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Cash Flow Patterns as a Proxy for Firm Life Cycle

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ABSTRACT: This study develops a firm life cycle proxy using cash flow patterns. The patterns provide a parsimonious indicator of life cycle stage that is free from distributional assumptions (i.e., uniformity). The proxy identifies differential behavior in the persistence and convergence patterns of profitability. For example, return on net operating assets (RNOA) does not mean-revert (spread of 7 percent after five years between mature and decline firms) when examined by life cycle stage, which has implications for growth rates and forecast horizons. Further, determinants of future profitability such as asset turnover and profit margin are differentially successful in generating increases in profitability conditional on life cycle stage. Finally, investors do not fully incorporate the information contained in cash flow patterns and, as a result, undervalue mature firms. The cash flow proxy is a robust tool that has applications in analysis, forecasting, valuation, and as a control variable for future research.

Keywords: *life cycle; fundamental analysis; forecasting; profitability; rates of return; return on assets.*

Data Availability: *All data are available from public sources identified in the paper.*

I. INTRODUCTION

Business firms are evolving entities, with the path of evolution determined by internal factors (e.g., strategy choice, financial resources, and managerial ability) and external factors (e.g., competitive environment and macroeconomic factors). Firm life cycles are distinct phases that result from changes in these factors, many of which arise from strategic activities undertaken by the firm. Although firm life cycle stages have important implications for understanding the financial performance of firms, research efforts to develop a robust approach to

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measuring firm life cycle stages and investigating their implications for financial analysis and valuation are sparse at best (Anthony and Ramesh 1992).

Capturing life cycle at the firm level (rather than at the individual product or industry level)[1] is a difficult undertaking. Firms are aggregations of multiple products, each with a distinct product life cycle stage. Additionally, the firm can compete in multiple industries, such that its product offerings are quite diverse. As a result, *firm-level* life cycle stage is difficult to assess because it is a composite of many overlapping, but distinct, *product* life cycle stages. However, the economics literature has addressed individual attributes of life cycle theory such as production behavior (Spence 1977, 1979, 1981; Wernerfelt 1985; Jovanovic and MacDonald 1994), learning/experience (Spence 1981), investment (Spence 1977, 1979; Jovanovic 1982; Wernerfelt 1985), entry/exit patterns (Caves 1998), and market share (Wernerfelt 1985). By combining the implications from these research studies, I develop a parsimonious firm-level life cycle proxy based on the predicted behavior of operating, investing, and financing cash flows across different life cycle stages.[2] Unlike prior attempts at developing life cycle proxies (e.g., Anthony and Ramesh 1992), my classification methodology is "organic" in that life cycle stage identification is the result of firm performance and the allocation of resources, as opposed to an *ad hoc* assignment.[3]

This study is important for several reasons. First, several financial accounting and financial statement analysis textbooks frequently refer to the link between cash flows and life cycle stage (see, for example, Stickney et al. 2010, 210–212; Kieso et al. 2010, 1246–1247; Kimmel et al. 2009, 606; among others). While these books often graphically depict cash flows over the product life cycle, there is scarce empirical evidence to support these assertions. This study provides a rigorous analysis of the relation between cash flows, future performance, and life cycle fundamentals.

Second, I find that the cash flow pattern proxy is better aligned with the functional form of firm profitability than competing classification schemes. Economic theory predicts a nonlinear relation between life cycle stages and performance variables such as earnings, return on net operating assets (RNOA),[4] asset turnover (ATO), profit margin (PM), sales revenue, leverage, dividend payout, size, and age, which is consistent with the distribution that results from using cash flow patterns as a life cycle proxy.

Third, the cash flow pattern proxy for life cycle identifies differential behavior in the persistence and intertemporal convergence patterns of profitability. Previous research documents that profitability measures mean-revert over time (Brooks and Buckmaster 1976; Freeman et al. 1982; Fairfield et al. 1996; Fama and French 2000; Nissim and Penman 2001) and understanding the evolution of profitability improves predictability. Specifically, I find that RNOA maintains a differential spread of 3 to 10 percent between decline and mature firms even

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[1] The following studies examine the validity of product life cycle for the following industries: German automobile manufacturers (Brockhoff 1967); pharmaceuticals (Cox 1967); tobacco, food, and personal care products (Polli and Cook 1969); and household cleansers (Parsons 1975).

[2] Lev and Zarowin (1999) document that: (1) the rate of business change has increased over time, and (2) the value-relevance of earnings has decreased over time. Taken together, these findings suggest that a non-earnings-based measure that captures firm life cycle stage would be useful to investors and creditors.

[3] Anthony and Ramesh (1992) conducted one of the first studies to demonstrate the usefulness of firm life cycle in explaining market performance. However, their sample period ended before the Statement of Cash Flows was a required disclosure. Therefore, their life cycle measure relied on a composite of economic characteristics such as sales growth, dividend payout, capital expenditures, and firm age. By necessity, their life cycle proxy had to rely on portfolio sorts to draw distinctions between life cycle stages.

[4] RNOA removes the effect of financing from profitability and is measured as operating income divided by net operating assets (NOA) (Nissim and Penman 2001). NOA excludes financial assets from the denominator because they are already valued at fair value on the balance sheet. NOA also subtracts out operating liabilities from operating assets. This adjustment is made because operating liabilities reflect a source of leverage that can increase profitability.

five years after initial life cycle portfolio formation. This difference is economically significant and suggests that differences in firm life cycle are an impediment to the mean-reversion of profitability.

Fourth, the life cycle measure developed in this study possesses explanatory power for future profitability. Prior research has demonstrated that changes in future accounting returns (specifically RNOA) are explained by level and change of current profitability, growth in net operating assets, and by increases in asset turnover (ATO) (Fairfield and Yohn 2001). Given that firm life cycle stage differentially explains profitability, including the cash flow pattern proxy for life cycle also provides incremental information about future change in RNOA, and the cash flow pattern proxy outperforms alternative life cycle proxies. Further, I find that the effect of changes in ATO for changes in future RNOA is concentrated in mature firms. This pattern is consistent with theory that predicts competitive pressures drive mature firms to focus on efficiency and cost containment (Selling and Stickney 1989). Also, Penman and Zhang (2006) find that increases in profit margin (PM) result in negative future RNOA because those increases are achieved through a reduction of operating expenses that are not sustainable. Again, this effect is concentrated in mature firms, where product differentiation efforts (which manifest in PM) have reached a stage of diminishing returns (Oster 1990; Shy 1995).

Finally, the cash flow pattern proxy is associated with market inefficiency with respect to equity share prices. Because life cycle stage affects convergence of profitability and interacts with the determinants of future profitability, the cash flow pattern classification plays a role in understanding firm value and in predicting stock returns. The market does not fully incorporate information provided by the life cycle proxy, such that mature firms earn positive excess returns in the year following life cycle stage signal. This finding indicates that investors underestimate the persistence of the elevated profitability of mature firms and instead expect their profitability to mean-revert to "normal" levels during the subsequent year.

In summary, this study presents and validates cash flows patterns as a parsimonious proxy for identifying firm life cycle stage. The classification potentially benefits both practitioners (e.g., investors, creditors, analysts, auditors, and regulators) and researchers in the following contexts: (1) to better assess growth rates and forecast horizons in valuation models; (2) to better understand how economic fundamentals affect the level and convergence properties of future profitability; (3) to identify firms for which potential unidentified risk factors and/or market mispricing exist based on differences in life cycle stage; and (4) as a control variable for distinct economic characteristics related to firm life cycle that affect performance.

II. DEVELOPMENT AND DESCRIPTIVE VALIDATION OF THE CASH-FLOW-BASED LIFE CYCLE CLASSIFICATION

Gort and Klepper (1982) define five life cycle stages: (1) *introduction* where an innovation is first produced; (2) *growth* where the number of producers increases dramatically; (3) *maturity* where the number of producers reaches a maximum; (4) *shake-out* where the number of producers begins to decline; and (5) *decline* where there is essentially a zero net entry. I propose that cash flows capture the financial outcome of these distinct life cycle stages. Livnat and Zarowin (1990) document that the decomposition of cash flows into operating, investing, and financing activities differentially affects stock returns. Therefore, cash flows capture differences in a firm's profitability, growth, and risk, and the combination of the three types of cash flows are mapped into life cycle theory to derive the life cycle classification used throughout the study. Table 1 summarizes a survey of economic theory related to life cycle and the related predictions of cash flows by type.

TABLE 1

Economic Links to Cash Flow Patterns

Cash Flow Type	Introduction	Growth	Mature	Shake-Out	Decline
Operating	Firms enter market with knowledge deficit about potential revenues and costs (Jovanovic 1982)	Profit margins are maximized during period of greatest investment (Spence 1977, 1979, 1981)	Efficiency maximized through increased knowledge of operations (Spence 1977, 1979, 1981; Wernerfelt 1985)	Declining growth rates lead to declining prices (Wernerfelt 1985) Routines of established firms hinder competitive flexibility (Hannan and Freeman 1984)	Declining growth rates lead to declining prices (Wernerfelt 1985)
	(−) Cash Flows	**(+) Cash Flows**	**(+) Cash Flows**	**(+/−) Cash Flows**	**(−) Cash Flows**
Investing	Managerial optimism drives investment (Jovanovic 1982) Firms make early large investments to deter entry (Spence 1977, 1979, 1981)	Firms make early large investments to deter entry (Spence 1977, 1979, 1981)	Obsolescence increases relative to new investment as firms mature (Jovanovic 1982; Wernerfelt 1985)	Void in theory	Liquidation of assets to service debt
	(−) Cash Flows	**(−) Cash Flows**	**(−) Cash Flows**	**(+/−) Cash Flows**	**(+) Cash Flows**
Financing	Pecking-order theory states firms access bank debt then equity (Myers 1984; Diamond 1991) Growth firms increase debt (Myers 1977; Jensen 1986; Barclay and Smith 2005)	Pecking-order theory states firms access bank debt then equity (Myers 1984; Diamond 1991) Growth firms increase debt (Myers 1977; Jensen 1986; Barclay and Smith 2005)	Focus shifts from acquiring financing to servicing debt and distributing excess funds to shareholders, such that mature firms decrease debt (Myers 1977; Jensen 1986; Barclay and Smith 2005)	Void in theory	Focus on debt repayment and/or renegotiation of debt
	(+) Cash Flows	**(+) Cash Flows**	**(−) Cash Flows**	**(+/−) Cash Flows**	**(+/−) Cash Flows**

Cash Flows' Mapping to Life Cycle Theory

The combination of cash flow patterns represents firms' resource allocations and operational capabilities interacted with their strategy choices. Predictions about each individual cash flow component (operating, investing, or financing) are derived from economic theory, which forms the basis for the life cycle proxy.

Cash Flows from Operations

Introduction firms lack established customers and suffer from knowledge deficits about potential revenues and costs, both of which result in negative operating cash flows (Jovanovic 1982). Profit margins are maximized during increases in investment and efficiency (Spence 1977, 1979, 1981; Wernerfelt 1985), which means that operating cash flows are positive during the growth and maturity stages. Wernerfelt (1985) points out that declining growth rates eventually lead to declining prices, such that operating cash flows decrease (and become negative) as the firm enters the decline stage.

Cash Flows from Investing

Managerial optimism (Jovanovic 1982) encourages firms to make early investments that deter competitors' entries into the market (Spence 1977, 1979, 1981). Consequently, investing cash flows are negative for introduction and growth firms. While mature firms decrease investment relative to growth firms, they continue to invest to maintain capital (Jovanovic 1982; Wernerfelt 1985). If maintenance costs increase over time (i.e., rising prices), then investing cash flows are negative for mature firms, although at a lesser magnitude than investing cash outflows for introduction and growth firms. Decline firms liquidate assets in order to service existing debt and to support operations, which results in positive cash flows from investing.

Cash Flows from Financing

Pecking order theory predicts firms initially access bank debt followed later by equity issuances (Myers 1977, 1984; Diamond 1991). Barclay and Smith (2005) explain that firms attempt to balance the tax benefits of debt (i.e., deductibility of interest expense) against costs of distress from over-borrowing. Introduction or growth firms need debt to grow, but as they increase their leverage, they will eventually need to decrease cash flow as they service debt (Myers 1977; Barclay and Smith 2005). However, Barclay and Smith (2005) point out that the anticipation of less liquidity in the future leads to underinvestment in positive net present value projects as the firm grows. Taken together, financing cash flows are expected to be positive for at least introduction (and likely growth) firms as they access credit for expansion.

By their definition, mature firms have exhausted their positive net present value projects, meaning they have fewer investment opportunities in the future (unless they propel themselves back to the growth stage). This lack of opportunity minimizes the need for additional borrowing, even though these firms are in the best financial position to do so (Barclay and Smith 2005). However, Jensen (1986) suggests the opposite is true in that mature firms generate positive cash flows and consequently overinvest in their core business (or an unrelated acquisition), albeit at lower returns.

Mature firms then, either begin to service debt and distribute cash to shareholders because they have exhausted their positive net present value investment opportunities, or they overinvest in suboptimal projects that diminish their overall profitability. The signaling literature indicates that firms distribute free cash flows to investors to prove that they are not investing in value-destroying endeavors (Jensen 1986; Barclay and Smith 2005; Oler and Picconi 2010). Assuming signaling theory and lack of opportunities outweigh the overinvestment problem, I predict that mature firms pay down their debt and/or repurchase equity, resulting in negative financing cash flows. There is a void in the literature with respect to financing cash flows for decline firms so no directional prediction is made *ex ante*.[5]

Formulation of the Life Cycle Proxy

The *combination* of a firm's net operating, investing, and financing cash flows provide a firm life cycle mapping at each financial statement date. Varying the sign (positive or negative) of the three types of net cash flows, results in eight possible cash flow pattern combinations.[6] I collapse the eight classifications into five theoretical life cycle stages (mentioned at the beginning of the section): introduction, growth, mature, shake-out, and decline, based on expected cash flow behaviors from Table 1.[7]

A benefit of the cash flow pattern proxy is that it uses the entire financial information set contained in operating, investing, and financing cash flows rather than a single metric to determine firm life cycle. As mentioned in the previous section, prior research sorts on variables such as age, sales growth, capital expenditures, dividend payout, or some composite of these variables to assess life cycle stage (Anthony and Ramesh 1992; Black 1998). The drawback of these methods, however, is that an *ex ante* assumption is inherently required with respect to the underlying distribution of life cycle membership. Forming portfolios sorted on a single variable (or a composite of variables), assumes that a uniform distribution of firm-observations across life cycle stages is descriptive. Conversely, cash flow pattern classification is the organic result of firms' operations and achieves better congruence with economic theory (i.e., a normal distribution).

Size and Age as Life Cycle Proxies

Both size and firm age are common proxies for life cycle found throughout the literature.[8] An implicit assumption when using size or age as a proxy is that a firm moves monotonically through its life cycle. This assumption arises because *product* life cycles are characterized by forward progression from introduction to decline. However, a firm is a portfolio of multiple products, each potentially at a different product life cycle stage. Substantial product innovations, expansion into

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[5] Likewise, the literature is silent regarding cash flows for shake-out firms. Consequently, shake-out firms are classified by default if the cash flow patterns do not fall into one of the other theoretically defined stages.

[6] Incorporating sign *and* magnitude of cash flows would likely improve performance of the proxy. However, if positive (negative) cash flows were separated into low- and high-positive (negative) cash flows, then the number of patterns would increase to 64, which is less straightforward when connecting to economic theory. Only the sign is considered in this study.

[7] There are three net cash flow activities (operating, investing, and financing) and each type can take a positive or negative sign, resulting in $2^3 = 8$ possible combinations. The eight patterns are collapsed into five stages as follows:

	1 Introduction	2 Growth	3 Mature	4 Shake-Out	5 Shake-Out	6 Shake-Out	7 Decline	8 Decline
Predicted Sign								
Cash flows from operating activities	−	+	+	−	+	+	−	−
Cash flows from investing activities	−	−	−	−	+	+	+	+
Cash flows from financing activities	+	+	−	−	+	−	+	−

[8] Recent accounting research that relies on firm size or age to capture life cycle effects includes Bradshaw et al. (2011), Bhattacharya et al. (2004), Caskey and Hanlon (2007), Chen et al. (2002), Desai et al. (2006), Doyle et al. (2007), Khan and Watts (2009), Klein and Marquardt (2006), and Wasley and Wu (2006). An abstract search for "firm age" in SSRN yielded 592 results, while a search for "firm size" exceeded the maximum results of 1,000 studies.

new markets, and/or structural change can cause firms to move across life cycle stages nonsequentially. For that reason, *firm* life cycle can be cyclical in nature, and a firm should strive to maintain its life cycle position somewhere between the growth and mature stages where the reward-risk structure is optimized.

Theoretically, firms can enter decline from any of the other stages. The management literature documents a "liability of newness" phenomenon (Stinchcombe 1965; Jovanovic 1982; Freeman et al. 1983; Amit and Schoemaker 1993), which means that the level of initial endowments (monetary resources, technological or managerial capability, etc.) interacts with mortality rates.[9] As such, firms in the decline stage are likely to include young firms that succumb to initially high mortality rates.

Finally, experiential learning causes a divergence between firm life cycle and firm age. Firms of the same age can learn at different rates because of imperfections in their feedback mechanisms (i.e., accounting quality). All of the factors mentioned above lead to a misalignment between performance and firm age, manifesting in a nonlinear relation between life cycle and age. Based on theoretical predictions outlined throughout this section, size and age are expected to adopt an inverted U-shape across life cycle stages (from introduction to decline). However, both factors will be maximized in the mature stage because of the decrease in moral hazard rates for firms that successfully reach maturity.

Validation of the Cash Flow Patterns Proxy

The first step in the analysis is to validate whether life cycle stages based on cash flow patterns are consistent with economic theory. I describe the sample below and then outline the validation process.

Sample Selection

The sample is comprised of firms listed on the NYSE, AMEX, and NASDAQ exchanges (excluding ADRs) with necessary data on Compustat. The sample period extends from 1989 (first year the Statement of Cash Flows was available for all firms) through 2005. Firms with average net operating assets (NOA), sales revenue, absolute book value of equity, or market value of equity less than $1 million are excluded from the sample because small denominators skew profitability ratios. Finally, financial firms are excluded because capital constraints materially alter their cash flow structure relative to other industries. These criteria result in a final sample of 48,369 firm-year observations.

Frequency Distribution by Life Cycle Stage

Mature firms are characterized by stability, while the decline stage is transitory. Given these characteristics, I expect the greatest (lowest) frequency of observations in the mature (decline) stage. Table 2, Panel A confirms this prediction with 41 (5) percent of firm-observations classified as mature (decline).

Descriptive Analysis of Alternative Life Cycle Proxies

Table 2 examines whether economic characteristics vary predictably with life cycle stages as determined by cash flow patterns (Panel A) and by the Anthony and Ramesh (1992; hereafter, AR)

[9] Jovanovic (1982) presents an analytical model where firms' hazard rates (probability of failure) initially increase in early life cycle stages.

TABLE 2

Economic Characteristics by Life Cycle Stage

Panel A: Life Cycle Stage Defined by Cash Flow Patterns

	Pooled	Introduction	Growth	Mature	Shake-Out	Decline
n	48,369	5,752	16,423	19,920	3,861	2,413
% of total n	100.00%	11.89%	33.95%	41.18%	7.98%	4.99%
EPS	0.61	−0.19	0.71	0.98	0.30	−0.47
RNOA	8.61%	−11.81%	9.37%	10.68%	7.23%	−31.45%
PM	4.57%	−6.79%	5.63%	5.62%	3.65%	−20.15%
ATO	1.95	2.02	1.85	2.03	1.90	1.80
GrSALES	9.97%	18.93%	16.54%	6.61%	2.03%	4.86%
GrNOA	7.28%	24.09%	19.00%	1.40%	−7.58%	−1.75%
MB	1.91	2.05	2.05	1.88	1.56	1.74
LEV	0.19	0.10	0.30	0.22	−0.02	−0.28
ASSET BETA	0.73	1.02	0.74	0.63	0.83	1.31
DIVPAY	15.38%	2.60%	13.54%	21.95%	15.05%	3.18%
ADVINT	0.98%	1.23%	0.82%	1.02%	1.03%	1.09%
INNOV	4.97%	14.47%	2.74%	1.54%	4.44%	24.55%
SEGMENTS	2.59	1.99	2.57	2.80	2.71	2.09
MERGER	17.70%	18.40%	27.05%	11.68%	10.05%	12.22%
SIZE	5.39	4.36	5.68	5.78	4.85	4.28
AGE	10.43	6.18	9.19	15.13	11.87	6.96

Panel B: Life Cycle Stage defined by Anthony and Ramesh (1992)

	Pooled	Growth	Gr/Mat	Mature	Mat/Stag	Stagnant
n	48,369	8,169	7,135	7,814	7,640	11,527
% of total n	100.00%	19.32%	16.87%	18.48%	18.07%	27.26%
EPS	0.61	0.20	0.40	0.46	0.65	1.39
RNOA	8.61%	4.72%	8.18%	8.40%	8.26%	9.53%
PM	4.57%	1.98%	4.11%	4.17%	4.17%	5.90%
ATO	1.95	1.96	1.98	1.99	1.95	1.82
GrSALES	9.97%	20.85%	12.45%	9.34%	7.05%	5.36%
GrNOA	7.28%	15.11%	8.98%	6.13%	4.01%	3.76%
MB	1.91	2.27	1.99	1.80	1.68	1.84
LEV	0.19	−0.10	0.07	0.16	0.27	0.44
ASSET BETA	0.73	1.21	0.87	0.75	0.66	0.53
DIVPAY	15.38%	1.20%	3.78%	8.12%	15.35%	39.11%
ADVINT	0.98%	1.05%	0.95%	0.93%	0.80%	0.95%
INNOV	4.97%	10.03%	5.57%	4.42%	3.32%	1.18%
SEGMENTS	2.59	1.94	2.27	2.41	2.78	3.52
MERGER	17.70%	24.31%	19.67%	16.38%	14.54%	13.22%
SIZE	5.39	5.11	5.12	4.96	5.27	6.62
AGE	10.43	4.33	7.56	10.37	16.27	27.86

The sample period is from 1989 to 2005. All data presented are the mean of annual medians except for total number of observations, dividend payout ratio, advertising, innovation, number of segments, and mergers, which are the means of annual means.

(continued on next page)

TABLE 2 (continued)

All profitability variables are computed as in Nissim and Penman (2001) and are defined in Appendix A. Variables are measured as follows: Earnings per share (*EPS*) is measured before extraordinary items (#58). Return on net operating assets (*RNOA*) = Operating Income (OI_t)/Average Net Operating Assets (*NOA*). Profit margin (*PM*) = Operating Income (*OI*)/Net sales (#12). Asset Turnover (*ATO*) = Net Sales)/Average Net Operating Assets (*NOA*). Growth in Sales (*GrSALES*) is defined as (Net Sales/Lagged Net Sales$_t$) − 1. Growth in *NOA* (*GrNOA*) is defined as (*NOA*/*NOA*) − 1. Market-to-Book (*MB*) = Market Value of Equity/Book Value of Equity (#60). Leverage (*LEV*) = Net Financial Obligation/Common Equity (#60). *ASSET BETA* = mean market model beta from a regression of daily raw returns on the value-weighted market return over the prior 250 days adjusted for leverage. Dividend Payout Ratio (*DIVPAY*) = Common Dividends (#21)/Net Income (#172). Advertising Intensity (*ADVINT*) = Advertising Expense (#15)/Net Sales (#12). Innovation (*INNOV*) = [R&D (#46) plus Amortization Expense (#65)/Net Sales (#12)]. *SEGMENT* = number of segments reported in the Compustat segment files. *MERGER* = percentage of firms that have "AA" codes in Compustat (AFTNT1). *SIZE* = log of market value of equity. *AGE* = log of the number of years since the firm's first appearance in the CRSP database. All variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme values.

classification (Panel B).[10,11] AR compute the median values of dividend payout, sales growth, and capital expenditures (scaled by market value) over a five-year horizon. Those values, along with age, are used to assign scores to each observation.[12] Their study uses composite scores to form five equal-sized portfolios, which they label growth, growth/mature, mature, mature/stagnant, and stagnant.

Economic theory predicts that profitability is maximized in maturity, as evidenced by earnings per share (*EPS*) and return on net operating assets (*RNOA*) in Panel A. However, the AR classification (Panel B) displays maximum profitability in the stagnant stage, which is inconsistent with expectations. Next, I examine the components of profitability, profit margin, and asset turnover, all of which are a function of strategy and the competitive environment. Selling and Stickney (1989) indicate that product-differentiating firms focus on research and development, advertising, and capacity growth. Such expenditures should result in a higher profit margin (*PM*), which the cash flow pattern results (Panel A) show is maximized in the growth (5.63 percent) and mature (5.62 percent) stages. Once again, the AR measure (Panel B) reports the maximum in the stagnant stage (5.90 percent).

Selling and Stickney (1989) also predict that, as firms mature, competition intensifies and the operational emphasis shifts to cost reduction and improved capacity utilization. This prediction translates into elevated expected asset turnover ratios (*ATO*) in maturity, confirmed in Panel A (2.03 for mature firms). The high level of *ATO* in the introduction stage (2.02) could be explained by investments in uncapitalized assets such as research and development and/or operating leases. Immediate expensing of these expenditures results in lower GAAP asset levels, which in turn increases *ATO* relative to mature stage firms.[13] *ATO* using the AR measure, however, does not substantially vary across life cycle stages, except for a lower turnover for stagnant firms (1.82 in Panel B), which is also found in the cash flow pattern classification. The *EPS*, *RNOA*, *PM*, and *ATO* results indicate that cash flow patterns are better aligned with profitability than is the AR proxy.

[10] Table 2 is not a test of any hypotheses, but provides descriptive evidence on how a parsimonious accounting-based life cycle classification can capture potentially complex inter-relationships among firm characteristics that are suggested by economic theory.

[11] Age quintile classification results are qualitatively similar to the AR measure for all economic variables.

[12] Terciles of low to high dividend payout, high to low sales growth, high to low capital expenditure, and young to old age were given scores of 1 to 3, respectively. The composite scores ranged from 3 to 9 as in Anthony and Ramesh (1992).

[13] I thank one of the reviewers for this insight.

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Growth in sales (*GrSALES*) and in capital investment (*GrNOA*) should monotonically decrease across life cycle stages (Spence 1977, 1979, 1981), both of which are verified in Panel A (cash flow patterns) for introduction through shake-out (median *GrSALES* and *GrNOA* decline from 18.93 to 2.03 percent and from 24.09 to −7.58 percent, respectively). The negative median *GrNOA* for the shake-out and decline stages is consistent with these firms liquidating net operating assets (either via restructuring or distress). The AR measure (Panel B) also declines monotonically from growth to Stagnant, by construction (median *GrSALES* and *GrNOA* decline from 20.85 to 5.36 percent and from 15.11 to 3.76 percent, respectively). Market-to-book (*MB*) has been used in prior research to proxy for both expected growth and risk, suggesting that mature firms should demonstrate the lowest relative market-to-book as compared with the tail observations. However, Panel A demonstrates a monotonic decline in *MB* through shake-out firms (similar results obtain for the AR measure in Panel B), which indicates that the *MB* measure appears to better reflect growth, than risk. Overall, both life cycle proxies capture growth as predicted by economic theory.

With respect to other measures of risk, I examine financial leverage (*LEV*) and asset beta (*ASSET BETA*) (an unlevered measure of business risk). Firms are expected to utilize more debt in the growth stage (Myers 1984; Diamond 1991) and growth firms demonstrate maximum *LEV* in Panel A (0.30). Using the AR measure (Panel B), however, stagnant firms report the highest *LEV* (0.44). Asset beta is expected to be minimized for mature firms (confirmed in Panel A, mature = 0.63). Again, the AR measure reports the minimum *ASSET BETA* for stagnant firms (0.53), contrary to theory. Dividends (*DIVPAY*) are more likely to be paid by mature firms due to decreased investment opportunities (confirmed by the maximum dividend payout of 21.95 percent for mature firms in Panel A). Conversely, stagnant firms display the highest *DIVPAY* (by construction) for the AR proxy (39.11 percent) in Panel B. Clearly, the cash flow proxy is a better indicator of economic expectations than the AR measure, with respect to risk and the investment opportunity set.

Next, I investigate advertising, innovation, and acquisition behavior. Advertising intensity (*ADVINT*) and research and development (*INNOV*) are predicted to be higher in early-stage firms as they build their initial technology. Cash flow patterns (Panel A) report elevated *ADVINT* and *INNOV* in the introduction stage (1.23 percent and 14.47 percent of sales revenue, respectively). Decline firms also appear to increase their research and development (24.55 percent of revenue), perhaps in either a turnaround attempt or because revenue has decreased at a faster rate than the decrease in R&D spending. Similarly, the AR measure (Panel B) reports the maximum *ADVINT* and *INNOV* for growth firms (1.05 percent and 10.03 percent of revenues, respectively). The number of segments (*SEGMENTS*) is expected to increase through maturity, as growth is executed via product and/or geographical expansion, which are borne out in the results (the highest number of segments is found among mature firms in Panel A). Conversely, the highest number of segments is found in the stagnant stage for the AR measure. This finding is questionable because distressed firms will likely restructure and/or sell off underperforming segments to raise capital. Merger activity (*MERGER*) is predicted to be higher for growth firms, as they are likely to be acquisition targets. The results in Panel A indicate that the introduction and growth stages are where the highest degree of activity takes place (18.40 and 27.05 percent of all merger activity, respectively). The AR measure (Panel B) is similar; however, merger proportions are less distinct across stages than in the cash flow pattern classification. Taken together, the cash flow pattern proxy is more consistent with economic predictions for advertising, innovation, and acquisition behavior than is the AR classification scheme.

Finally, size (*SIZE*) and age (*AGE*) are maximized for mature firms in Panel A (5.78 and 15.13, respectively), consistent with life cycle being nonlinear in both of these variables. In Panel B, both size and age are maximized for stagnant firms (6.62 and 27.86, respectively), which highlight the linearity of the AR measure. To summarize the descriptive statistic results, the cash flow patterns proxy is more consistent with economic theory underlying the life cycle phenomenon.[14] Thus, the results in Table 2, demonstrate that cash flow patterns successfully capture firm life cycle stage.

Survivorship and Transition

Survivorship

Survivorship bias is an inherent issue in intertemporal analyses. Table 3, Panel A examines the proportion of firms that survive five subsequent years beyond life cycle identification at year *t*. The sample period now spans from 1989 to 2000 to ensure that each firm-observation has five years of data available for analysis, which reduces the sample size to 33,088 firm-year observations. Only 78.15 percent of firms survive five years ahead in the pooled sample. Mergers, transition to private ownership, or bankruptcy are possible reasons for sample attrition. The last two columns of Table 3, Panel A display the proportion of firms that delist for merger or performance-related reasons according to their life cycle stage membership in the year prior to delisting.[15] Z-statistics (two-tailed) are reported on tests of whether delisting proportions by life cycle stage significantly differ from a uniform distribution across stages (all Z-statistics are statistically significant at $p < 0.05$). Over 65 percent of merger activity involves growth or mature firms, and over 68 percent of performance-related delistings involve introduction or decline firms.

I repeat the survivorship analysis on the proportion of surviving firms in each life cycle stage relative to that of the pooled sample for each year subsequent to life cycle identification. Z-Statistics (two-tailed) are computed for differences in proportion between each life cycle stage and the pooled sample. Survival rates for mature (decline) stage firms are significantly higher (lower) than survival rates for the pooled sample in all subsequent years. The introduction and growth survival rates are significantly lower than that of the pooled sample for year $t+3$ through $t+5$. Therefore, the survivorship analysis confirms the stable nature of mature firms relative to the remaining life cycle stages.

Transition

Table 3, Panel B examines the transition of firm-observations from one life cycle stage to another in subsequent periods. Once again, a reduced sample ($n = 33{,}088$) is necessary to ensure five years of data subsequent to initial life cycle stage classification. Bold data represent the proportion of firms that remain in their initial stage beyond the initial portfolio formation year. For example, 60.13 percent of mature firms remain in mature one year after initial classification and this proportion monotonically decreases to 55.97 percent by year $t+5$, noting that the mature proportions are highest among the life cycle classifications in each subsequent year.

Several observations are worth noting from this analysis: (1) introduction firms are likely to stay in introduction or to move to the growth or mature stage (over 80 percent of observations at the

[14] It is possible that results reported in Table 2 are due to industry effects. If life cycle is actually an industry phenomenon, then a simple industry control would capture differences across firms. The economics literature suggests industry life cycle patterns occur because the rate of innovation and intensity of competition change over the industry life cycle. However, individual firms' life cycle stages can differ *within* an industry because innovation is a continuing process with firms entering and exiting the market throughout the entire industry life cycle. Furthermore, life cycle stages of individual firms within an industry vary due to differences in a firm's knowledge acquisition, initial investment and re-investment of capital, and adaptability to the competitive environment. All tests throughout this study were replicated on industry-adjusted samples using Fama and French (1997) industry classifications (results untabulated). Results are consistent with those reported in the tables. Therefore, firm life cycle stage is a distinct phenomenon from industry life cycle stage.

[15] Cash flow data are insufficient for computing life cycle stage in the year in which the delisting takes place. Delisting codes of 200–299 are categorized as merger and codes of 500–599 are categorized as performance-related (Beaver et al. 2007).

TABLE 3
Survival Rate and Transition Matrix Analyses

Panel A: Survival Analysis: Proportion of Firms that Survive beyond Portfolio Formation Period[a]

Stage at Portfolio Formation	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5	Percent Delisted Merger	Percent Delisted Perf.
Pooled n = 33,088	100.00%	93.45%	87.74%	82.77%	78.15%		
Introduction	100.00	93.11	86.70	81.36	76.44	15.30	41.53
Z-stat	—	*−0.796*	*−1.887*	***−2.230***	***−2.477***	***−4.615***	***15.008***
n = 4,121							
Growth	100.00	92.98	86.84	81.53	76.95	32.04	11.98
Z-stat	—	*−1.732*	***−2.518***	***−3.020***	***−2.677***	***9.640***	***−6.858***
n = 11,742							
Mature	100.00	94.26	89.20	84.75	80.33	33.79	7.78
Z-stat	—	***3.233***	***4.401***	***5.179***	***5.198***	***10.382***	***−10.891***
n = 13,424							
Shake-Out	100.00	92.82	87.17	82.07	76.59	10.87	11.68
Z-stat	—	*−1.161*	*−0.790*	*−0.849*	*−1.760*	***−8.753***	***−7.820***
n = 2,409							
Decline	100.00	91.74	85.42	79.45	75.14	8.01	27.03
Z-stat	—	***−2.459***	***−2.536***	***−3.167***	***−2.624***	***−12.186***	***5.183***
n = 1,392							

Panel B: Transition Analysis: Proportion of Observations by Life Cycle Stage beyond Portfolio Formation Period (n = 33,088)[b]

Stage at Portfolio Formation	Stage in Future Period	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5
Introduction	Introduction	**36.93**	**30.11**	**27.48**	**26.21**	**23.66**
	Growth	22.46	23.64	25.75	27.58	27.73
	Mature	19.72	23.80	25.33	27.26	29.13
	Shake-Out	8.28	8.82	8.50	8.04	8.43
	Decline	12.61	13.62	12.94	10.90	11.07
Growth	Introduction	7.71	6.84	6.30	6.26	5.89
	Growth	**51.39**	**45.06**	**42.47**	**40.92**	**38.66**
	Mature	33.11	38.27	40.71	41.82	43.23
	Shake-Out	5.72	7.36	7.45	7.85	8.66
	Decline	2.07	2.47	3.07	3.15	3.55
Mature	Introduction	4.44	5.07	5.24	5.10	4.98
	Growth	27.68	29.07	28.42	28.58	28.85
	Mature	**60.13**	**57.02**	**56.63**	**56.13**	**55.97**
	Shake-Out	6.11	7.03	7.78	8.17	8.13
	Decline	1.64	1.81	1.94	2.01	2.07
Shake-Out	Introduction	10.07	9.53	10.02	10.26	9.35
	Growth	22.99	25.30	26.62	25.46	28.17
	Mature	41.57	41.80	42.89	43.85	43.72
	Shake-Out	**18.41**	**16.09**	**14.07**	**13.31**	**12.78**
	Decline	6.96	7.28	6.39	7.11	5.98

(continued on next page)

TABLE 3 (continued)

Stage at Portfolio Formation	Stage in Future Period	t+1	t+2	t+3	t+4	t+5
Decline	Introduction	28.18	29.04	28.91	26.23	25.83
	Growth	14.16	17.03	20.24	19.69	23.36
	Mature	16.78	18.76	19.39	22.50	20.31
	Shake-Out	13.07	11.30	11.31	11.25	12.49
	Decline	**27.81**	**23.86**	**20.15**	**20.33**	**18.02**

[a] Base years range from 1989 to 2000 so that five subsequent years are available for each observation (sample period extends to 2005).

Delisting data are extracted from the CRSP Event database and are computed for all observations with adequate cash flow data to compute the life cycle stage in the *year prior* to delisting. CRSP categorizes delistings as follows: 200–299 are mergers and 500–599 are dropped securities due to performance. The proportion of delistings due to mergers (inadequate performance) is computed by life cycle stage and reported in the second to the last (last) column.

Z-statistics (in italics below the proportion) from a test of equal proportions is computed for each life cycle stage relative to the pooled sample for the years subsequent to life cycle identification; and for each stage relative to a uniform distribution for the delisting categories. Z-statistics in bold indicate a significant difference in proportions at $p < 0.05$ significance level (two-tailed).

[b] Base years range from 1989 to 2000 so that five subsequent years are available for each observation (sample period extends to 2005). For each life cycle stage at the time of portfolio formation (year *t*), this table reports the proportion of surviving firms by life cycle stage for each year subsequent to the life cycle identification year.

Bold data represent the proportion of firms that remain in their initial stage beyond the initial portfolio formation year.

end of five years), (2) growth firms are fairly stable, but a large proportion (ranging from 33.11 in year *t*+1 to 43.23 percent by year *t*+5) will move to mature, (3) growth and mature firms are not likely to move to decline (less than 3.6 and 2.1 percent, respectively, are in decline by year *t*+5), (4) mature firms are stable and approximately 30 percent transition back to growth over the next five years (i.e., re-innovate), (5) a small proportion of decline firms remain in decline (only 18 percent after five years), but movement to introduction (25 percent by year 5), growth (23 percent), mature (20 percent) or shake-out (12 percent) is also fairly common. Taken together, introduction and decline firms tend to improve their position, whereas growth and mature firms are relatively stable in subsequent periods.

III. LIFE CYCLE AND FUTURE PROFITABILITY

Previous research documents that profitability measures mean-revert over time (Brooks and Buckmaster 1976; Freeman et al. 1982; Fairfield et al. 1996; Fama and French 2000; Nissim and Penman 2001) and understanding the evolution of profitability improves predictability. Stigler (1963) reports that profitability displays a strong central tendency, but that convergence is incomplete. He states that impediments to complete convergence stem from disturbances related to shifts in demand, advances in technology, and macroeconomic factors. I posit that another potential impediment to convergence is differential profitability by firm life cycle stage.

Properties of Profitability by Life Cycle Stage

Convergence Properties of Profitability by Life Cycle Stage

Nissim and Penman (2001) suggest that truncated horizons can be used in forecasting if valuation attributes "settle down" to permanent levels within the forecast horizon. Therefore, understanding convergence properties of profitability can lead to better decisions with respect to growth rates and forecast horizons. Specifically, if convergence properties differ across life cycle stage, this information can be used to refine valuation parameters for subsets of firms according to their current life cycle stage.

To examine the convergence characteristics of profitability by life cycle stage, I examine the mean of annual median values of *RNOA* over a five-year period subsequent to the initial life cycle identification period. These results are reported in Table 4, Panel A. Pooled *RNOA* is relatively constant over time, ranging from 8.30 to 9.12 percent. Likewise, the mature stage is characterized by stable profitability with *RNOA* ranging between 10 and 11 percent. However, *RNOA* of both introduction and decline firms increase monotonically over time.

Figure 1 depicts median values from Table 4, Panel A. Median *RNOA* by life cycle stage partially converges by the third year, but the difference in median *RNOA* between mature firms (10.41 percent) and decline firms (3.26 percent) is distinct five years subsequent to year *t* (difference of 7.15 percent, which is substantial given that the median *RNOA* for the sample is 9.12 percent in the portfolio formation year). Growth and shake-out firms have relatively stable *RNOA* over the subsequent five years, but the magnitude of *RNOA* is lower than that of mature firms. In fact, mature firms maintain a sustainable advantage over the other life cycle stages, while introduction firms earn considerably less even after five years (*RNOA* is 10.41 percent for mature firms compared to 5.31 percent for introduction firms). Therefore, convergence of *RNOA* remains incomplete at the end of five years, indicating that life cycle stage information substantially impacts forecasts of future *RNOA*.

Magnitude of Profitability by Life Cycle Stage

Nissim and Penman (2001, Figure 4b) form deciles of *RNOA* and examine convergence of the deciles over five years subsequent to decile formation to document how *RNOA* evolves over time. They report a persistent difference in *RNOA* between the highest and lowest decile of *RNOA* even after five years. If the differences in persistence are attributable to firm life cycle, then I would expect to see an over-representation (under-representation) of introduction and decline (mature) firms in the lowest (highest) *RNOA* deciles. To test this assertion, I examine the frequency of observations by *RNOA* decile membership across life cycle stages in Table 4, Panel B.

Consistent with expectations, Table 4, Panel B shows that nearly two-thirds of introduction firms (66 percent) and three-fourths of decline firms (78 percent) reside within the lowest three deciles of *RNOA*. Comparatively, only 17 percent of mature firms are contained within the lowest three *RNOA* deciles. Therefore, a partial explanation for the non-convergence of *RNOA* reported in Nissim and Penman's (2001) study is attributable to differences in firm life cycle stage. Specifically, the mean-reversion of Nissim and Penman's (2001) lowest deciles of firms is driven largely by improvements in performance experienced by introduction firms and by decline firms that survive beyond the decile formation year. However, the highest deciles (those shown to decline over time in Nissim and Penman [2009]) are not overpopulated in any particular life cycle stage. Therefore, consideration of life cycle stage explains the mean-reversion properties of low-profitability firms.

Explaining Future Profitability by Life Cycle Stage

Benchmark Model of Future Profitability

Given the differences in *RNOA* demonstrated in the previous sections, information about firm life cycle stage should be useful in explaining *future* profitability. I adapt Fairfield and Yohn's (2001) model of future profitability to test the incremental effect of life cycle stage in explaining one-year-ahead change in *RNOA*.[16] I include current profitability (both level and change in current *RNOA*) in the benchmark model because current profitability is known to be serially correlated with

[16] Forecasts of future profitability are improved when based upon operating income rather than GAAP net income (Fairfield et al. 1996; Nissim and Penman 2001). Therefore, excluding the financing portion of the firm focuses the analysis on the sustainability of operating profitability.

TABLE 4

Analysis of Return on Net Operating Assets (*RNOA*) by Life Cycle Stage

Panel A: Median *RNOA* by Life Cycle Stage beyond Portfolio Formation Period

	Pooled	Introduction	Growth	Mature	Shake-Out	Decline
n	33,088	4,121	11,742	13,424	2,409	1,392
% of total n	100.00%	12.45%	35.49%	40.57%	7.28%	4.21%
Year Relative to Formation						
t	9.12%	−4.18%	9.54%	11.01%	8.26%	−16.30%
t+1	8.53	−1.75	8.38	10.74	7.85	−9.08
t+2	8.30	1.30	7.86	10.34	7.96	−4.86
t+3	8.43	3.15	7.84	10.27	8.37	0.30
t+4	8.71	4.56	8.03	10.50	8.60	0.59
t+5	8.93	5.31	8.19	10.41	9.45	3.26

Panel B: Proportion of Observations in Each *RNOA* Decile across Life Cycle Stages

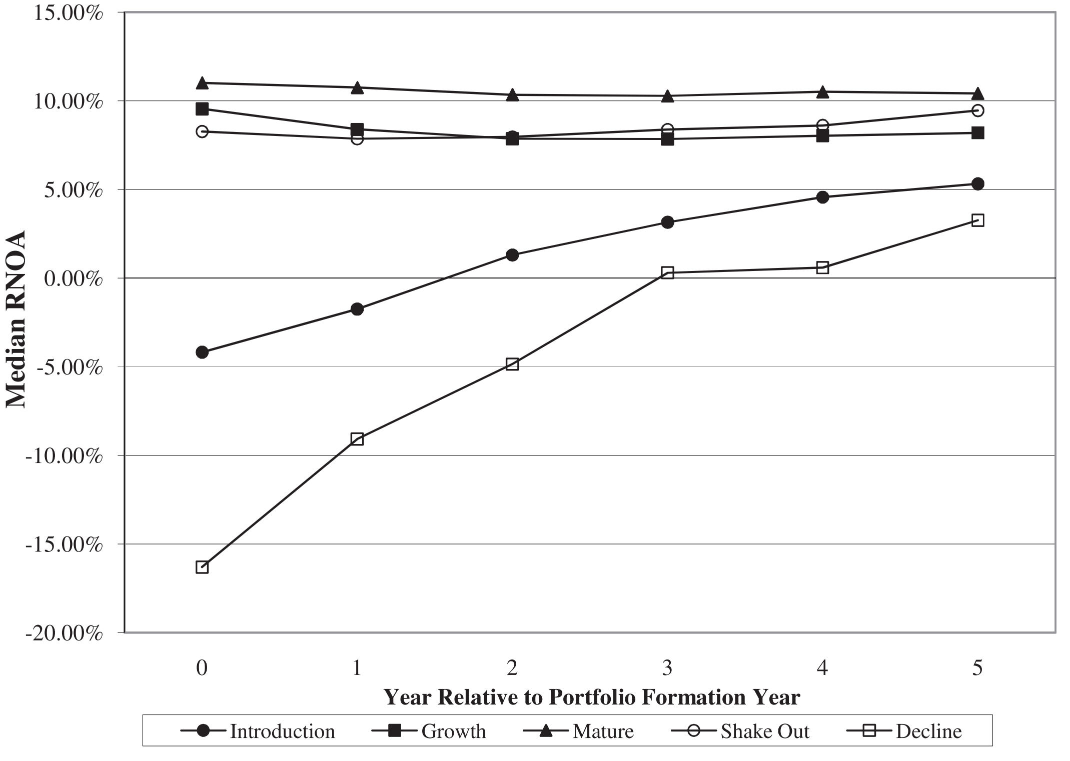
	Pooled	Introduction	Growth	Mature	Shake-Out	Decline
n	48,369	5,752	16,423	19,920	3,861	2,413
% of total n	100.00%	11.89%	33.95%	41.19%	7.98%	4.99%
RNOA Decile						
Lowest		35.95%	3.57%	2.44%	12.04%	50.73%
2		19.66	8.32	6.57	14.69	19.31
3		10.57	10.97	8.92	12.04	7.67
4		7.09	11.54	10.48	8.70	4.68
5		5.49	11.70	11.31	7.10	2.86
6		5.09	11.37	11.71	7.46	2.49
7		5.18	10.91	12.08	7.80	1.82
8		4.73	9.89	12.86	7.93	2.98
9		3.76	10.13	12.73	9.35	2.69
Highest		2.47	11.59	10.90	12.90	4.77
Total		100.00%	100.00%	100.00%	100.00%	100.00%

Likelihood Ratio Chi-Square: 11,311.17 ($p < 0.001$).

The sample period is 1989 to 2000 for Panel A and from 1989 to 2005 for Panel B.
Panel A requires five subsequent years of portfolio formation to ensure that the results are not affected by a truncated time period. Return on net operating assets (*RNOA*) is the mean of the annual medians and is measured as Operating Income (OI_t)/Average Net Operating Assets (*NOA*).
In Panel B, the proportion of each *RNOA* decile is analyzed by life cycle stages. A test of equal proportions across *RNOA* deciles by life cycle stage is rejected with a Likelihood Ratio Chi-Square of 11,311.17 ($p < 0.001$).

future profitability. Coefficients on current *RNOA* and Δ*RNOA* are expected to be negative, insofar as prior research has shown profitability to be mean-reverting (Brooks and Buckmaster 1976; Freeman et al. 1982; Fairfield and Yohn 2001). Future changes in profitability are also affected by the denominator, or growth in NOA. The model controls for growth (*GrNOA*) to ensure that changes in future profitability are not driven solely by changes in investment. Prior research has shown the coefficient on *GrNOA* to be negative because investment in NOA is subject to diminishing returns (Fairfield and Yohn 2001).

FIGURE 1
Convergence Analysis
Median *RNOA* by Life Cycle Stage beyond Portfolio Formation Period
(n = 33,088)



For the sample period 1989 to 2000, Life Cycle Stage is determined at time zero and the means of the annual median *RNOA* for each life cycle stage is computed for each of the five subsequent years to initial life cycle portfolio formation.

RNOA is decomposed into two components: asset turnover (ATO) and profit margin (PM). Asset turnover indicates the amount of assets needed to generate sales, whereas profit margin indicates a firm's ability to convert sales into profit. A cost leadership strategy is aimed at improving asset turnover, while a product differentiation strategy is oriented toward improving profit margin. Fairfield and Yohn (2001) examine the effect of both levels and changes in ATO and PM on future change in RNOA.[17] Changes in ATO are indicative of increased efficiency in production and should represent permanent sources of profitability, such that a positive relation with future profitability is expected (Fairfield and Yohn 2001; Penman and Zhang 2006). Penman and Zhang (2006) find a negative relation between change in profit margin and future profitability. They suggest that an increase in PM is derived from a current reduction in operating expenses, which is not sustainable and thus has negative consequences for future profitability.

[17] Fairfield and Yohn (2001) report that current levels of ATO and PM are not informative in forecasting one-year-ahead change in RNOA but that *change* in ATO is positively related to one-year-ahead change in RNOA.

Incorporating Life Cycle into Future Profitability Models

Next, I add alternate life cycle proxies (i.e., cash flow patterns, Anthony and Ramesh's [1992] classification, and age quintiles) to determine which classification scheme best explains future profitability. Thus, Model 1 is:

$$\Delta RNOA_{t+1} = \alpha + \beta_1 RNOA_t + \beta_2 \Delta RNOA_t + \beta_3 GrNOA_t + \beta_4 \Delta ATO_t + \beta_5 \Delta PM_t + \sum_{k=1}^{4} D_k LC_t + \varepsilon_{t+1}. \quad (1)$$

Life cycle stages are captured by indicator variables set to 1 if the firm-year observation is in that stage, 0 otherwise. Thus, the intercept captures either mature firms (for cash flow patterns and the AR classification) or middle-aged firms (for age quintiles).[18] Table 5 reports results from estimating Model 1. All standard errors reported throughout the analyses are robust with respect to firm and year clustering (Gow et al. 2010) and all tests of significance are two-tailed. The profitability coefficients (*RNOA*, Δ*RNOA*, *GrNOA*, Δ*ATO*, and Δ*PM*) in Model 1 are statistically significant (with the exception of the Δ*PM*) and are in the predicted direction for each of the three life cycle proxy specifications.

To facilitate the discussion of the life cycle variables, Table 5 reports (and I will discuss) life cycle coefficients as the total effect on change in future profitability (the intercept representing mature firms plus the incremental effect for each of the remaining life cycle stages in turn, D_k), but t-statistics reported in the table pertain to the incremental difference in coefficients between each life cycle stage and the reference group, i.e., mature/mature/old (captured in the intercept).

Each of the life cycle stage coefficients are statistically significant in the cash flow patterns specification, with the mature stage representing positive future change in profitability (coefficient = 0.039, $p < 0.01$). Remaining life cycle stages are all negatively related to future change in profitability (although the shake-out stage is only marginally negative). In the AR classification, the introduction stage is significantly and negatively related to future change in profitability (coefficient = −0.040, $p < 0.01$), similar to the cash flow patterns proxy. However, the AR specification displays significant positive associations with future profitability for the shake-out and decline stages (coefficients = 0.023 and 0.035, respectively, both with $p < 0.01$), which is counter to theory. All age quintile life cycle stages, with the exception of mature, have significant associations with one-year-ahead change in profitability, but the results are, again, counter-intuitive. Specifically, shake-out and decline firms (representing mid-old and old firms, respectively) are positively related to future profitability (coefficients = 0.026 and 0.034, respectively, both with $p < 0.01$). Again, the results using age as a life cycle proxy are inconsistent with expectations. Therefore, life cycle stage as measured by cash flow patterns is most aligned with theoretical expectations of future profitability.

Incorporating Life Cycle Interactions into Future Profitability Models

Fairfield and Yohn (2001) find ΔATO to be informative for explaining future profitability, and economic theory suggests that mature firms should benefit most from improvements in efficiency (Spence 1977, 1977, 1981; Wernerfelt 1985). This expectation occurs because mature firms generate higher-than-normal profits, which attracts competition from existing firms and new

[18] The following alignments were made across classification schemes (cash flow patterns/AR/age quintiles): introduction/growth/young, growth/growth-mature/mid-young, mature/mature/middle, shake-out/mature-stagnant/mid-old, and decline/stagnant/old.

TABLE 5

Explanatory Power of Life Cycle Stages for Future Change in RNOA (t-statistics in parentheses) (n = 48,369)

Variable	Predicted Sign	CF Pattern Model 1	CF Pattern Model 2	A&R Model 1	A&R Model 2	Age Quintiles Model 1	Age Quintiles Model 2
RNOA	–	**−0.327**	**−0.326**	**−0.297**	**−0.299**	**−0.298**	**−0.296**
		(−24.24)	(−24.11)	(−23.54)	(−23.59)	(−23.58)	(−23.20)
Δ*RNOA*	–	**−0.074**	**−0.073**	**−0.079**	**−0.080**	**−0.079**	**−0.079**
		(−5.80)	(−5.56)	(−6.18)	(−6.30)	(−6.16)	(−6.17)
GrNOA	–	**−0.019**	**−0.020**	**−0.027**	**−0.022**	**−0.022**	**−0.023**
		(−3.45)	(−3.59)	(−4.10)	(−3.94)	(−3.92)	(−4.06)
Δ*ATO*	+	**0.014**		**0.015**		**0.015**	
		(3.25)		(3.48)		(3.52)	
Δ*PM*	–	−0.013		−0.017		−0.015	
		(−0.69)		(−0.88)		(−0.81)	
Introduction	–	**−0.121**	**−0.081**	**−0.040**	**−0.042**	**−0.030**	**−0.033**
		(−11.81)	(−11.37)	(−3.77)	(−4.09)	(−4.05)	(−4.34)
Growth	+/–	**−0.031**	**0.008**	0.001	0.001	**−0.019**	**−0.018**
		(−7.92)	(−7.82)	(1.01)	(0.76)	(−3.18)	(−3.10)
Mature	+	**0.039**	**0.038**	−0.007	−0.005	0.005	0.005
		(14.89)	(15.23)	(−1.48)	(−1.14)	(0.96)	(0.98)
Shake-Out	+/–	**−0.001**	**−0.000**	**0.023**	**0.023**	**0.026**	**0.026**
		(−4.42)	(−4.31)	(4.52)	(4.38)	(3.52)	(3.64)
Decline	–	**−0.142**	**−0.146**	**0.035**	**0.035**	**0.034**	**0.034**
		(−8.54)	(−8.64)	(8.68)	(8.57)	(5.43)	(5.64)
Introduction × Δ*ATO*			0.011		0.017		0.012
			(−1.39)		(0.69)		(−0.91)
Growth × Δ*ATO*			**0.007**		0.022		0.020
			(−2.15)		(1.04)		(−0.14)
Mature × Δ*ATO*	+		**0.028**		0.010		**0.022**
			(3.59)		(1.65)		(2.29)
Shake-Out × Δ*ATO*			0.007		0.022		0.012
			(−1.64)		(1.07)		(−0.69)
Decline × Δ*ATO*			0.018		0.010		0.000
			(−0.64)		(0.04)		(−1.53)
Introduction × Δ*PM*			−0.016		**0.069**		0.036
			(1.26)		(3.08)		(1.45)
Growth × Δ*PM*	+		−0.074		−0.012		−0.066
			(−0.18)		(1.03)		(−0.67)
Mature × Δ*PM*	–		**−0.066**		**−0.060**		−0.031
			(−2.07)		(−2.17)		(−0.78)
Shake-Out × Δ*PM*			−0.011		−0.049		−0.098
			(0.93)		(0.19)		(−1.12)
Decline × Δ*PM*			**0.029**		−0.093		−0.097
			(1.98)		(−0.64)		(−0.84)
Adj. R^2		16.54%	16.65%	16.09%	16.27%	16.08%	16.23%

(continued on next page)

TABLE 5 (continued)

Vuong Test Comparing:	Model 1		Model 2	
	Z-statistic	p-value	Z-statistic	p-value
CF Patterns over A&R	4.19	<0.01	2.04	0.042
CF Patterns over Age	3.89	<0.01	1.67	0.095

The sample period is from 1989 to 2005.
Coefficients that are significant at $p < 0.05$ (two-tailed) are in bold. All t-statistics in parentheses are adjusted for clustering by firm and year (Gow et al. 2010).
The dependent variable is $\Delta RNOA_{t+1}$. The reported coefficients for the life cycle variables are the total effect on $\Delta RNOA_{t+1}$ (the intercept capturing the reference group, mature, plus the incremental effect of the other life cycle stage, estimated with indicator variables). However, the t-statistics pertain to whether the mature stage coefficients are different from zero or whether the other life cycle coefficients are statistically different from the mature stage coefficient.
Vuong statistics (two-tailed) report the explanatory power of the cash flow pattern classification over the AR or age classifications.
The following alignments were made across classification schemes (cash flow patterns/AR/age quintiles): introduction/growth/young, growth/growth-mature/mid-young, mature/mature/middle, shake-out/mature-stagnant/mid-old, and decline/stagnant/old.
All profitability variables are computed as in Nissim and Penman (2001) and are defined in Appendix A. Return on net operating assets (*RNOA*) = Operating Income (*OI*)/Average Net Operating Assets (*NOA*). Growth in *NOA* (*GrNOA*) is defined as (*NOA*/Lagged *NOA*) − 1. Asset turnover (*ATO*) = Net sales (Compustat #12)/Average Net Operating Assets (*NOA*). Profit margin (*PM*) = Operating Income (*OI*)/Net sales (#12). All variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme values.

entrants into the product market. In order to maintain the level of current profitability, mature firms must concentrate on cost containment and production efficiency as competition intensifies. Selling and Stickney (1989) suggest that operational gains in efficiency are reflected in improvements in ATO. Therefore, I predict that the explanatory power of ΔATO for future profitability is concentrated in mature firms (i.e., a positive coefficient on the interaction term $Mature \times \Delta ATO$).

Product differentiation efforts should be reflected in higher profit margins (Selling and Stickney 1989), and growth firms are likely to exert the greatest effort to establish their brand identity and market share (Spence 1977, 1979, 1981). This suggests that growth firms have the greatest benefit in the future from current expenditures on product differentiation, such that I expect a positive coefficient on the interaction between growth firms and change in PM, $Growth \times \Delta PM$. However, given the results in Penman and Zhang (2006) that increases in profitability due to increases in profit margin are not sustainable, I expect the incremental benefit of the product differentiation strategy to be mitigated by the time a firm reaches maturity. This reasoning suggests that the interaction, $Mature \times \Delta PM$, should be negatively correlated with future changes in profitability. Model 2 below tests:

$$\Delta RNOA_{t+1} = \alpha + \beta_1 RNOA_t + \beta_2 \Delta RNOA_t + \beta_3 GrNOA_t + \beta_4 \Delta ATO_t + \beta_5 \Delta PM_t + \sum_{k=1}^{4} D_k LC + \sum_{k=1}^{4} \delta_{4k}(\Delta ATO_t \times LC_k) + \sum_{k=1}^{4} \delta_{5k}(\Delta PM_t \times LC_k) + \varepsilon_{t+1}. \quad (2)$$

Table 5 also reports results from estimating Model 2. As in Model 1, life cycle indicator variables are included for the introduction, growth, shake-out, and decline stages, whereas the mature firms are captured through the intercept. ΔATO and ΔPM capture the mean effect of those variables on $\Delta RNOA_{t+1}$ for mature firms. The interaction terms model the incremental effect of the remaining life cycle stages on $\Delta RNOA_{t+1}$. However, similar to Model 1, Table 5 (Model 2) coefficients represent the total effect (the mature effect in the intercept plus the incremental effect for each life cycle stage) on $\Delta RNOA_{t+1}$. Reported tests of significance (t-statistics), however, pertain to whether mature stage coefficients are different from zero, or in the case of the other life cycle stages, whether coefficients are statistically different from those of mature stage firms.

As predicted, increases in *ATO* have the largest (and statistically significant) effect on future profitability for mature firms, and this effect is captured by the cash flow patterns (coefficient = 0.028, $p < 0.01$) and age (coefficient = 0.022, $p < 0.01$) classifications. Therefore, improving efficiency is more important for mature firms once the market is saturated. Contrary to predictions, increases in *PM* are not associated with increases in $\Delta RNOA_{t+1}$ for growth firms in any life cycle classification.[19] However, consistent with predictions, the negative and statistically significant relation between ΔPM and $\Delta RNOA_{t+1}$ documented in Penman and Zhang (2006) is concentrated in mature firms for both the cash flow pattern (coefficient = –0.066, p = 0.038) and AR (coefficient = –0.060, p = 0.030) classifications.

In light of the cash flow patterns' ability to explain expected economic outcomes, along with the parsimony of its computation, the cash flow patterns proxy provides a versatile life cycle measure. Age is also a parsimonious proxy, but the interpretation of future profitability based on age can be ambiguous. For example, while older firms likely intersect with maturity, age does not provide a distinct separation of introduction stage versus decline stage among young firms (Stinchcombe 1965; Jovanovic 1982; Freeman et al. 1983; Amit and Schoemaker 1993).

As a final sensitivity test, cash outflows for research and development are included in the Statement of Cash Flows as operating activities, but are more representative of investing cash flows. In an untabulated analysis, I re-estimate cash flow patterns with research and development reclassified as investing cash flows, finding no substantial change from the reported results. In summary, the cash flow patterns proxy is a robust classification for firm life cycle and is effective in explaining both the magnitude and persistence of future profitability relative to alternative classification methods.

IV. ROLE OF LIFE CYCLE IN PREDICTING FUTURE STOCK RETURNS

Previous sections demonstrate that cash flow patterns provide a reliable and parsimonious proxy for firm life cycle. Results thus far indicate that the highest level of profitability is attained (and persists) in maturity (Figure 1). However, investors could potentially undervalue mature firms if they do not fully recognize the valuation implications of life cycle (i.e., recognize the signal of the cash flow patterns at the financial statement date). If this potential undervaluation arises, then the mature signal should be positively associated with future excess returns.[20] This finding would indicate that the market inefficiently underestimates the persistence of RNOA in mature firms. On the other hand, if investors recognize the economic fundamentals of firm life cycle, and specifically the superior profitability of mature firms, this signal is impounded into price and future excess returns related to the mature signal will be indistinguishable from zero (i.e., the market is efficient with respect to the information contained in the life cycle signal).

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[19] Some economics research claims that the benefits of product differentiation techniques such as advertising and marketing are difficult to capture at the individual firm level because advertising partly serves to increase demand for the entire market (Oster 1990; Shy 1995), i.e., there is a free-rider effect. Additionally, gains in innovation are difficult to capture because of the mobility of labor among competing firms (Porter 1980; Jovanovic and Nyarko 1995). These factors could mitigate the ability of product differentiation efforts to result in persistent increases in profitability.

[20] Because the majority of firms are in the mature stage at any given point (41.18 percent of the sample), investing in firms with a mature signal is easily implementable.

I examine whether investors recognize the persistent profitability of mature stage firms by computing one-year-ahead buy-and-hold size- and book-to-market-adjusted returns.[21] I form portfolio returns based on both market capitalization decile and book-to-market decile (resulting in 100 portfolios returns) each month and subtract the appropriate portfolio return from a firm's raw monthly return to arrive at the excess return. I accumulate excess returns from the beginning of the fourth month of year $t+1$ through the third month of year $t+2$ following the life cycle stage signal at the end of year t. This procedure ensures that published financial statement data are available to investors prior to portfolio formation. Delisting returns are used whenever possible and delisted firms without a corresponding delisting return in the CRSP database are assumed to have a return of zero (Piotroski 2000) unless the delisting occurred for performance-related reasons, in which case the missing delisting return is set to −100 percent.[22]

I regress excess returns on indicator variables representing life cycle stage using a no-intercept model. A no-intercept model complicates the interpretation of R^2 (consequently I omit it from the results), but the advantage of the no-intercept specification is that it allows for a straight-forward interpretation of the significance of the coefficients.[23] Table 6 reports results from estimating the regression with reported standard errors robust to clustering by firm and year (Gow et al. 2010). Reported tests of significance are two-tailed.

Mature firms earn positive and significant ($p < 0.01$) annual excess returns of 1.6 percent indicating that investors do not fully appreciate the persistent profitability of the mature life cycle stage, although the magnitude of the excess return is small. While *ex ante* predictions about the other life cycle stages are not hypothesized, the evidence shows that on average, introduction and growth firms earn significantly negative excess returns in the year following the cash flow pattern signal (−4.8 percent and −1.2 percent, respectively; $p < 0.01$ and $p = 0.015$, respectively). Counter to intuition, decline stage firms earn one-year-ahead positive excess returns of 13.5 percent ($p < 0.01$). However, this result should be interpreted with caution. By construction, 12 months of return data are necessary from the fourth month of year $t+1$ through the third month of year $t+2$. This specification imparts a survivorship bias in that only decline firms that survive for at least 15 months subsequent to the cash flow pattern signal are included in the sample. In untabulated results, the regression was repeated using contemporaneous excess returns as the dependent variable. As expected, mean annual excess returns for decline stage firms are −7.8 percent ($p < 0.01$), which is consistent with the market expecting these firms, on average, to underperform in the future.

Overall results suggest that investors do not fully recognize the fundamental life cycle information embodied by the cash flow pattern signal with respect to future excess returns. Further, a profitable and relatively low-risk trading strategy is possible by forming a long buy-and-hold portfolio of mature stage firms. Therefore, cash flow patterns represent a parsimonious and implementable tool to identify stocks that are, at least temporarily, mispriced.

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[21] The results are invariant to replacing size- and book-to-market-adjusted returns with size-adjusted returns or market-adjusted returns.

[22] Prior research has used −30 percent for NYSE and AMEX firms (Shumway 1997; Mohanram 2005) and −55 percent for NASDAQ firms (Shumway and Warther 1999) that are delisted for performance. Sloan (1996) uses −100 percent for performance-related delistings. Because missing delisting returns for mergers are likely to be understated when setting to zero, I make no upward correction for merger-related missing returns to bias against finding results.

[23] If using an intercept, then one of the life cycle stage indicators would be omitted and the omitted stage's mean effect would be captured in the intercept. In this case, the remaining coefficients and t-statistics would reflect the incremental effect of each of the remaining life cycle stage compared to the reference group (the omitted indicator variable). Alternatively, a no-intercept model captures the mean effect of each of the five life cycle stages on annual excess returns individually and significance is computed on whether each coefficient differs from zero. However, when the intercept is omitted from the model, R^2 is no longer a proportion of the variation explained (Greene 2007).

TABLE 6

Regression of One-Year-Ahead Buy-and-Hold Annual Excess Returns on Life Cycle Stage (t-statistics in parentheses) (n = 44,838)

Variable	Predicted Sign	Coefficient (t-statistic)
Introduction	+/−	**−0.048**
		(−4.35)
Growth	+/−	**−0.012**
		(−2.44)
Mature	+	**0.016**
		(3.88)
Shake-Out	+/−	**0.025**
		(2.12)
Decline	+/−	**0.135**
		(5.47)

The sample period is from 1989 to 2005.
Coefficients that are significant at $p < 0.05$ (two-tailed) are in bold. All t-statistics in parentheses are adjusted for clustering by firm and year (Gow et al. 2010).
One-year-ahead buy-and-hold annual excess returns are regressed on life cycle stage measured by cash flow patterns. Introduction, growth, mature, shake-out, and decline are indicator variables set to 1 when the observation is in that category at the end of the current year, and 0 otherwise. A no-intercept model is used so that each life cycle stage is interpreted as excess returns that are significantly different from zero (two-tailed).
The sample size is reduced in size compared to previous tests because one-year-ahead stock returns were utilized in this specification.
Excess returns for each firm are computed as the firm's buy-and-hold annual return minus the buy-and-hold annual return of an equally weighted benchmark portfolio matched on size and book-to-market deciles. Returns are accumulated from the beginning of the fourth month of year $t+1$ through the third month of year $t+2$. Delisting returns are used when included in the CRSP database. Delisted firms without a corresponding delisting return are assumed to have a return of −100 percent in the delisting period when delisted for performance-related reasons (delisting codes between 200 and 299), 0 percent otherwise (Sloan 1996; Piotroski 2000).

V. SUMMARY AND CONCLUSION

This study develops and validates an effective and parsimonious proxy for firm life cycle using cash flow patterns. Several performance measures and firm characteristics such as profitability, size, and age are nonlinearly related to firm life cycle. For that reason, monotonic sorts on those measures to determine life cycle stage result in misclassification. More importantly, a simple sort on univariate measures makes a distributional assumption of uniformity that is not supported by economic theory.

To explore cash flow patterns as a proxy for firm life cycle, I first investigated whether the proxy was consistent with extant economic theory. Next I examined how cash flow patterns capture the economic concept of life cycle relative to proxies used in past research (i.e., Anthony and Ramesh's [1992] classification and firm age quintiles). The cash flow measure explains varying persistence among firms, such that patterns of mean-reversion of future profitability differ by life cycle stage. Specifically, the spread in RNOA is 3 to 10 percent between mature and decline firms five years subsequent to portfolio formation (where portfolios are formed according to cash flow pattern signal). This spread of 7 percent is economically significant, given that median RNOA for the sample period is just over 8 percent. The valuation and forecasting implications of the study are that growth rates and forecast horizons should be conditioned on firms' current life cycle stage.

Additionally, past research on the decomposition of RNOA has shown that change in asset turnover is an important driver of future changes in RNOA (Fairfield and Yohn 2001), but that improvements in future profitability due to increases in profit margin are not sustainable (Penman and Zhang 2006). As predicted, both results are primarily concentrated in mature firms. Increases in operational efficiency are critical for mature firms due to increased competition that is attracted to the product market by superior profits. At the same time, diminishing returns to product differentiation efforts are evident among these same firms.

Finally, I investigate the market valuation consequences of life cycle stage (as captured by cash flow patterns) finding that positive future excess returns are earned for mature firms. This finding indicates that the market does not efficiently use life cycle information contained in the Statement of Cash Flows, although the inefficiency is small. Consequently, investors can exploit the empirical regularities encompassed in the data to engage in an implementable trading strategy based on firm life cycle stage.

In summary, this study uses basic accounting information to capture the construct of firm life cycle. Life cycle information (using the cash flow pattern proxy) allows investors, creditors, auditors, analysts, regulators, and researchers to investigate and control for differences in resources, rates of investment, obsolescence rates, learning and experience curves, adaptation, product-differentiation, and production efficiencies in a parsimonious measure. The cash flow pattern proxy outperforms other life cycle proxies from the literature (including age), and better explains future profitability (both in rates of return and stock returns).

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APPENDIX A
VARIABLE DEFINITIONS

Profitability variables are defined as in Nissim and Penman (2001) and are presented in alphabetical order:

Asset Turnover (*ATO*) = Net Sales (Compustat #12)/Average Net Operating Assets (*NOA*);

Common Equity (*CSE*) = Total Common Equity (Compustat #60) plus Preferred Treasury Stock (Compustat #227) minus Preferred Dividends in Arrears (Compustat #242);

Comprehensive Net Income (*CNI*) = Net Income (loss) (Compustat #172) minus Preferred Dividends (Compustat #19) plus the change in the Marketable Securities Adjustment (Δ in Compustat #238) plus the change in the Cumulative Translation Adjustment in Retained Earnings (Δ in Compustat #230);

Financial Assets (*FA*) = Cash and Short-Term Investments (Compustat #1) plus Long-Term Receivables, Investments and Advances to Affiliated Companies (Compustat #32);

Financial Obligations (*FO*) = Debt in Current Liabilities (Compustat #34) plus Total Long-Term Debt (Compustat #9) plus Preferred Stock (Compustat #130) minus Preferred Treasury Stock (Compustat #227) plus Preferred Dividends in Arrears (Compustat #242);

Growth in NOA (*GrNOA*) = (Net Operating Assets [*NOA*]/Lagged Net Operating Assets [*NOA*]) minus 1;

Leverage (*LEV*) = Net Financial Obligation (*NFO*)/Common Equity (*CSE*);

Marginal Tax Rate = applicable highest federal tax rate + 0.02 to approximate state taxes. This definition is taken from Nissim and Penman (2001). The federal tax rates applicable to this sample are 34 percent for years 1989–1992 and 35% for 1993–2005;

Net Financial Expense (*NFE*) = (Interest Expense [Compustat #15] * [1 minus the Marginal Tax Rate]) plus Preferred Dividends (Compustat #19) minus (Interest Income [Compustat #62] * [1 minus the Marginal Tax Rate]) plus lagged Marketable Securities Adjustment (Compustat #238) minus Current Marketable Securities Adjustment (Compustat #238);

Net Financial Obligation (*NFO*) = Financial Obligations (*FO*) minus Financial Assets (*FA*);

Net Operating Assets (*NOA*) = Net Financial Obligation (*NFO*) plus Common Equity (*CSE*) plus Minority Interest (Compustat #38). This definition is used rather than the more common expression Operating Assets (*OA*) minus Operating Liabilities (*OL*) to be consistent with prior research and due to incomplete data in the Compustat variables related to operating liabilities;

Operating Assets (*OA*) = Total Assets (Compustat #6) minus Financial Assets (*FA*);

Operating Income (*OI*) = Comprehensive Net Income (*CNI*) plus Net Financial Expense (*NFE*);

Operating Liabilities (*OL*) = Operating Assets (*OA*) minus Net Operating Assets (*NOA*);

Profit Margin (*PM*) = Operating Income (*OI*)/Net Sales (Compustat #12); and

Return on Net Operating Assets (*RNOA*) = Operating Income (*OI*)/Average Net Operating Assets (*NOA*).