusting the emphases, it suggests that it is possible for products to succeed in spite of the uncontrollable external environment (Cooper and Kleinschmidt 1990), as long as initial planning and strategic reaction is appropriate to the situation.

I. T_0 strategic preparedness is higher absolutely for success cases. This readiness confirms that resources and skills must be anticipated and assembled ahead of time (Abell 1978; Abell and Hammond 1979) to ensure timely execution and a successful outcome. However, temporal evolution in strategy constructs suggests decisions cannot be made at the initial screen, implemented and left to age gracefully. Success cases increased their abilities to deal with newness, barriers, project, final product and market research requirements over time. Failure cases declined in this ability vis-à-vis newness, resources and the market (see Figure 5-9). This supports those calling for a dynamic (Porter 1991) strategy.

II. Though uncontrollable variables have had only limited support (Cooper 1979b, 1980b, 1981; Cooper and de Brentani 1984) in the NPD modelling literature, their initial and continuous assessment is needed to achieve dynamic balance (Abell and Hammond 1979; Porter 1980, 1985, 1991). Suggesting that new products succeed in spite of their external or market environment (Cooper 1983; Cooper and Kleinschmidt 1990) is imprecise. Rather, initial accurate assessment of internal and external antecedents, effective strategy based on this assessment and intelligent strategic alignment over time (Kotler 1994) is the foundation of success. Despite arguments of external variable overemphasis (Cooper and Kleinschmidt 1993) the evidence is clear. New products succeed or fail, *not in spite* of uncontrollable environments but *in consideration* of them. Internal and external antecedent uncertainty and evolution seem to be catalysts for successful planning (Abell and Hammond 1979).

- Successful teams meet problematic barriers to entry (Bain 1956; Karakaya and Stahl 1989; Porter 1980, 1985) "head on" and at increasingly statistically significant levels over time. "Barriers to *entry*" do not disappear *after entry* but remain a problem to be dealt with at least through the introduction period. With failure cases declining absolutely in this strategic ability over time, these elements demand constant attention, analysis and strategic action/re-action.
- A strategy to deal with market problems is important to avoiding failure (see Figure 5-9). Strategy to take advantage of large growing markets has been suggested as important (Cooper 1979b, 1980b, 1985; Link 1987). It has been validated by Zirger and Maidique's hypothesis (H_8,1984) that *markets that are large and growing are positively related to successful outcomes and negatively*

related to failures. However, the situation is more complex for many given that mistakes are made, inadequate markets entered and correction necessary. Success cases did not increase significantly in their ability to deal strategically with market problems. However, failures decreased in this ability at p=.05 and failed to compensate strategically for poor markets once entered. Clearly, teams unable to adapt to market problems are inclined to fail. This may indicate that, whilst market strategy doesn't give overwhelming advantage, lack of market strategy can hasten failure.

III. The necessity of adequate resources to develop and then to adjust strategy is confirmed (Ansoff 1965; Calantone and Cooper 1981; Cooper 1979b, 1980b, 1985a, 1985b, 1990, 1992; Cooper and de Brentani 1984, 1991; Cooper and Kleinschmidt 1986, 1987a, 1987b, 1987c, 1990; de Brentani 1986; Link 1987; Maidique and Zirger 1984; Peters and Waterman 1982; Zirger and Maidique 1990) as important to strategic alignment. Though success case ability to modify product and project strategy through launch grew systematically, the decline experienced by failure cases was not significant. This may indicate that early problems with product/project issues does not predestine failure. But left uncorrected, failure can be expected. The need to earmark resources to react to the unknown may be another reason for practitioner lack of spending on the front end of the process (Cooper and Kleinschmidt 1988).

IV. Uncovering an *evolving* role for marketing research in NPD strategy formulation is quite significant. It confirms its importance (Calantone and Cooper 1979; Calantone and Di Benedetto 1988; Cooper 1976, 1979a, 1980b, 1983; Cooper and Kleinschmidt 1986, 1988; Hopkins 1980; Lazo 1965) in NPD activities. And it confronts criticism of marketing research noted by others (Crawford 1977; Gomory 1989; Tauber 1974). Executives sceptical about its strategic value (Mahajan and Wind 1992) or viewing research as discrete and ending at launch are short-sighted. Matching discontinuous marketing research efforts to a continuous process of product and marketing strategy advancing together (Crawford 1986) is a mistake, especially during rapid change. Determining what characteristics are required of robust product design families (Rothwell and Gardiner 1988) in the eyes of an evolving, target market and strategy, requires consistency of effort after commercialisation.

At one extreme, managers spend too much time putting out fires to the exclusion of strategic planning (Gorchels 1995). At the other, formalised strategic principles may be taken to excess (Lubatkin and Pitts 1985). The acceptance of H_4 suggests that in between lies a position where new product managers halt "management only by crisis". Rather, they must clarify the strategic dimensions in support of early probabilities for success and provide the resources necessary to create and implement conditional plans based on posterior probabilities leading to T_1 dimensional targets.

Chapter Six - Summary and conclusions

6.1 Introduction

Chapter six synthesises this work's findings, lists its limitations and suggests a framework for future scholarship. By using a discrete simulation design, evolution of perceived success/failure antecedents, dimensions and models was illustrated. Demonstrably:

1. Many antecedents of success and measures of objective attainment are perceived by NPD managers to differ significantly over time.
2. Complimentary linear functions define the perceived beginning and end of the NPD process.
3. Reactive strategy, NPD multigenerational history and a superior product are the most important dimensions of success through one year post launch.
4. Current linear screening models constructed using retrospective methods produce average prescriptive dimensions which exhibit measurement timing error when used at the initial screen.
5. Success dimensions evolve from somewhat deterministic to more stochastic over time.
6. Model forecasting accuracy rises as launch approaches based on better data availability.
7. Product market PiLC and order of entry/level of innovation alter aggregate success model accuracy and dimension rank.
8. Proper initial dimensional alignment and intra-process realignment based on changing environments is critical to a successful project through one year post launch.

Whilst these findings temporally validate and synthesise much from the NPD literature, further temporal and conditional study should lead to improved model validity, accuracy and parsimony. However, practitioners should not wait for better models to be developed. They can benefit immediately from the results of this work if they: (1) benchmark reasons for their current product market success, failure and kill historical "batting average"; (2) enhance and/or replace contributing/offending processes and systems based on these history lessons; (3) choose or reject aggregate or conditional success/failure models based on team forecasting ability; (4) concentrate on the selected model's time specific dimensions of success and (5) provide/reserve adequate resources to adapt strategically over time to both internal and external antecedent changes in the NPD environment.

The future research path is clear. Scholars should improve on this work's rudimentary understanding of evolution by learning more about the temporal, conditional and strategic trade-offs of internal and external dimensions of success.

Building on Calantone and Di Benedetto's beginning (1990), this can be accomplished best by combining linear and curvilinear methods to validate more elegant NPD intra-process simulations.

6.2 Summary of conclusions

Six of seven hypotheses were accepted.

6.2.1 Hypothesis H_1a conclusion

Many variables perceived important to a new product's success *are* dynamic and evolve over the life of the NPD process in both significance and magnitude. Because many variables were significant at both data recollection points, much from seminal work has been validated at both the initial screen and one year post launch. However, because many display temporal instability, re-examination under simulated or longitudinal conditions is in order.

A 43% change in the original T_0 significant variable environment over time combined with a 37.5% change in antecedent magnitude illustrates at least two similar but critically different NPD environments (see Figure 4-2, 4-3 and 4-4). Established variables showing stability between environments relate to: (1) R&D, engineering, marketing research, management, sales and distribution resource requirements; (2) the need for continuous problem solutions regarding product, customer and competitive newness and (3) uniqueness of a clearly superior product in a high need high growth market. Those exhibiting temporal instability relate to: (1) advertising and promotion resources; (2) product protocol vis-à-vis its relationship to competitive offerings and (3) growth in the dollar size of the market.

Some new to the field variables such as expected speed and magnitude of competitive retaliation, general strategic alignment and speed to market were discovered to be temporally stable. Others such as high end innovativeness, innovation strategy and contribution margin exhibited temporal instability. This demonstration of temporal significance in both established and new antecedents is important given recent confirmation of temporal differences in performance measurement criteria (Hultink and Robben 1995; Ronkainen 1985).

6.2.2 Hypothesis H_1b conclusion

The factors constructed from screening variables whilst dynamic, *do not* evolve over time. This is probably due to the normalisation process. Individual antecedent environments do change before they are normalised. Following normalisation they differ again based on their selection by unique linear regression functions.

6.2.3 Hypothesis H_1c conclusion

Factors significant to a new product's successful introduction *are* dynamic. As more information becomes known to the firm over time, the dimensions of success evolve from inadequate to more adequate. They also change by selection and influence as they are used by unique linear regression functions.

The T_0 linear regression model demonstrates a deterministic/prescriptive character based in large part on both the early influence of a certain product market history and the speculative characteristics of early information. The T_0 model evolves into a T_1 model exhibiting a decidedly stochastic/descriptive character. As information becomes known over time, the model improves in rigour. Dimensional priorities change based on learning and implementing "history lessons" and tighter strategic alignment with external and internal requirements.

The dramatic change from T_0 to T_1 combined with the T_1 function's close reflection of NewProd implies Cooper's model is handicapped by measurement timing error when used to describe the dimensions of a successful project at the initial screening. This confirms Cooper's suspicion that NewProd describes the dimensions as they turn out much later in the process (Cooper 1992). Importantly, problems stemming from measurement timing error could cause teams to over concentrate on the development of the 8^{th} most important dimension at T_0, "superior product", at the risk of violating the 6^{th} most important dimension, "late to enter". Thus, measurement timing error manifest in the "superior product" dimension could cause the project to become a "leapfrogging follower" subject to a follower positioning strategy (see 6.2.6 below).

6.2.4 Hypothesis H_1d conclusion

As the factors contributing to a new product's success evolve, the resulting post screen model becomes *more accurate*. 81.2% T_0 accuracy improves to 83.85% over time based on improved downstream information states of nature. Though statistically significant, the small improvement seems meaningless until the validity of the model producing the change is considered. Then, its improved fit, predictive certainty and reduction in ECE leading to an increase in EVII help explain managers' avoidance of speculative front-end activities and their concentration on more certain downstream processes.

6.2.5 Hypothesis H_2 conclusion

Factors significant to a new product's successful introduction *do vary* by PiLC. Model validity, factor and accuracy changes suggest scholars should consider fuzzy criteria for validation in the stage gate paradigm. Categorisation results in a dramatic reduction in success dimensions and allows other new to the field factors to surface. "Dynamic change" becomes important to success for those who understand its value. This repudiates those who unconditionally recommended its avoidance (Cooper and Calantone 1977; Cooper 1980b). Contradiction between the NewProd prescription and selective successful dynamic experience may cause avoidance by the most active NPD populations.

6.2.6 Hypothesis H_3 conclusion

Factors significant in contributing to a new product's successful introduction *do vary* as a function of its order of entry and relative level of innovativeness. Again, when aggregate models are constrained, model validity, factors and accuracy differ by categorical condition. Whilst controlling for order/innovation also reveals new dimensions, the most exciting conclusion here is the demonstrable normative positioning strategies available for followers wishing to "leap-frog" the pioneer. A superior product well positioned (Crawford 1984, 1986, 1994; Lambkin 1988; Levitt 1965, 1966; Urban and von Hipple 1988) over time seems the key to overcoming the pioneer's advantage.

6.2.7 Hypothesis H_4 conclusion

Firms which develop precise initial strategy but react flexibly to deal with deficiencies in early assumptions of internal and external environments *are* more successful than those that do not. Observing strategic variable construct change by success/failure category is enlightening. But the aggregate strategic dimension's movement from second to first place over time is truly exciting. Strategy appears to be the "dynamic link" (Porter 1991) to dimensions requiring *"exactly X"* amount of alignment by one year post launch. This implies that NPD intra-process *health* can be *diagnosed* and improved based on precise amounts of *prescribed* strategic effort.

6.3 Scholarly implications

Scholarly implications from this work's findings are numerous. All relate to the need for dynamic methodologies, conditional models and additional temporal success dimension validation.

6.3.1 Methods

Third generation process empiricism requires a break from single generation deterministic designs. These are inappropriate where time is a critical factor (Burns and Austin 1985) and produce models laden with measurement timing error. This reduces the temporal validity of intra-process dimensional prescription.

Dynamic methods are recommended to shed light on gates, activities and critical paths. These require the use of time series analysis, queuing theory, Bayesian statistical analysis, canonical correlation and/or discrete/continuous simulation in a PERT network[74]. All would help to explain the temporal trade-offs of intra-process NPD activities and resources and their result on success/failure outcome. The canonical correlation design used by Calantone and Di Benedetto (1990) to find compounding interaction within and between controllable and uncontrollable variables is an instructive beginning. Extension is recommended, but in a temporal context.

6.3.2 Models

Whilst the 1981 NewProd model was quite extraordinary, today it is neither the most parsimonious, accurate, dynamic or valid. This work demonstrates five models more valid and accurate than NewProd (see shaded cells in Table 6-1 below), twelve with lower standard error and fourteen more parsimonious than Cooper's most famous work. However, all models require re-examination by field scholars. Though findings are tentative, it would appear that inflexible, prescriptive, information hungry models adding little accuracy over simple success, failure and kill history, should give way to stochastic multiple model explanations. This is consistent with Crawford's (1986) admonishment that newer evaluation techniques should be incremental and concerned with doing only part of the job - but better! The process control and conditional models which follow are good examples.

6.3.2.1 Statistical process control models

Dimension level alignment may be inappropriate for small firms. They might be better off using incremental models doing only part of the job. Benchmarking significant process control variables over time (rather than success dimensions) might allow a more precise understanding and implementation of strategic alignment issues.

A simple process control model using this work's "critical six" antecedents is demonstrated in Figure 6-1. These variables are quite similar to those found by

[74] Similar to Microsoft Project, SPSS has recently developed *CLEAR Process*. This component uses one's SPSS data to simulate process behaviours. It generates most probable outcomes based on changing allocations in resources and Monte Carlo probability distribution theory.

Calantone and Cooper (1979) which discriminated between success/failure. Research at the critical variable level would allow construction of normative strategic alignment success/failure parameters in the NPD TQM (total quality control) effort. Measuring and "fine tuning" key activities along the success path might be useful to

Table 6-1: Comprehensive model comparison

PiLC = constrained for PiLC; order/innovation. = constrained for order/innovation aggregate = aggregate model sorted by category. Shading = more valid and accurate than NewProd.

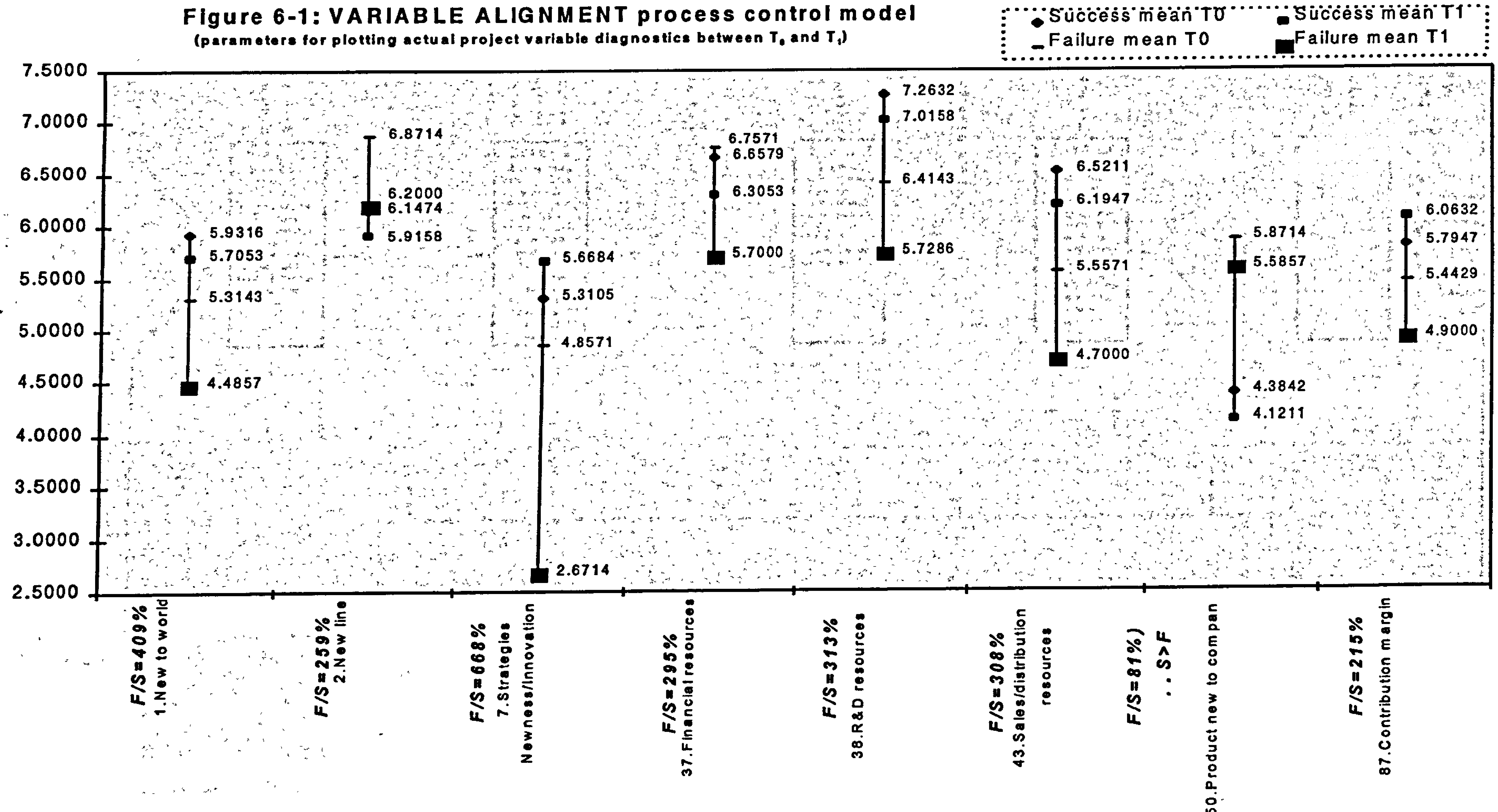
T0	*T1*
A NewProd: Cooper, Robert G. (1981) R=.648074, R^2=.420, Adj. R^2=.395, F =16.83 with 8df Standard error = 2.73 accuracy = 84.1%	not applicable
B Aggregate at T_0 R=.56589, R^2= .32023, Adj. R^2=.29857, F=14.78065 at .0000 with 8df Std err = *2.58869* accuracy = 81.2 %	***C*** Aggregate at T_1 R=.68961, R^2=.47556, Adj. R^2=.45450, F =22.57937 at .0000 with 10df Std err = *2.28289* accuracy = 83.8%
D PiLC short at T_0 R=.29718, R^2=.08832, Adj. R^2= .07510, StdErr=3.14585, F=6.68410, Sig=.0118, 1df - PiLC =71.8% aggregate =71.8%	***E*** PiLC short at T_1 R=.77053, R^2=.59371, Adj. R^2=.54857, StdErr= *2.19779*, F= 13.15189, Significant=.0000, 7df, order/innovation. =90.1%, aggregate =84.5%
F PiLC medium at T_0 R=.61923, R^2=.38345, Adj. R^2=.35776, StdErr=*2.49795*, F=14.92635, Sig=.0000, 3df - PiLC =80.3%, aggregate =86.8%	***G*** PiLC medium at T_1 R=.64116, R^2=.41108, Adj. R^2=.37790, StdErr=*2.45847*, F=12.38996, Sig=.0000, 4df, order/innovation. =81.6%, aggregate =86.8%
H PiLC long at T_0 R=.69685, R^2=.48560, Adj. R^2=.44603, StdErr=*2.42112*, F=12.27196, Sig=.0000, 4df, PiLC=78.9%, aggregate =80.7%	***I*** PiLC long at T_1 R=.73641, R^2=.54229, Adj. R^2=.49742, StdErr=*2.30608*, F=12.08508, Sig=.0000, 5df, order/innovation. =86%, aggregate =82.5%
J Order/Inn 1st/high at T_0 R=.69861, R^2= 48806, Adj. R^2= .44211, StdErr= *2.18485*, F= 10.62295, Sig=.0000, 7df, PiLC=88.4 %, aggregate =87.2 %	***K*** Order/Inn 1st/high at T_1 R=.75437, R^2=.56908, Adj. R^2=.52488, StdErr=*2.03578*, F=12.87591, Sig=.0000, 8df, order/innovation. =86.2 %, aggregate =87.4%
L ORDER/Inn middle/medium at T_0 R=.45458, R^2=.20664, Adj. R^2=.17830, StdErr=2.74777, F=7.29289, Sig=.0002, 3df, PiLC=72.7%, aggregate =77.3 %	***M*** Order/Inn middle/medium at T_1 R=.73505, R^2=.54030, Adj. R^2=.50582, StdErr=*2.21350*, F=15.67086, Sig=.000, 6df, order/innovation. =88.5 %, aggregate =86.2%
N Order/Inn late/low at T_0 R=.63341, R^2=.40121, Adj. R^2=.36378, StdErr=*2.60917*, F=10.72048, Sig=.0000, 5df, PiLC =82.6 %, aggregate =79.1%	***O*** Order/Inn late/low at T_1 R=.61038, R^2=.37257, Adj. R^2=.33335, StdErr=*2.55363*, F=9.50070, Sig=.000, 5df, order/innovation. = 80.2 %, aggregate =77.9 %

practitioners not capable of using complex linear regression diagnostic techniques. Observation of a few key variable tolerances might be all small firms can cope with. Surely, greater use of simpler models is better than serious under-utilisation of complex models.

6.3.2.2 Discrete stochastic simulation models

This work's two stage simulation should evolve to more complex probabilistic forms explaining aggregate and conditional intra-process stages, dimensions and activities. Following this work's demonstration of T_0 (M_1) and T_1 milestones (see Figure 6-2), scholars need to demonstrate conditional adaptation (see Figure 6-3) and intra-process milestones represented by points M_2, M_3, M_4 M_5, T_2 and T_3 (see Figure 6-4).

Figure 6-1: VARIABLE ALIGNMENT process control model
(parameters for plotting actual project variable diagnostics between T_0 and T_1)



F/S ratio is the % failure range divided by the % success range (a TQM tolerance test statsitic).

Figure 6-2: Intra-process longitudinal, and/or simulation model requirements- from Cooper, Robert G., Stage-Gate Systems, A New Tool for Managing New Products, *Business Horizons*, May-June 1990, p46. (Future research variable, and dimensional requirements are shaded with dotted outline)

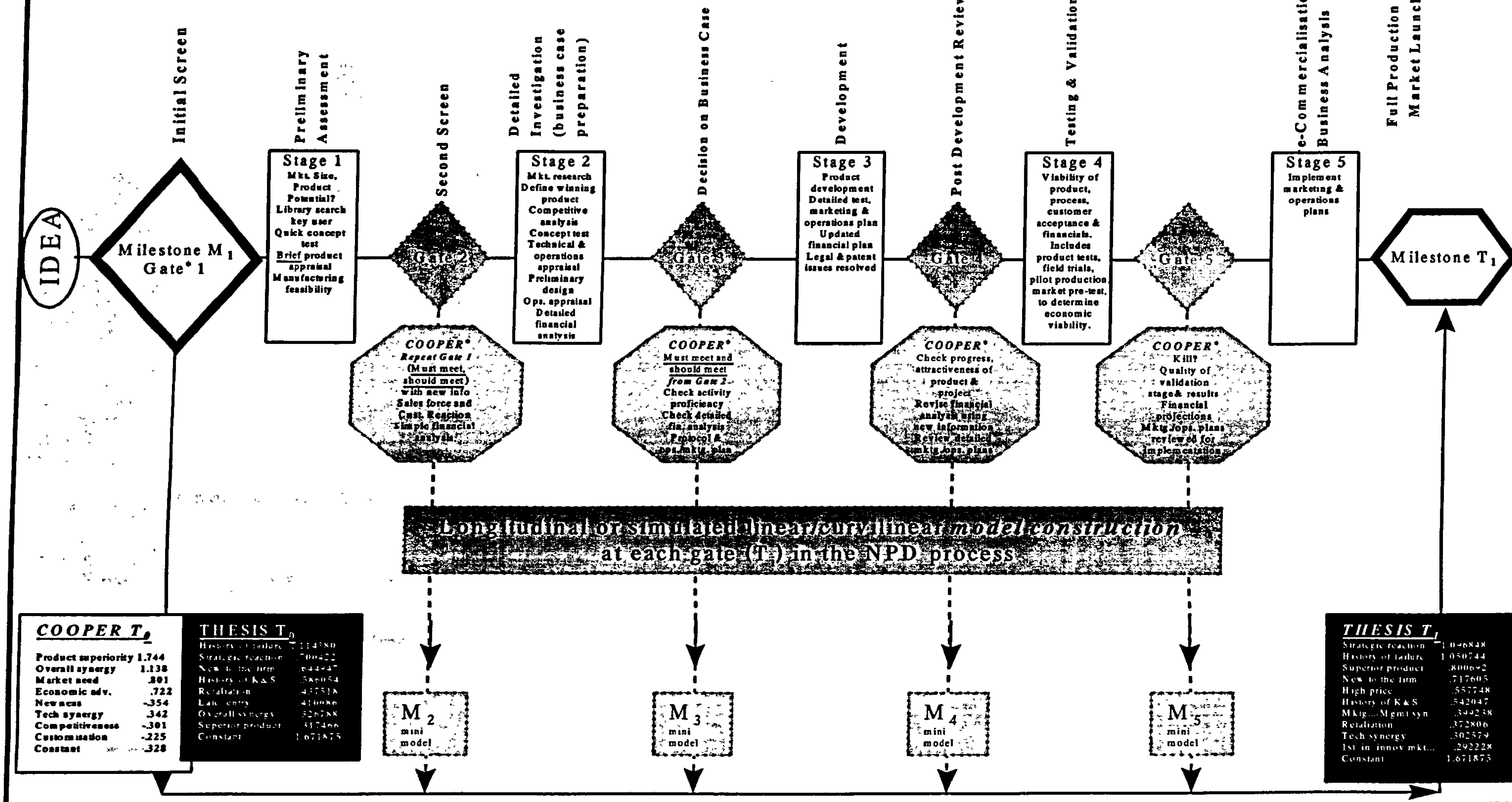


Figure 6-3: "Fuzzy"(PLC and ORDER conditioned) model selection for third generation processes

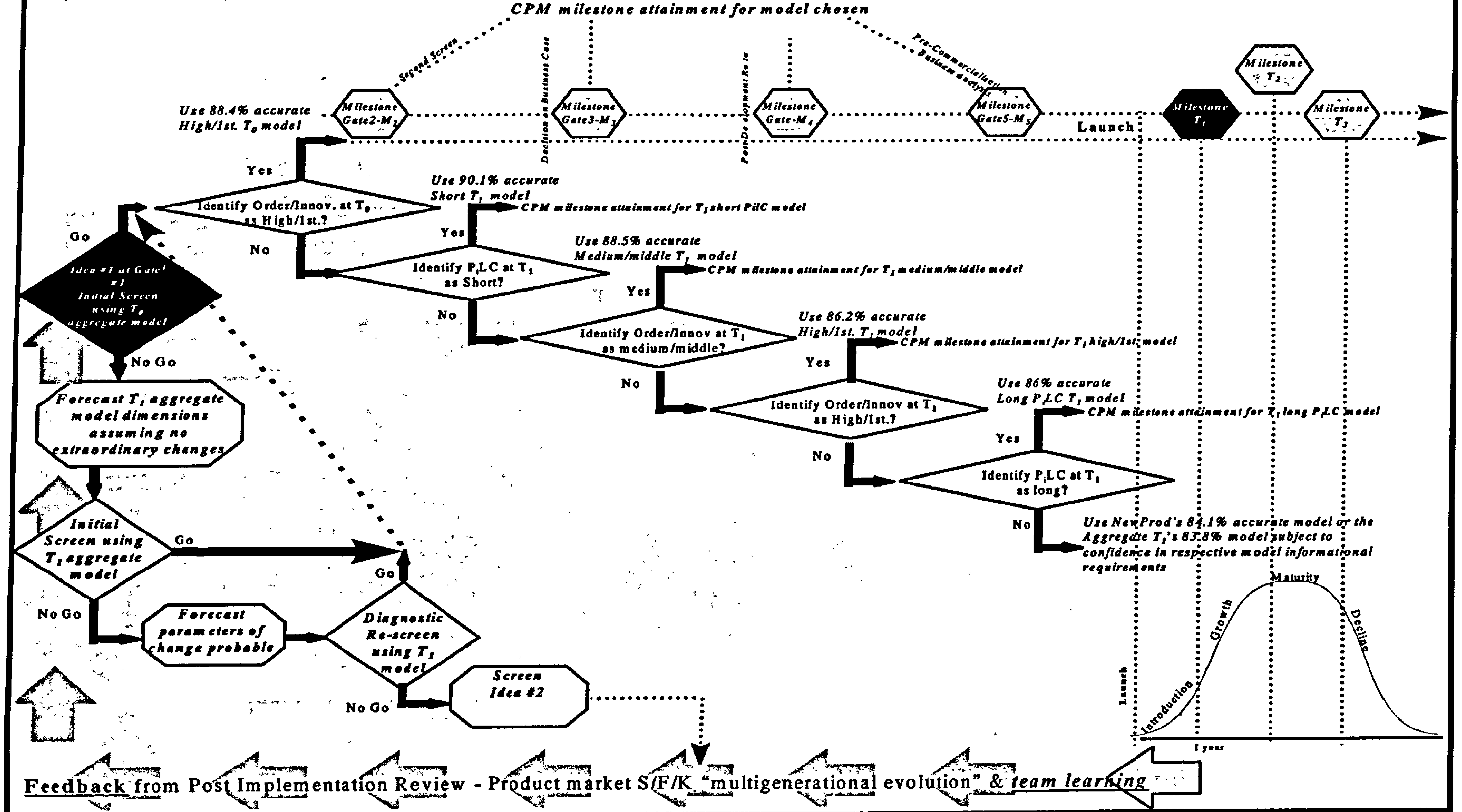


Figure 6-4: PERT simulation framework for "fuzzy" third generation model building [1] modification of Cooper, Robert G., Third Generation New Product Processes, *Journal of Product Innovation Management*, 1994;11:3-14

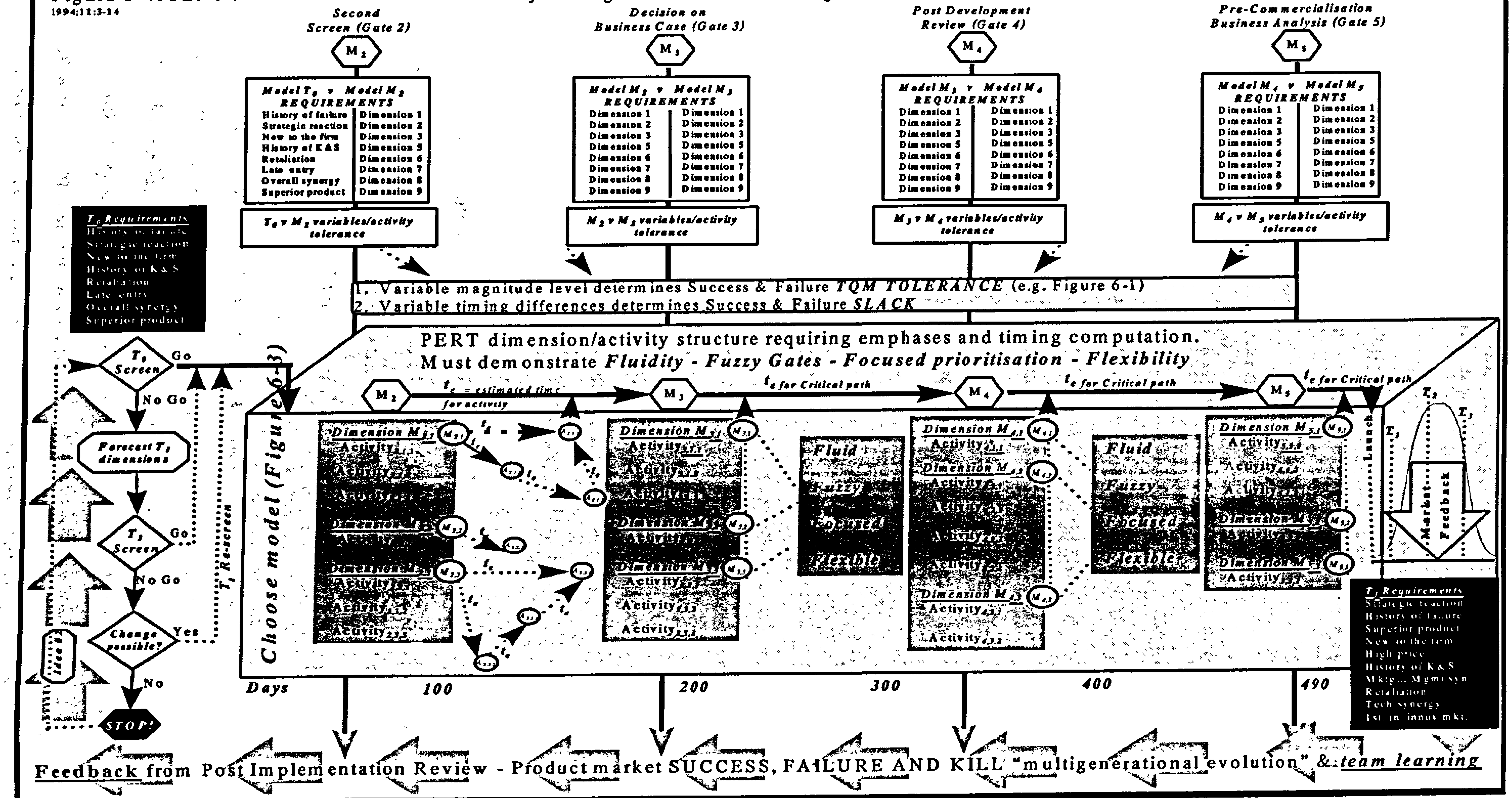


Figure 6-4 is consistent with Cooper's request for "4F" fluidity, fuzzy gates, focused prioritisation and flexible process routing (Cooper 1994b). It illustrates intra-process activity which is fluid and adaptable based on overlapping stages. This yields greater speed and is enhanced by fuzzy gates where conditions can assume varying conditional and situational states of nature. All projects are properly focused and prioritised by optimal, dire and most probable expected value scenarios, with each project having the flexibility to choose a unique route through the network. Linear programming of expected gate conditions could optimise objective(s) realisation. With every project decision/resource allocation compared against all others, "pipeline churn" from frequently changing development priorities would be reduced. This would reduce confusion and frustration whilst speeding up development activity. Reducing churn would ultimately help achieve "pipeline balance", the ability to successfully develop new product platforms whilst extending existing product lines.

6.3.3 Dimensions

Whilst no established variables, dimensions or models of success are irrelevant, reactive strategy, NPD history and the development of a superior product are clearly the most important success factors at the one year post launch point. None-the-less, investigation of both new and established factors should continue in the context of multi-disciplinary factor evolution. New research should concentrate on: (1) the deterministic characteristics of multigenerational product market history; (2) strategic alignment criteria; (3) dimensions "enabled" by time, PiLC and order/innovation conditions and (4) factor/antecedent interaction over time.

6.3.3.1 Product market history

Reflection on the human condition of one member rising above a family's failed, resource poor past is important to understanding the history dimension's deterministic relationship to downstream stochastic dimensions. Like Darwin's theory of natural selection (1859), the "nature" of the team's uncontrollable product market history colours strategic "nurturing" activities. How teams overcome a predilection to failure by nurturing precisely the right activities in a timely fashion, requires a better understanding of organisational learning systems (Kiechel 1990; Mumford 1992; Nonaka 1988, 1991; Shrivastava 1988; Shrivastava and Souder 1987). Lack of timely learning may explain why a history of failure can lead to more failure despite production of a superior product. Because understanding multigenerational product market history and appropriate supportive/remedial system development is probably the key to appropriate, timely NPD planning and strategic action, scholars should address the power of a failed history on early success and ways of quickly overcoming bad habits.

6.3.3.2 Strategic alignment criteria

Failure to understand strategy's relationship to all other dimensions is tantamount to not understanding the $T_0 \Rightarrow T_1$ model metamorphosis. Ultimately strategy is the most important determinant of success or failure. It is strategic antecedent/dimensional dis-equilibrium which propels the successful team into strategic action. Its implicit link to NPD dimensional emphases should encourage many from outside the field to diagnose precise types and levels of reaction required for specific dis-equilibrium problems. This would allow *strategic physicians* to *prescribe* the best *medicine* for the *NPD illness*.

6.3.3.3 Enabled dimensions

Dimensions "enabled" (Day 1981) by time, PiLC and order/innovation conditions herald external environments as appropriate for NPD study again. The T_0 aggregate model includes two external dimensions, "alertness to threat of competitive retaliation" and "late market entry". The T_1 model includes "1st in new highly innovative market". These invite scholars interested in uncontrollable product market phenomena to investigate the influence of PLC, order of entry, levels of innovativeness, dynamic change and competitive assessment on short and long-term NPD success. Outlook is particularly bright for those using time sensitive, curvilinear methods which can calibrate rate of change relationships over time.

6.3.3.4 Factor/antecedent interaction

Temporal understanding of the interrelationship of internal and external dimensions may be more important than scholars rallying around dimensional "sacred cows". Slight difference in rank is secondary to the trade-offs in NPD intra-process activities and resources over time. The work of Calantone and Di Benedetto (1990) is quite important here and should be extended in a temporal, dynamic context. The result would be a better understanding of "must meet, should meet" activity which would expose simplest deterministic proclamations as naive and imprecise.

6.4 Managerial implications

This work's discovery of multiple screening model options is good news for practitioners. Managers should re-examine their negative pre-dispositions to "one-size-fits-all" models, especially if their dissatisfaction is based on NPD prescriptions incongruous with temporal or conditional information realities.

6.4.1 Multiple model systems approach

The multiple model approach demonstrated here should result in faster, more flexible decision making based on temporally appropriate information. Unless T_0 scores are appalling with little hope for improvement over time, practitioners need not be preoccupied early on with meeting long-term dimensional requirements. To get a GO! managers need to either pass the less demanding T_0 screen or, failing it, favourably assess the probability of approaching the aggregate or conditional T_1 model target by one year post launch. Such flexibility underscores Crawford's advice to managers that evaluating new products is a system not an act (Crawford 1986). Having a *potentially* superior product advantage at T_0 is enough to get by the initial screen - as long as factor construct scores should rise *systematically* by launch and perceived impact is forecast to systematically become financial success by T_1. This approach should speed up the process considerably as it reduces cycle time.

6.4.2 Relative conditional models

Practitioners with sufficient product market knowledge may achieve proposed third generation model advantages today. Sporting accuracy rates from 86% to 90.1%, versus NewProd's 84.1%, five are more valid and accurate than NewProd whilst requiring far less information (see Table 6-1). Using any of them can result in substantial time and budget savings whilst selectively improving accuracy. However, model choice is a function of team ability to forecast its product market condition as well as having the capacities to deliver the appropriate model's dimensions. Benefits of choice must be weighed against the risk of incorrect condition estimates leading to inappropriate model selection and possible incorrect dimensional emphases. None-the-less, in diagnostically uncertain product markets, the aggregate T_0 and T_1 models are the equal of NewProd and Stanford whilst still more parsimonious and relative to informational states of nature.

6.4.3 Learning systems

There is nothing more important for practitioners to take from this research than the importance of the benchmarking⇒learning⇒strategic action/reaction process. Without benchmarked learning systems supporting this concept, strategic action could decay into random walk theory. All evidence from this work confirms that "Those who cannot remember the past are condemned to repeat it"[75]. No matter how difficult, practitioners must benchmark key variables and dimensions of history and

[75] George Santayana (1863–1952). US philosopher. Used by William L. Shirer as an epigraph in The Rise and Fall of the Third Reich (1959).

then learn from them. This involves building/maintaining successful organisational learning systems and disposing of schemes which do not enhance required levels of success.

To benefit from the deterministic effects of history teams must eradicate cultures, systems and procedures which have led to past failures, as they enhance processes which have led to success. Griffin (1993) is correct. To capitalise on history repeating itself or to reverse a failed process, benchmarks must measure the quality and magnitude of NPD process change. Without benchmarking the results of organisational learning and implementation systems, continued attempts at 3rd generation improvement will be chaotic and fourth generation neural learning and expert NPD systems will be fantasy.

6.4.4 Dimensional implications

All dimensional findings contain practitioner lessons, but some are more important than others.

6.4.4.1 Natural History versus Nurturing Strategy

Understanding the influence of NPD past performance is a dual edged sword. Whilst deterministic in its character to continue the success/failure of the past, teams with poor product market performance records are not predestined to fail - if they put in place, historical learning systems which support initial and reactive strategic decision making. These are the keys to changing past failure patterns and emulating successful scenario.

6.4.4.2 Order of entry

All things being equal, entering early with highly innovative projects is best. Being late limits one's strategic options. However, the good news is that the PiLC and order/innovation models yield alternatives to followers positioned by mistake or by default.

6.4.4.3 Competition

Competitive analysis is important to success. Those suggesting otherwise are wrong or tell only half truths. Whilst what one does for oneself is more useful than worrying what the competition is doing, strategic action/reaction is a function of competitive feedback. Unequivocally, vigilant competitive awareness through one year post launch is associated with success whilst failing to monitor and react appropriately to competition is associated with failure. This is a wake-up call to practitioners lulled into a false sense of security by those suggesting external dimensions are secondary in importance (Cooper 1979b, 1980b, 1981, Cooper and Kleinschmidt 1993).

6.4.5 Realistic informational requirements

Multiple, realistic, parsimonious models lessen inappropriate information assessment, collection burdens and associated costs. This is good news to resource poor teams requiring expensive research into uncertain environments. The T_0 model dimensions are far less demanding and almost as accurate as currently available models. The 81.2% accurate but gentle T_0 model allows teams to forecast a "null (no change)" strategic scenario. If the null scenario results in a predicted failure, this should stimulate re-examination of history, start the discussion of T_1 dimensional requirements, force estimates of how much and what type of change effort is warranted and generate probability distributions for success scenario based on those changes. Thereafter, the evolution of internal and external environments reveals the more certain, less expensive T_1 information requirements to be used to diagnose one's progress. Using this simple dual simulation allows better strategic diagnosis and adaptation based on time appropriate information. Such realism in the context of a familiar simulation technique should appeal to managers.

6.5 Contributions

This work has made five contributions to field knowledge. It has:

1. *demonstrated a successful, inexpensive discrete simulation technique.* This extends seminal deterministic methods with a simple stochastic alternative. The procedure is cost effective for simulating longitudinal internal and external process dynamic change over time. This demonstration was fundamental to and invites empirical demonstration of probabilistic NPD research designs including proposed CPM/PERT network paradigms (Grossman and Gupta 1974; Hart and Baker 1994; Lilien and Kotler 1983; Urban and Hauser 1980; Wasson 1978).
2. *delivered on Montoya-Weiss and Calantone's (1994b) request for a temporal assessment and synthesis of established antecedents and dimensions of success.* Many dimensions found important to success in five year retrospectives were found more or less significant by time period. This improved their temporal construct validity at the initial screen and one year post launch by reducing perceived measurement timing error and survivor bias. Dimensions out of favour but discriminating between early success and failure have become important again. These include order of entry, level of innovativeness and the importance of competitive awareness to strategic planning.
3. *delivered on Wind and Mahajan's (1988) request for greater NPD interdisciplinary perspective.* This allowed field knowledge to be integrated with and related to other branches of the literature. New dimensions of success including NPD history, order of entry, level of innovation, competitive assessment and strategic action/reaction were found to be arbiters of established dimensions.

4. *demonstrated five conditional models more valid and accurate than NewProd, twelve with lower standard error and fourteen less demanding in terms of information requirements.* This supports Cooper's request for conditional/situational schemes (1994b) in support of accelerated product development (Cooper 1995).
5. *shed early light on a provocative debate between deterministic and stochastic model value.* This debate features the struggle between the "nature" of one's NPD product market success, failure and kill "natural history" and the "nurturing" effects of change based on strategic alignment/realignment. Both arguments are powerful, undecided and important to understanding the requirements of a "learning/changing organisation" (Kiechel 1990; Mumford 1992; Shrivastava 1988; Shrivastava and Souder 1987; Slater and Narver 1995).

6.6 Limitations

Six limitations of this research must be noted. Future efforts should address: (1) an overly ambitious questionnaire possibly leading to non-response bias; (2) selection, experimental and measurement timing error potential; (3) failure to capture curvilinear phenomena; (4) the information vacuum and limited usefulness of predictive output; (5) "beginner bias" and (6) conditional model sample size.

6.6.1 Overly ambitious questionnaire

Whilst the instrument used was creative, it was too ambitious, intellectually taxing and expensive. This limited the response rate and will limit new replication. However, potential non-response error was offset by the fact that such bias may be to the researcher's advantage, when the relationships being studied are more important than extrapolation to the general population (Suchman 1962). Building models primarily for active NPD populations is consistent with this exception and thus, non-response bias was judged not to be a significant problem.

To increase response rate the questionnaire length should be reduced by using cluster, factor or chaid[76] analysis. Internally inconsistent construct variables at the end of the scree loading on factors insignificant to robust linear regression functions, and variables loading at <.5 on significant dimensions of success, should be eliminated in future aggregate validations. Also, modern delivery methods such as FAX and spreadsheet/database templates on diskette might be used to make responding more fun (MacElroy and Geissler 1994). Most creative, "WWW[77] e-surveys" would allow perpetual international data collection in over 140 countries. Population specification error could be minimised by utilising an *e-mail⇒write-back⇒call-back* system to qualify respondents after the fact.

[76] Chi-squared Automatic Interaction Detector - a relatively new statistical application useful for dividing populations into segments which are mutually exclusive and exhaustive. It can be used to reduce useless data and combine categories which do not differ significantly.
[77] World Wide Web of the Internet

6.6.2 Potential selection, experimental and measurement timing error

Postal surveys are particularly vulnerable to selection error - the variation between a representative sample and the sample obtained using non-probability methods (Tull and Hawkins 1993). Selection error is recognised by Cooper (1979a, 1979b, 1981). It exists here also along with post hoc bias typical of retrospective success/failure work. However, post hoc bias has been shown to be minimised by objectively worded scales such as those used here (Cooper and Kleinschmidt 1994).

This work's use of dual recollection points fails to address perfectly, measurement timing error in "real time". Whilst an improvement, the technique remains susceptible to experimental *or* measurement timing error *but not both*. Either the technique leads to experimental error by implying different answers *or* the process leads to measurement timing error by averaging dimensions over time.

If significant variable selection and change in variable magnitude was universal, charges of "leading", gross experimental error would be legitimate. If variables failed to change universally due to averaging effects, charges of gross measurement timing error would be legitimate. The results of the independent t-tests show that 93.3% of the variables significant at T_0 remained significant at T_1, whilst 17.33% did not become significant until time T_1. This represents a 43% change in the original T_0 significant variable environment. When combined with a paired-samples t-test demonstrating a 37.5% changed in magnitude over time, this indicates that neither type of error occurred in substantial proportion. Clearly, undue experimental or measurement timing error, whilst possible, is not probable here. However, a fixed panel in support of a longitudinal validation would be a welcome addition if panel measurement problems (Churchill 1991) could be overcome.

6.6.3 Failure to capture curvilinear phenomena

Even though some phenomena may not be linear (Kleinschmidt and Cooper 1991), linear methodologies were used for consistency in the validation and synthesis of seminal literature. Curvilinear results would have been irreconcilable with NewProd and Stanford. None-the-less, temporal phenomena similar to those uncovered in diffusion research (Bass 1969; Mahajan, Muller and Bass 1990) may respond better to curvilinear methods. In future research, these may prove useful to measure the changing contribution to success of time related variables such as levels of innovation, order of entry and PLC.

Curve fitting exercises were attempted with some success. Logistic regression showed the greatest potential with accuracy rates of up to 98.55% for successes and 82.35% for failures. Unfortunately, these additions would have been a huge undertaking though worthy of future application.

6.6.4 Information vacuum and inadequate output

This research has been useful in determining states of nature at T_0 and T_1. However, these are indicative only of beginning and ending dimensions. What is lacking is an explanation of discrete gates/activities between T_0 and T_1 and the long-term dimensions of success at T_2 and T_3. Viewed in the context of Cooper's stage gate paradigm (1990) and modified rhetorically to reflect a CPM/PERT nomenclature (see Figure 6-2 and Figure 6-4) the gap between Milestone/Gate M_1 and Milestone T_1 represents intra-process dimensional confusion. Knowing only normative beginning and ending states of nature limits model diagnostic usefulness. Empirical validation of intra-process activities is needed to build on this work's dual milestone foundation. These components are cardinal to the future of NPD decision support using expert systems which "learn" from neural networks.

The output demonstrated here represents only one part of a much larger information requirement. The need to account for current versus projected dimensional difference and portfolio balancing (Wind and Mahajan 1988; Cooper 1994b) could be satisfied by intra-process sampling based on probable states of nature. This would yield output on dimension specific objective attainment, project(s) expected monetary value and ROI.

6.6.5 Beginner bias

This work represents a beginners' bias - the antithesis of survivor bias. Rather than over-representing late successes and under-representing early failures, it fails to measure what happens after the one year benchmark. As such, it says nothing about projects considered a failure one year post launch which become successful at T_2 or T_3 due to additional investment and strategic attention. Conversely, one may conclude quite erroneously that because the successful project follows the T_0 prescription and evolves to the T_1 state in a precise and timely manner, the project will continue to be successful at T_2 and T_3.

6.6.6 Conditional model sample size

Sample sizes for each category of PiLC and order/innovation were small. This is manifest in low model F values. Life expectancy broke down into samples sizes from n=57 to 76 yielding F values of 6.68410 to 14.92635. Order/innovation sample sizes were n=86 to 88 resulting in F values from 7.29289 to 15.67086. Whilst adequate to illustrate hypothetical gross model differences, their value to the discussion of normative strategic planing is limited. Future research into conditional models require larger sample sizes to confirm this work's findings.

6.7 Future research

Limitations found in testing this work's eight hypotheses combine with new findings to chart the course for future research. Future inquiries should concentrate in two areas: (1) temporal validation of established and new success factors and (2) conditional methods and models required by third generation processes.

6.7.1 Temporal re-examination

A number of variables, normalised environmental factors and dimensions thought significant to success previously were validated here by time periods. However, in support of field synthesis (Montoya-Weiss and Calantone 1994) and since all previous work was static, these findings should be re-examined under real longitudinal or perceived simulated conditions to confirm evolutionary differences uncovered here.

6.7.1.1 Variables

Because this work's antecedent evaluation was exploratory its temporal findings need re-examination (see Table 4-3 and Figures 4-2, 4-3 and 4-4). This is especially true for the "critical six" which exhibit both success and failure tolerance parameters (see Figure 6-1). Viewed as simple process control elements in the strategic alignment process they include:

- new-to-the-world innovation
- new product line innovation
- level of financial resource adequacy
- level of R&D skills adequacy
- sales force &/or distribution resource adequacy
- newness to the company

Range ratios[78] characterising success as less forgiving than failure needs explanation. The use of chaid analysis is recommended to isolate variable importance on intra-process success paths.

[78] % failure range divided by % success range.

6.7.1.2 Environmental factors

New to the field normalised environmental factors need re-examination in both aggregate and conditional NPD contexts. These include:

- dynamic change in fast growing market
- strategic reaction capability
- 1st in new, highly innovative market
- alertness to threat of competitive retaliation
- exogenous timing variables
- moderate innovation
- incremental innovation
- innovative strategy in highly competitive market
- late market entry
- differentiation barriers
- NPD history of kills and success
- NPD history of failure
- government capital barriers
- contribution margin
- financial barriers
- differentiation barriers

Understanding their usefulness in a richer, industry and/or product market specific context might prove very valuable.

6.7.1.3 Dimensions

Whilst all dimensions of success found here need re-validation, those requiring particular attention include:

- *NPD history* - The effects of success, failure and kills needs clarification. Important questions include "what underlies the relationship of kills to successes", "how much failure history is too much to overcome", "what is the critical level of success, such that success leads to more success despite failure in other dimensions", "what characterises and how does one determine and overcome a failed history", "why do high kill ratios lead to failure" and "why is a failed history more important to avoid than a successful history is to attain"?
- *strategic reaction capability* - The quality of strategic reaction depends on benchmarked learning from product market experience. Discovery of normative NPD strategic reactions based on T_0 history and in pursuit of ideal T_1 dimensional targets would be valuable to practitioners. Probable effects of "must-react" $\Rightarrow$"should react" strategic activities would aid understanding of what requires a significant rather than an ephemeral response.
- *superior product* - Re-examination of NewProd's most significant conclusion concerning the primacy of "superior product" at the initial screen is in order. Its rise in importance over time and the evolution of its variable constructs suggests the dimension exhibits measurement timing error at the initial screen. This needs clarification because of the dimension's implication on timing and deployment of production, management and research resources.
- *resource/synergy* - Simply declaring that synergy is important to success is inadequate. Normative "resource/synergy mixes" in response to dimensional dis-

equilibrium would be more helpful to practitioners than vague statements supporting short pass strategy. This, along with better understanding of normal resource diminution over time, could prevent over/under funding of intra-process activities.

Finally, dimensions unique to PiLC and order/innovation conditional models require investigation. Those in neither this study's aggregate models, NewProd or Stanford include:

- *dynamic change (short PiLC model at T_1)* - Dynamic markets can become a quagmire of problems relating to competitive one-upmanship (Calantone and Cooper 1977). However, Cooper's advice to avoid dynamic markets where users' needs change often and new product introductions are frequent (Cooper 1979b, 1981) is conditionally incorrect. How successful companies use this environment to their advantage needs exploration.
- *innovative strategy in highly competitive market (1st/high order/innovation model at T_0)* - This is the least understood dimension in this work. It requires exploration of the "time left⇒ competitive level⇒ innovation level" relationship.
- *long life cycle, high price/high quality strategy (1st/high order/innovation model at T_0)* - The benefit of developing long lived innovative products is intuitive. However, the negative impact of this factor at T_0 calls for re-examination of the conclusion that development of long PLC projects with potentially high margins is always congruent with success. Since every product cannot be long lived, the role of lower priced, moderately innovative products in robust family platforms (Meyer and Utterback 1993; Urban and von Hipple 1988) needs examination as life cycles get shorter. None-the-less, in aggregate model work this internally inconsistent dimension should be eliminated.

6.7.2 Methods and models

This work provides temporal validation and synthesis in the context of seminal methods. However, this does not mean that new designs useful for validating third generation processes should not be explored. Except for Gate #1, no empirical justification exists for Cooper's stage-gate "must meet - should meet" criteria. Figure 6-4 proposes a complex discrete simulation as a better future design.

6.7.2.1 Methods

Attempting to develop and synthesise new knowledge based on only the NewProd or the Stanford design is a mistake. Both use deterministic, monomorphic linear methods to optimise only one objective function. Neither is an acceptable rallying point for synthesis because they exhibit measurement timing error. This is due to data, relationships and variables failing to remain constant over time (Burns and Austin 1985). They should not be the starting gate for third generation empiricism. Rather, this work's simulation framework in the context of a network analysis provides the most promising analytical paradigm. It should be validated by others (Hart and Baker 1994).

Discrete simulation, where the variables change at specified points in time or continuous simulation, where they change continuously, would best allow temporal synthesis, field advancement and practitioner acceptance. These methods would allow construction of pessimistic, most probable and optimistic probability distributions for calculation of Type I and Type II error[79] and EVII. This might demonstrate why practitioners have avoided initial screen models. More importantly, simulation models would minimise measurement timing error whilst allowing synthesis of NewProd and Stanford results *at the appropriate time period.* This would allow seminal work to be judged in conjunction with dynamic, intra-process conditional influences such as PiLC, order/innovation and other time related dimensions. Following this work's method will prevent 3rd generation flexibility from unravelling.

6.7.2.2 Models

Many dimensions and constructs uncovered here are quite complex, governed by probabilistic events and change in priority over time. Timely intra-process advice to practitioners based on more precise incremental models is needed to build systematic, go/no-go/continue decisions. New more accurate models need validation in light of recent findings concerning changing go/no-go/continue (Ronkainen 1985) and performance measurement (Hart 1993; Hultink and Robben 1995) criteria. These models would be more temporally appropriate, their internal dimensional construct validity would be high and new dimensions might be uncovered based on intra-process criteria change by time period.

As cited by Crawford (1986) such multiple models would use less information per solution. They would not predict actual success/failure but only the outcomes of key events at points along the critical path to success. Estimated path duration would be determined as follows:

$$t_e = \frac{t_o + 4t_m + t_p}{6}$$ (Meredith 1992)[80].

This would help to implement Cooper's "four Fs", fill the knowledge gaps at M_2, M_3, M_4, M_5, T_1, T_2 and T_3 (see Figure 6-4) and provide a research path for field expansion.

[79]Type I = $P(T_1|S_2) * P(S_2) * |V_2|$ *AND* Type II = $P(T_2|S_1) * P(S_1) * |V_1|$ where $|V_2|$ is the absolute value of the payoff for State of nature 2 and $|V_1|$ is the value of the payoff for State of nature 1 (Tull and Hawkins 1993).

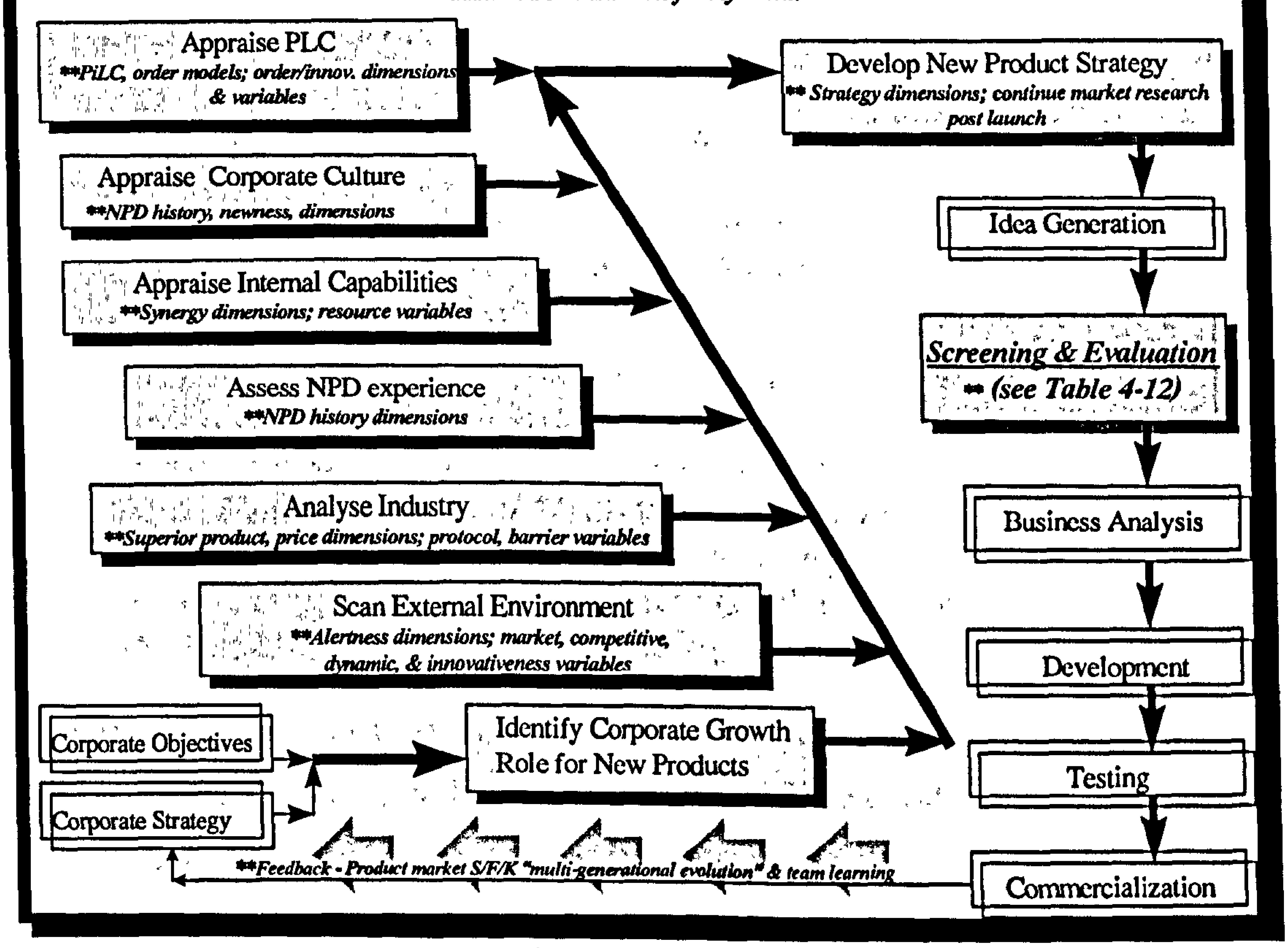
[80] o = the optimistic time estimation, m = the most likely estimate and p = the pessimistic estimate.

6.8 Conclusion

Important seminal findings have been temporally validated with new knowledge added to the initial screening literature (see Table 4-12). Moreover, some synthesis has resulted vis-à-vis the strategic nature of the process (see Figure 6-5). Unfortunately, though encouraging, little impact will be seen on failure rates until organisations learn from their own multigenerational history.

> *"Men make their own history, but they do not make it just as they please; they do not make it under circumstances chosen by themselves, but under circumstances directly found, given and transmitted from the past."* (Karl Marx from The Eighteenth Brumaire of Louis Bonaparte, Sct. 1 1852. repr. in Selected Works, Vol. 2, 1942, Columbia University Press 1993).

Figure 6-5: Strategic synthesis in the context of Booz, Allen and Hamilton's (1982) *Strategic Approach* to New Product Planning. ** *indicates a contribution to field synthesis.*



Regrettably, new product development *as an historical learning vehicle* has been largely ignored. This must change (Moran 1996). Achieving rising success rates requires all to learn what successful teams already know - that better assessment, learning and implementation of history lessons, combined with adequate resources to adapt strategically to changing environments, leads to success. Failing to grasp this hypothetically extends Darwin's theory of natural selection (1859) to an industrial setting. He theorised long ago that:

> *"Variability is not actually caused by man; he only unintentionally exposes organic beings to new conditions of life and then nature acts on the organism and causes it to vary. But man can and does select the variations given to him by nature and thus accumulates them in any desired manner".*
>
> *"It is certain that he can largely influence the character of a breed by selecting, in each successive generation, individual differences so slight as to be inappreciable except by an educated eye".*
>
> *"In the survival of favoured individuals and races, during the constantly-recurrent struggle for existence, we see a powerful and ever-acting form of selection".*
>
> *"More individuals are born than can possibly survive. A grain in the balance may determine which individuals shall live and which shall die, - which variety or species shall increase in number and which shall decrease, to finally become extinct".*
>
> *"The slightest advantage in certain individuals, at any age or during any season, over those with which they come into competition, or better adaptation in however slight a degree to the surrounding physical conditions, will in the long run, turn the balance".*
>
> *"As natural selection acts solely by accumulating slight, successive, favourable variations, it can produce no great or sudden modifications; it can act only by short and slow steps. Hence, the canon of "Natura Non Facit Saltum", which every fresh addition to our knowledge tends to confirm, is on this theory intelligible"* (Charles Darwin 1859 p 621-626).

137 years later, Charles Darwin, Chief Executive Officer, might extend his grandfather's work by adding <u>The theory of NPD "natural outcome"</u>:

> *"The optimisation of strategic resources across competing product market species over time affords survival of the fittest to those which learn and adapt best to lessons learned from multigenerational product market history. Some are "naturally selected" for success by their natural understanding of "past product market outcomes". This knowledge is handed down, quite normally, through family member experiences. As such, new projects are better prepared to take repetitive competitive advantage of*

conditional changes in the environment, product generation after product generation. Each succeeding successful generation gets stronger naturally, playing out the hand its product market family history deals whilst passing on even deeper understanding. Unless interrupted purposefully by overt action, by catastrophic dimensional omission or by a significant change in its environment, a most "natural outcome" can be expected at one year post launch.

Multigenerational product market history entombs a product market family success/failure imprint. The successful use this imprint "naturally", almost unknowingly. From strong programmes and robust family designs they continue to evolve slowly to states of being, even higher than the preceding product generation. The opposite is true of weak product market families. Failing to learn from ancestor projects, they are unable to adapt as well to conditions recognised by the successful. Being disadvantaged, barring overt strategic dimensional realignment towards T_1 targets, a most "natural outcome" is inevitable. Though distressing to the family ancestors, failing and not fully understanding why precludes them from re-teaching successful survival lessons to the next generation. As a result, they beget only weaker product offsprings".

And so it goes.

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APPENDIX A - Questionnaire

Thank you for participating in The Product-Wars Project, a British and American University collaboration designed to improve new product success rates by improving the GO/NO GO decision. In return for answering this 15 minute questionnaire, you will receive a free copy of Product-Wars 1.1©, an interactive decision support tool designed to help you assess market entry decisions. Please choose either a SUCCESSFUL OR FAILED new product introduced within the last three years and complete the questionnaire below as it applies to only the project chosen. Read each of the statements determining the extent to which it describes the product both at the initial idea screening and at the end of year #1 of market entry (two different answers for the same question indicates that over time the situation changed between the initial product idea screening and the end of the first year of commercialisation). Please use the postage paid self-addressed envelope provided to mail the completed questionnaire to John B. Green, Jr., Assistant Professor of Business Administration and Director of Institutional Research, Brenau University, 1 Centennial Circle, Gainesville, GA 30501. If you have any questions please call him at 404/534-6215. Please check *Product-Wars*© disk size ____3.5" or ____5.25" Format______. Thank you!

Evaluator______________________Title___________________Company___________________ Parent Company's Country of Origin____________
Telephone # (___)______—____________Product ______________________Product market__________Primary market: Industrial___Consumer___
Product type: Hardware/Machine___Software___Peripheral___Component/Accessory___
Supplies___Commodity___Other (specify)______________________

This Product was a: Success____Failure____
In the last 3 years in this product market we have had (how many?) ***# Successes____# Failures____# Killed ideas (Booz, Allen and Hamilton 1982; Boston Consulting Group 1972; Darwin 1859)***
If product was modified after entry (when?) During yr. 1___Between yr. 1-2___Between yr. 2-3___After yr. 3______
If product was killed after entry (when?) During yr. 1___Between yr. 1-2___Between yr. 2-3___After yr. 3______
The Mo./Yr. of Initial Idea Screening:___/___Mo./Yr.
The Mo./Yr. of first Market entry:___/___
Its life expectancy in original form before modifications was: #____Yrs.#____Mos. (Cooper and de Brentani (1984)

Please circle answers for both the period of Initial Screening of the idea and at the end of Year #1 (Indicating if your feelings (the rating) changed between the time of the initial screen and the end of year #1 after launch)	0 = strongly disagree 10 = strongly agree	0 = strongly disagree 10 = strongly agree
	At Initial Screen	**At end of year #1**
NEWNESS/INNOVATIVENESS		
This product was (please rate ALL as they apply to the new product:)		
1. • New-to-the-world (a true innovation in the product marketplace listed above)	Booz Allen 1982	Booz Allen 1982
2. • A new product line	Booz Allen 1982	Booz Allen 1982
3. • An addition to an existing product line	Booz Allen 1982	Booz Allen 1982
4. • Improvement in or revision to an existing product	Booz Allen 1982	Booz Allen 1982
5. • A repositioning	Booz Allen 1982	Booz Allen 1982
6. • A cost reduction	Booz Allen 1982	Booz Allen 1982
7. Our firm developed clear strategies to deal with deficiencies/problems in the area of Newness/Innovation	Porter 1991	Porter 1991
SUCCESS FACTORS/STRATEGY	**FAILURE-#8 ONLY**	**SUCCESS-#8 ONLY**
8. After the 1 year entry period, this product was considered a **Failure/Success** **(-5=great failure +5=great success)**	**-5 -4 -3 -2 -1**	**+1 +2 +3 +4 +5**
9. This product should have been killed	0 1 2 3 4 5 6 7 8 9 10	0 1 2 3 4 5 6 7 8 9 10
10. We should have modified this product more radically than we did	0 1 2 3 4 5 6 7 8 9 10	0 1 2 3 4 5 6 7 8 9 10
This success/failure judgement was based on the attainment of objectives to (please rate ALL objectives below:)		
11. • Increase market penetration	Mahajan & Wind 1992	Mahajan & Wind 1992
12. • Capitalise on existing markets	Mahajan & Wind 1992	Mahajan & Wind 1992
13. • Combat major competitive entry	Mahajan & Wind 1992	Mahajan & Wind 1992
14. • Capitalise on new technology	Mahajan & Wind 1992	Mahajan & Wind 1992
15. • Establish a foothold in a new market	Mahajan & Wind 1992	Mahajan & Wind 1992
16. • Pre-empt emerging market segment	Mahajan & Wind 1992	Mahajan & Wind 1992
17. • Utilise excess capacity	Mahajan & Wind 1992	Mahajan & Wind 1992
18. • Offset seasonal cycle	Mahajan & Wind 1992	Mahajan & Wind 1992
19. • Utilise by-products	Mahajan & Wind 1992	Mahajan & Wind 1992
20. • Produce products at a lower cost	Mahajan & Wind 1992	Mahajan & Wind 1992
Please rate degree of success at each time period according to the following performance measurement criteria:		
21. • Financial measures (profit, ROI, payback period etc.)	Cooper & Kleinschmidt 1987a	Cooper & Kleinschmidt 1987a
22. • Window of Opportunity measures (to new markets, categories etc.)	Cooper & Kleinschmidt 1987a	Cooper & Kleinschmidt 1987a

Please **circle answers for both the period of Initial Screening of the idea and at the end of Year #1** (Indicating if your feelings (the rating) changed between the time of the initial screen and the end of year #1 after launch)	**0 = strongly disagree** **10 = strongly agree**	**0 = strongly disagree** **10 = strongly agree**
	At Initial Screen	**At end of year #1**
23. • Market Impact measures (effect on domestic/foreign market share)	Cooper & Kleinschmidt 1987a	Cooper & Kleinschmidt 1987a
BARRIERS TO ENTRY		
The following were important in the GO/NO GO decision process (please rate ALL barriers to entry):		
24. • Cost advantages of incumbents (economies of scale)	Porter 1980	Porter 1980
25. • Product differentiation (proprietary product differences) of the incumbents	Porter 1980	Porter 1980
26. • Brand identity	Porter 1980	Porter 1980
27. • Customer switching costs	Porter 1980	Porter 1980
28. • Capital requirements	Porter 1980	Porter 1980
29. • Access to distribution channels	Porter 1980	Porter 1980
30. • Absolute cost advantages (learning curve, access to inputs, proprietary design etc.)	Porter 1980	Porter 1980
31. • Government Policy	Porter 1980	Porter 1980
32. • Expected retaliation	Porter 1980	Porter 1980
33. Expected speed of competitive retaliation was an important consideration in this market entry decision	Porter 1980	Porter 1980
34. Expected magnitude of competitive retaliation was an important consideration in this market entry decision	Porter 1980	Porter 1980
35. The product would have done better if marketed by almost any of our major competitors	Cooper 1975	Cooper 1975
36. Our firm developed clear strategies to deal with deficiencies in the area of Barriers to Entry	Porter 1991	Porter 1991
RESOURCES REQUIRED		
37. Our company's financial resources were more than adequate for this project	COOPER 1992	COOPER 1992
38. Our company's R&D skills & people were more than adequate for this project	COOPER 1992	COOPER 1992
39. Our company's engineering skills & people were more than adequate for this project	COOPER 1992	COOPER 1992
40. Our company's marketing research skills & people were more than adequate for this project	COOPER 1992	COOPER 1992
41. Our company's management skills were more than adequate for this project	COOPER 1992	COOPER 1992
42. Our company's production resources or skills were more than adequate for this project	COOPER 1992	COOPER 1992
43. Our company's sales force &/or distribution resources & skills were more than adequate for this project	COOPER 1992	COOPER 1992
44. Our company's advertising & promotion resources & skills were more than adequate for this project	COOPER 1992	COOPER 1992
45. Our firm developed clear strategies to deal with deficiencies in the area of Resource Requirements	Porter 1991	Porter 1991
NATURE OF PROJECT/NEWNESS TO FIRM		
46. Our product was highly innovative - totally new to the market	COOPER 1992	COOPER 1992
47. The product specifications - exactly what the product will be - were very clear	COOPER 1992	COOPER 1992
48. The technical aspects - exactly how the technical problems will be solved - were very clear	COOPER 1992	COOPER 1992
49. The potential customers for this product were totally new to our company	COOPER 1992	COOPER 1992
50. The product class or type of product itself was totally new to our company	COOPER 1992	COOPER 1992
51. We had never made or sold products to satisfy this type of customer need or use before	COOPER 1992	COOPER 1992
52. The competitors we face in the market were totally new to our company	COOPER 1992	COOPER 1992
53. The product "fit in" with a family of products we already had on the market	COOPER 1992	COOPER 1992
54. The product which entered the market was significantly different than that approved at the initial screen	Crawford 1986	Crawford 1986
55. Our firm developed clear strategies to deal with deficiencies in the Nature of the Project	Porter 1991	Porter 1991
THE FINAL PRODUCT		

Please circle answers for both the period of Initial Screening of the idea and at the end of Year #1 (Indicating if your feelings (the rating) changed between the time of the initial screen and the end of year #1 after launch)	0 = strongly disagree 10 = strongly agree	0 = strongly disagree 10 = strongly agree
	At Initial Screen	**At end of year #1**
56. Compared to competitive products (or whatever the customer was using) our product offered a number of unique features, attributes or benefits to the customer	COOPER 1992	COOPER 1992
57. Our product was clearly superior to competing products in terms of meeting customer needs	COOPER 1992	COOPER 1992
58. Our product permitted the customer to reduce his/her costs, when compared to what he/she was using	COOPER 1992	COOPER 1992
59. Our product permitted the customer to do a job or do something that he/she could not do with what was available on the market	COOPER 1992	COOPER 1992
60. Our product was of higher quality - however quality is defined in this market - than competing products	COOPER 1992	COOPER 1992
61. Our product was priced considerably higher than competing products	COOPER 1992	COOPER 1992
62. Our firm developed clear strategies to deal with deficiencies in the Final Product	Porter 1991	Porter 1991
THE MARKET FOR THE PRODUCT		
63. Potential customers had a great need for this class or type of product	COOPER 1992	COOPER 1992
64. The dollar size of the market (either existing or potential market) for this product was large	COOPER 1992	COOPER 1992
65. The market for this product was growing very quickly	COOPER 1992	COOPER 1992
66. The market was characterised by intense price competition	COOPER 1992	COOPER 1992
67. There were many competitors in this market	COOPER 1992	COOPER 1992
68. There was a strong dominant competitor- with a large market share - in this market	COOPER 1992	COOPER 1992
69. Potential customers were very satisfied with the products (competitors' products) they were currently using	COOPER 1992	COOPER 1992
70. Users' needs changed quickly in this market - a dynamic market situation	COOPER 1992	COOPER 1992
71. We were the first to market this product	Maidique and Zirger 1984 Robinson & Fornell 1985	Maidique and Zirger 1984 Robinson & Fornell 1985
72. We were not first to market this product; we followed close behind however	Robinson & Fornell 1985	Robinson & Fornell 1985
73. We entered the market in its late growth stage	Robinson & Fornell 1985	Robinson & Fornell 1985
74. We entered the market somewhere between its maturity and decline	Robinson & Fornell 1985	Robinson & Fornell 1985
75. The fast rate of technological change was important in this product market	Ansoff & Stewart 1967	Ansoff & Stewart 1967
76. Competitors introduced new products into this market very quickly	Ansoff & Stewart 1967	Ansoff & Stewart 1967
77. Competitors withdrew products from this market very quickly	Ansoff & Stewart 1967	Ansoff & Stewart 1967
78. R&D in this market produced many advancements in the production process and ensuing products	Ansoff & Stewart 1967	Ansoff & Stewart 1967
79. Production methods in this market changed very quickly	Abernathy & Utterback 1978	Abernathy & Utterback 1978
80. The amount of change (technological leap/boundary distance) was important in this product market	Ansoff & Stewart 1967	Ansoff & Stewart 1967
81. New products introduced into this market were much more technologically sophisticated than those replaced	Ansoff & Stewart 1967	Ansoff & Stewart 1967
82. R&D in this market produced significant advancements in the production process and ensuing products	Abernathy & Utterback 1978	Abernathy & Utterback 1978
83. This product had a long life cycle in its original form (before modifications were necessary)	Ansoff & Stewart 1967	Ansoff & Stewart 1967
84. We spent a long time on the market research for this product	Cooper 1976	Cooper 1976
85. Market cyclicality was important in the decision to enter this market	Hopkins 1980	Hopkins 1980
86. Market seasonality was important in the decision to enter this market	Mahajan and Wind 1992	Mahajan and Wind 1992
87. The contribution margin was important in the decision to enter this market	Cooper and de Brentani 1984	Cooper and de Brentani 1984
88. The primary market for this product was domestic (over 50% in US)	COOPER AND DE BRENTANI 1984	COOPER AND DE BRENTANI 1984

Please circle answers for both the period of Initial Screening of the idea and at the end of Year #1 (Indicating if your feelings (the rating) changed between the time of the initial screen and the end of year #1 after launch)	0 = strongly disagree 10 = strongly agree	0 = strongly disagree 10 = strongly agree
	At Initial Screen	**At end of year #1**
89. Our firm developed clear strategies to deal with difficulties inherent in this market	Porter 1991	Porter 1991

APPENDIX B - Definitions

A priori probability - The probability measures before any additional information is obtained. It may be revised if further relevant information is revealed (Webster 1992).

Adjusted R Square - An estimate of how well the model will fit the population. A model estimated from a sample fits the sample better than it will fit the population. The sample R squared thus tends to overestimate the goodness of fit of the model in the population. Adjusted R squared corrects the optimistic bias of the sample R squared by taking sample size and the number of predictors into account. Unlike R squared, adjusted R squared does not necessarily increase as additional variables are added to an equation (Norusis 1993).

ANOVA (Analysis of Variance) - In regression, used to test the hypothesis that there is no linear relationship between the dependent variable and the independent variable(s). The total variation in the dependent variable is divided into two components--one which can be attributed to a particular regression model (labelled REGRESSION) and one which cannot (labelled RESIDUAL). If the observed significance level for the F-test is small, the hypothesis that there is no linear relationship can be rejected (Norusis 1993).

Canonical Correlation - The canonical correlation for a discriminant function is the square root of the ratio of the between-groups sum of squares to the total sum of squares. Squared, it is the proportion of the total variability explained by differences between groups (Norusis 1993).

Chi-square (in Crosstabs) - Statistic used to test the hypothesis that the row and column variables are independent (Norusis 1993).

Cluster analysis - A statistical procedure that identifies homogeneous groups or clusters of cases based on their values for a set of variables (Norusis 1993).

Conceptual definition (sometimes called a constitutive definition) - Defines a concept in terms of other concepts. It states the central idea or essence of the concept (Tull and Hawkins 1993).

Construct validity - Understanding the meaning of the obtained measurements (Tull and Hawkins 1993)

Critical path method (CPM) - A technique of project control, now usually incorporated in various software programmes. The technique puts all important steps of a given new product project into a sequential network (Crawford 1994).

Cronbach's alpha - A method for measuring factor extraction that considers the variables in the analysis to be a sample from the universe of potential variables (Norusis 1993).

Cycle time - See speed to market.

Degrees of freedom - Number associated with a test statistic which is used in determining the observed significance level (Norusis 1993).

Deterministic (versus) stochastic (random) models - A deterministic mathematical model is expressed as $Y=B_0 + B_1X_1$. Given any value for X, the value of Y can be determined with precision. A stochastic model contains one or more random components that lead to errors in efforts to predict and is written as $Y=B_0 + B_1X_1 + e$ (epsilon/error) (Webster 1992).

Discrete stochastic process - A dynamic, probabilistic process that involves elements of a system moving in an orderly manner among finite sets of states, the movement occurring at discrete points in time (Burns and Austin 1985).

Discriminant function - A linear combination of the discriminating variables that maximises the distance (separation) between groups. The maximum number of discriminant functions that can be derived is either one less than the number of groups, or the number of discriminating variables, whichever is smaller. When the independent variables are not in standardised form, their coefficients are called un-standardised discriminant function coefficients. Also called canonical variates and un-standardised canonical discriminant functions (Norusis 1993).

Duncan procedure - A multiple comparison procedure that ranks the group means from smallest to largest and uses the distance or number of steps that two means are apart in this ranking in computing the range value for each comparison. The test is based on the assumption that the larger the number of means being compared, the more likely that significantly different comparisons will occur. In this procedure, the probability of finding a significant difference, given that the two groups are in fact equal, is sometimes less than and never greater than, the specified significance level (Norusis 1993).

Eigenvalue - The ratio of the between groups to within groups sum of squares for each discriminant function. Large Eigenvalue are associated with functions that contribute to group separation. In factor analysis, the Eigenvalue for a factor is the variance associated with it (Norusis 1993).

Expected value of imperfect information (EVII) - What the researcher wishes to optimise, the expected value of imperfect information is the expected value of perfect information (EVPI) minus the expected cost of errors (ECE) caused by inaccuracy and research error (EVII = EVPI - ECE) (Tull and Hawkins 1993).

Expected value of perfect information (EVPI) - The difference between the expected value of a decision outcome with certain knowledge (EVDPI) and the expected value of the decision with current knowledge (EVD) i.e. EVPI = EVDPI - EVD (Tull and Hawkins 1993).

Expected value of the decision with perfect information (EVDPI) - The sum of the highest payoff for each market state multiplied by the probability of that market state occurring (Tull and Hawkins 1993).

F - The ratio of two mean squares. The larger mean square is conventionally placed in the numerator and the smaller in the denominator. The degrees of freedom associated with the numerator and denominator are used in the evaluation of F statistics (Norusis 1993).

Factor Analysis - Used to identify underlying factors that explain the correlations among a set of variables. Its purpose is often to summarise a large number of variables with a smaller number of factors (Norusis 1993).

Factor loading - The coefficients used to express a standardised variable as a linear combination of the factors. If the factors are un-correlated with each other, it is also the correlation between the variable and the factor. Also called the factor pattern matrix (Norusis 1993).

Imputation Estimates - Involve assigning attributes to the non-respondents (of a survey) based on the characteristics of the respondents in order to adjust for non-response (Tull and Hawkins 1993).

Innovativeness - (1) When applied to the seller, it is the degree to which the firm has the capability of and follows the practice of, being innovative. (2) When applied to a buyer, it is the extent to which that person or firm is willing to accept the risks of early purchase on an innovation (Crawford 1994).

Interval Scale - Numbers used to rank items such that numerically equal distances on the scale represent equal distances in the property being measured. The location of the zero point and the unit of measurement are determined by the researcher; consequently, ratios calculated on data from interval scales are not meaningful (Tull and Hawkins 1993)

Kurtosis - A measure of the extent to which observations are clustered in the tails. For a normal distribution, the value of the kurtosis statistic is 0. For samples from a normal distribution, the values of kurtosis will fluctuate around 0. If a variable has a negative kurtosis, its distribution has lighter tails than a normal distribution. If a variable has a positive kurtosis, a larger proportion of cases fall into the tails of the distribution than into those of a normal distribution. Kurtosis can be used, along with the skewness statistic, to assess whether a variable is normally distributed (Norusis 1993).

Likelihood ratio - A goodness-of-fit statistic similar to Pearson's chi-square. For large sample sizes, the two statistics are equivalent (Norusis 1993).

Linear regression - Estimation of the linear relationship between a dependent variable and one or more independent variables or covariates using the regression method. The regression method is a method for estimating factor score coefficients. The scores produced have mean of 0 and a variance equal to the squared multiple correlation between the estimated factor scores and the true factor values. The sum of squared discrepancies between true and estimated factors over individuals is minimised. The scores may be correlated even when factors are orthogonal (Norusis 1993).

Mahalanobis' distance - A measure of how much a case's values on the independent variables differ from the average of all cases. For a single independent variable, it is simply the square of the standardised value of the independent variable. A large Mahalanobis' distance identifies a case as having extreme values on one or more of the independent variables (Norusis 1993).

Measurement timing error - Occurs when the pre or post-measurement is made at an inappropriate time to indicate the effect of the experimental treatment (Tull and Hawkins 1993).

Meta-analysis - The application of statistical procedures to collections of empirical findings from individual studies, for the purpose of integrating, synthesising and making sense of them (Wolf 1986).

Monomorphic - Not changing form during development (The concise Oxford Dictionary 1990).

Multimorphic - The opposite of monomorphic. Changing form during development.

Multiple stage evaluation models - Different models used during the new product development process to account for varying R&D levels, cost, information uncertainty and go/no-go criteria (Albala 1975).

NPD product market history ("batting average") - The last 3 years of actual product market successes, failures and kills. It is comprised of the success ratio (S%), the failure ratio (F%) and the kill ratio (K%). The success ratio (S%) is = $\frac{S}{S+F+K}$ where S = the number of successes, F = the number of failures and K = the number of kills in the last 3 years in the same product market.

New product failure - A new product that does not meet the objectives of its developers. Depending on what those objectives are, a profitable new product can be a failure and an unprofitable new product can be a success (Crawford 1994).

New product strategy - Strategy that guides the product innovation programme. Is unique to new products and is a spin-off from overall corporate or division strategy (Crawford 1994).

Non-probability sample - One in which chance selection procedures are not used to draw the sample (Tull and Hawkins 1993).

NPD process (new product development process) - (1) The overall process of strategy, organisation, concept generation, product and marketing plan creation and evaluation and commercialisation, of a new product. (2) Sometimes restricted in meaning to that part of the process done by technical (R&D) departments. (3) Sometimes used to denote the person or persons engaged in the new product creation task. New product development concerns activity within an organisation, in contrast to the acquisition of finished new products from outside- (Crawford 1994).

Observed significance level - The basis for deciding whether or not to reject the null hypothesis. It is the probability that a statistical result as extreme as the one observed would occur if the null hypothesis were true. If the observed significance level is small enough, usually less than 0.05 or 0.01, the null hypothesis is rejected (Norusis 1993).

Operational Definition - A description of the activities the researcher must complete in order to assign a value to the concept to be measured. It translates the concept (e.g., brand loyalty) into one or more measurable events (e.g., purchase frequency) (Tull and Hawkins 1993).

Orthogonal (FACTOR) - Factors resulting from a factor analysis that are not correlated (Norusis 1993).

Pearson's R - A measure of linear association between two variables. The value of R ranges between -1 (a perfect negative relationship in which all points fall on a line with negative slope) and +1 (a perfect positive relationship in which all points fall on a line with positive slope). A value of 0 indicates no linear relationship (Norusis 1993).

PIC (product innovation charter) - The summary statement of strategy that will guide a department or project team in their efforts to generate new product volume. Specifies the arena within which the people will operate, their goals and objectives and the general approaches they will use (Crawford 1994).

PiLC - The product's life expectancy in original form (# of years and # of months) before modifications are necessary. From the variable statement "The products life expectancy in original form before modifications was: #_____Yrs.#_____Mos."

PIMS Database - A computerised database maintained by the Strategic Planning Institution, containing data on over 200 marketing, financial and operating performance variables collected from almost 2,0000 business units (Buzzell and Gale 1987).

Pipeline balance - The inability to successfully develop new product platforms whilst extending their existing product lines (Product Development & Management Association).

Pipeline churn - The problem of too often changing development priorities. This creates confusion and frustration and slows down development activity (Product Development & Management Association).

PLC (product life cycle) - The four stages that a new product is thought to go through from birth to death: introduction, growth, maturity and decline. Controversy surrounds whether products do indeed go through such cycles in any systematic, predictable way. The product life-cycle concept is primarily applicable to product forms, less to product classes and very poorly to individual brands (Crawford 1994).

Posterior probability - The probability measure which has been revised on the condition that some known event has occurred (Webster 1992).

Product introduction - The first stage of the product life cycle, during which the new item is announced to the market and offered for sale (Crawford 1994).

Project - The unit of activity in the product development process that usually deals with creating and marketing one new product. A project involves a multidisciplinary group of people and may often be part of a larger unit of work, a programme, which delivers a stream of new products, one from each project (Crawford 1994).

Protocol - A statement of the benefits (not features) a new product should have. A protocol is prepared after the full screen and business analysis, prior to the project being assigned to technical departments. The benefits statement is agreed to by all parties, thus the term protocol (Crawford 1994).

R Squared - A measure of the goodness of fit of a linear model. It is sometimes called the coefficient of determination. It is the proportion of the variation in the dependent variable explained by the regression model. It is also the square of the multiple R, the correlation of the observed and predicted values of the dependent variable. It can range in value from 0 to 1. Small values indicate that the model does not fit the data well (Norusis 1993).

Reliability - the extent to which a measurement is free of variable errors. This is reflected when repeated measures of the same stable characteristic in the same objects show limited variation (Tull and Hawkins 1993).

Scree - a plot of the variance associated with each factor. It is used to determine how many factors should be kept. Typically the plot shows a distinct break between the steep slope of the large factors and the gradual trailing of the rest (the scree) (Norusis 1993).

Screening (of ideas at the initial screen; T_0) - Evaluation steps prior to R&D and systems design in the product development process. They involve use of scoring models, checklists, or personal judgements and are base don information from experience and various market research studies (including concept testing) (Crawford 1994).

Significance of F - The observed significance level of F. If this probability is small enough, usually less than 0.05 or 0.01, the null hypothesis, that there is no linear relationship between the dependent and independent variables, is rejected (Norusis 1993).

Simulation - a widely used tool differing from others in that the interest is in replication of system behaviour over time. The emphases is one of "what if" rather than "what's best". Policies and strategies for improving system behaviour are usually manually generated rather than automatically generated by an optimisation algorithm (Burns and Austin 1985).

Single stage accuracy rate - The rate of prediction accuracy using a static model to maximise a linear regression or discriminant analysis objective function. Used to measure antecedent variables at one point in the new product development process.

Skewness - An index of the degree to which a distribution is not symmetric, or to which the tail of the distribution is skewed or extends to the left or right. The normal distribution is symmetric and has a skewness value of zero. A distribution with a significant positive skewness has a long right tail. A distribution with a significant negative skewness has a long left tail. Skewness is used, along with the kurtosis statistic, to assess if a variable is normally distributed (Norusis 1993).

Slack time - The delay allowed in activities off the critical path. All activities on the critical path have zero slack (Meredith 1992).

Speed to market - The speed of the development process or launch effort. Included are measures which refer to launch timing, development cycle time and first or second to market effects (Montoya-Weiss and Calantone 1994).

Standard error of the predicted values - The standard deviation of an average predicted value. The standard error of a predicted value depends on how close a case's value for the independent variable is to the average values of the independent variables for all cases. Prediction is least variable when independent variables have values near their means (Norusis 1993).

Strategic planning activities - Defining the mission, analysing the external environments, analysing the internal culture and environments, choosing objectives and goals, developing various strategies, preparing programmes, implementing the programmes and gathering feedback (Kotler 1994).

Strategy - The policies and key decisions adopted by management that have major impacts on financial performance. These policies and decisions usually involve significant resource commitments and are not easily reversible (Buzzell and Gale 1987).

Tracking - The act of checking on the progress of important aspects or issues in the marketing of a new product. May be comprehensive or causal. (Crawford 1994).

Tracking variable - A specific variable used to track a specific phenomenon (Crawford 1994).

Type I error - The error of T_1 (the designation of the market test) given S_2 (the true state of the market). It is conditional error since the indication of T_1 is an error only under the condition that S_2 is the true state of the market. Type I error is the result of falsely rejecting the null hypotheses. The conditional probability of the error occurring is show symbolically as $P(T_1|S_2)$ Type I error (its cost) = $P(T_1|S_2) * P(S_2) * |V_2|$. Type II error is the opposite (Tull and Hawkins 1993).

Validity - the measure of consistent or systematic error rather than variable error (Tull and Hawkins 1993).

Wilks' Lambda (DISCRIMINANT) - A statistic for evaluating the hypothesis that 2 or more groups come from populations with the same means for a set of variables. Lambda ranges between 0 and 1. Large values of Lambda indicate that group means do not appear to be different (it equals 1 if they're all the same). Small values indicate differences in group means. Sometimes called the U statistic (Norusis 1993).