A Comparison of Revenue Growth at Recent-IPO and Established Firms:
Influence of SG&A, R&D and COGS*

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We specify a production function that links aggregate resource allocation amongst SG&A, R&D and COGS expenses with a firm’s revenue. This function yields a set of hypotheses on the elasticity of SG&A and R&D, and the productivity of COGS, while controlling for the rate of growth in revenue. These hypotheses are tested on a dataset of 64 randomly selected firms that made an IPO, and a comparable set of established public firms. Results show that the manner in which recent-IPO firms allocate and utilize resources differs from their established counterparts. Managerial and policy implications of these elasticity and productivity results are offered.

1. Introduction

The goal for investment in innovation or research and development (R&D) effort is often identified as spurring growth and profitability (e.g., Minniti and Lévesque in press). Whereas spending on sales, general and administrative expenses (SG&A) is deemed to build up brand and create demand while covering allied overhead costs. Both SG&A and R&D are twin investment mechanisms that drive growth (Kohli and Jaworski 1990; Krishnan and Ulrich 2001). Managers in such decision scenarios wish to understand the balance between SG&A and R&D expenses that is required to grow profitably.

In addition, many firms profess before their initial public offering (IPO) that they will use the proceeds towards investments in R&D, marketing and administration efforts in order to foster growth. For instance, Rosetta Genomics (Genomeweb 2003) indicated in its IPO prospectus that “about $17 million from the proceeds of the offering will be used to fund research and development activities. Roughly $2.5 million from the IPO will fund intellectual property licensing and protection efforts, while about $6.6 million will go to business development activities such as personnel costs, legal and administrative fees, and general corporate purposes.” However, investments in growth have been known to be first among allocations that are scaled back either under competitive pressure or financial distress. For instance, Pfizer, the world’s
largest drug maker, cut its R&D budget significantly in 2007 (Rockoff 2009). The situation was even worse for IPOs, especially after the dot-com bubble. Buy.com had “eyed a $25 million advertising campaign” before its 2001 IPO but the company’s stock was worth pennies and was delisted from NASDAQ in 2002. The firm had to completely revamp its business model and resource allocation strategies to ensure its survival (Hibbard 2005).

Such examples raise questions about how a firm allocates resources towards SG&A and R&D expenses while trying to stimulate profitable revenue growth. The firm has to weigh into this decision the requirement for expenditure on current production in terms of costs of goods sold (COGS). The expense allocations are joint decisions because the amount of total allocations for SG&A, R&D and COGS must add up to the available working capital for any accounting period. These expense allocations are aggregated at the level of the firm as a whole, rather than a business unit within a diversified firm. Such aggregate allocations are a common practice in most innovation driven firms through their annual budgeting process (Anderson and Joglekar 2005, Chao et al. 2009). However, there are built-in tensions in these decisions: raising either the SG&A or the R&D investments in aggregate encourages revenue generation and growth, but it does so through different mechanisms. R&D establishes new products and access to new markets, while SG&A increases brand awareness (Hauser 1998) and funds corporate growth. They both add to expenses in the current accounting period and thus reduce profitability in the short term. These tensions are compounded by the fact that SG&A and R&D expenses can be either substitutes or complements for COGS.

In other words, for a given level of revenue, increasing an expense that substitutes COGS will reduce those costs, but increasing an expense that complements COGS will augment those costs. Hence, the overall effect of SG&A or R&D investments might be to either reduce or
enhance profitability. Such allocations are particularly important after IPOs, when the firms are infused with liquidity and are making choices to foster growth (Jain et al. 2008). Hence, we seek to understand three sets of issues: (i) Are there conditions where SG&A and R&D expenses act as substitutes or complements for COGS within firms that are trying to grow? (ii) Do firms adjust either SG&A or R&D allocations to be above (or below) their actual growth rate in revenue? (iii) Does the lifecycle of a firm (i.e., being recent-IPO versus more established publicly traded company) within an industry affect SG&A and R&D allocation balance?

To address these issues, we develop a production function that links a firm’s SG&A expenses, R&D expenses and COGS with that firm’s revenue. The specification of this function accounts for four decisions that a publicly traded firm must make and report in any given accounting period: the level of marketing and administrative intensity measured as the ratio of SG&A expenses to revenue; the level of R&D intensity measured as the ratio of R&D expenses to revenue; the growth rate in revenue; and the amount of COGS. Implicitly, these decisions also yield the actual operating margin measured as revenue minus SG&A, R&D expenses and COGS. SG&A and R&D expenses accumulate into two separate stocks, subject to some rates of obsolescence.

We draw upon ideas from Baumol et al. (1970) on the theory of firm growth to investigate the consequences of endowing a manager in this firm with the ability to adjust (i.e., scale up or down) the SG&A and R&D stocks in order to manage a targeted rate of growth in revenue. Wiklund et al. (2008) offer an integrative model of small firm growth that attempts to fine tune how key constructs that have been shown to affect growth actually act, while providing a “big picture” of the growth phenomenon. They find an indirect effect of resources on firm growth, leading to the conclusion that future research efforts should look into how resources are
in fact used. Our analysis herein moves a step in this direction by looking at the endogenous allocation between SG&A, R&D and production investments while a firm attempts to grow profitably. In particular, we seek to examine the empirical link between the variation in COGS productivity and the fraction of the revenue that gets allocated to SG&A and R&D. COGS productivity is defined as the ratio of the revenue and COGS in a given year, that is, it indicates the amount of revenue generated by each dollar spent on COGS. Since revenue is the sum of gross margin and COGS, another way to interpret variation in the COGS productivity is as a proxy for the inverse of gross margin ratio.

The specified production function, along with equations that govern the accumulation of SG&A and R&D stocks, yields an econometric relationship. We test this relationship for a panel dataset consisting of 128 firms spread over 1993 to 2007, each tracked for six contiguous years of growth starting with their IPO date. Half of these firms are randomly selected recent-IPO firms from the following four industry sectors: electronics, energy, medical devices and software. The other half consists of a comparable sample of established firms. Data on these established firms, also randomly drawn from the relevant industry sectors, is taken for identical years as the comparable recent-IPO firm. As articulated in Filatotchev and Piesse (2009), “[n]ewly listed firms provide a unique laboratory for further theory building since they represent a bridge between mature, publically listed companies and entrepreneurial firms” (p. 1261).

The contributions of our analytical and empirical efforts are threefold. First, we specify and test an aggregate production function, while controlling for relevant industry sector growth rates, and illustrate how the underlying elasticity of SG&A expense and R&D expense with respect to COGS can be imputed from a regression analysis. Second, we use these elasticity parameters to show that SG&A investment is a substitute to COGS during revenue generation,
whereas R&D investment is a complement. Third, we illustrate an asymmetry between observed productivities and observed SG&A and R&D allocation decisions made by the recent-IPO and established firms in terms of enhancing COGS productivity. Specifically, R&D investments and COGS are complement only for recent-IPO firms, while SG&A substitute COGS for both recent-IPO and established firms. Also, for the recent-IPO firms, both SG&A and R&D investments along with their related adjustments drive the revenue per unit of COGS, but two out of these four factors appear insignificant for the established sample.

The rest of the paper is organized as follows. We begin by describing the bodies of literatures that have influenced our ideas while developing this research. Then, we specify and analyze a growth-driven production function at the firm level. This exercise and the resulting formal model allow us to put forward a set of empirically testable hypotheses. Next, we lay out the empirical aspect of our study by describing the design of a comparable sample, as well as providing statistics on the aggregate data, key measures by industry sectors, and specification checks. On sequence, regression results and sensitivity analysis to test our hypotheses are addressed. We conclude by discussing the managerial and policy implications of the findings, and by identifying the limitations of our work and the scope for follow on effort.

2. Firm Growth Literature

There is a large literature on the growth of firm originating from the work of Penrose (1994). Baumol et al. (1970) were among the first to empirically examine a firm’s willingness to retain earnings in order to drive growth. There have been several economic models that explore allocation of capital and labor strategies under growth (Aghion and Howitt 1992), and growth through creative destruction (Schumpeter 1950). However, at the firm level, the key aggregate decision is not how to allocate the resources between labor and capital, but rather how many
resources to utilize and how to allocate them between relevant tasks such as marketing and overhead (controlled through the SG&A), R&D and production (Griffin and Hauser 1996, Krishnan and Ulrich 2001).

We propose a model to explore the balance between these three decisions in the context of firm growth. Methodologically, our development parallels the analyses offered in the macroeconomic literature (e.g., Solow 1956, Romer 1990, Mankiw et al. 1992). However, unlike that literature (where a country may be most interested in growing its gross domestic product), in our model the firm has a profitability motive while growing and we make all three factors of production – SG&A, R&D and COGS expenses – endogenous, as opposed to keeping one of them (or more) exogenous. For established firms, Kamien and Schwartz (1978) have looked at R&D self-financing, where both internal (Hauser 1998) and external (e.g., R&D tax credits; Hall and Van Reenen 2000) incentives are relevant. For startup firms, Joglekar and Lévesque (2009) argue that productivities of marketing and R&D activities are critical determinants of the proportion of financial resources to be allocated to each of these activities, while Chao et al. (2009) offer policies that determine the level of R&D investments in an endogenous manner as a function of revenue growth.

Entrepreneurship scholars have also been actively involved in the study of firm growth. For instance, Delmar et al. (2003) use a sample of high-growth Swedish firms, with growth being in terms of various employment and sales measures, to demonstrate that high growth is multidimensional and can occur in multiple distinct patterns. By also relying on Swedish firms, Chandler et al. (2009) study the relationship between sales growth and employment growth, whereas Davidsson et al. (2009) focused on the relationship between growth and profitability. Davidsson et al. (2009) argue that constraining growth initially may be a plus because early
profitability allows for delayed, yet sustainable, growth without having to tradeoff profitability. Their longitudinal sample supports this view and warns us of the danger in using growth (in sales) as a measure for success (return on assets).

This growth-profitability debate has also attracted the attention of those examining the IPO due to its promises for growth rather than profitability, especially during the Internet boom. Mudambi and Treichel (2005), for instance, have investigated cash burn of Internet firms prior to the late 90s crash to show that firm performance (based on cash left) depended on firm-specific characteristics (e.g., top management team) prior to IPO. Jain et al. (2008) have pushed forward this line of work by looking at pre-IPO factors to analyze the path-to-profitability post IPO. Another line of work focuses on growth through the internationalization of newly publically listed firms. Filatotchev and Piesse (2009) looked at France, Germany, Italy and the UK to find a positive relationship between R&D intensity and sales growth. They also show that “the growth of IPO firms is at its highest level just after the float” (p. 1273). In other words, sales growth diminishes over time after the IPO.

Nevertheless, we are unaware of any formal models that explore the endogenous balance between SG&A expenses, R&D expenses and production allocations in aggregate while a firm attempts to grow profitably. In terms of these three categories of expenditures (for SG&A, R&D and COGS), a comparative analysis of firm choices after a recent IPO against their established counterparts offers an opportunity for an empirical test of balanced growth at the firm level (Filatotchev and Piesse 2009). Analysis has been done in the financial literature to examine if first-day investors are rewarded by the IPO process (Ritter and Welch 2002), but we are again unaware of a comparative analysis of growth and profitability based on resource allocation decisions for SG&A, R&D and production following IPOs. In the next section, we therefore
offer a model that specifies SG&A, R&D and COGS as the relevant three factors of production while controlling for industry growth rates.

3. A Revenue Model with Controls for Growth

3.1. Production Function

Consider a firm that allocates its working capital for a given period to SG&A, R&D and COGS. SG&A and R&D investments in any one period have a cumulative effect, such that they create stocks. The stock of SG&A creates and sustains brand awareness (and supports allied coordination effort) that has been associated with revenue generation (Srinivasan et al. 2009). The R&D stock yields innovative products and services develop activities, which in turn refresh the portfolio and enhance revenue generation (Krishnan and Ulrich 2001).

The firm consumes at time period $t$ a proportion $s_{M,t}$ of its revenue, denoted by $Y_t$, towards SG&A in order to create a market presence. Specifically, over time the firm’s growth in SG&A stock $M_t$ is directly proportional to $s_{M,t}Y_t$ (e.g., based on the Nerlove-Arrow, 1962, advertisement capital model). Also, due to competitive forces, the firm’s SG&A stock decreases exponentially over time at a rate denoted by $d$. In other words, SG&A stock accumulates goodwill and branding, but with some losses due to competition. Formally, growth in SG&A stock satisfies (without a loss of generality, time is continuous in this formulation)

$$\dot{M}_t = s_{M,t}Y_t - dM_t.$$  (1)

That firm also consumes at time period $t$ a proportion $s_{R,t}$ of its revenue to innovate, that is, to build its R&D stock. Specifically, over time the firm’s growth in R&D stock $R_t$ is directly proportional to $s_{R,t}Y_t$ (Kamien and Schwartz 1982). Owing to trials associated with novelty, a firm’s R&D stock decreases exponentially over time at a rate denoted by $e$. In other words, and
symmetric to the law of motion for SG&A stock, innovation accumulates expertise and knowhow, but with some losses due to obsolescence of technologies (e.g., Stinchcombe 1965, Bruderl and Schussler 1990, Choi and Shepherd 2005). Formally, growth in R&D stock satisfies

\[ \dot{R}_t = s_{R,t} Y_t - eR_t. \]  

(2)

Firm’s output (i.e., revenue) depends on the laws of motion for the SG&A stock and for the R&D stock given by Eq. (1) and Eq. (2), and on its COGS. The production function is thus, assuming constant returns to scale and a Cobb-Douglas functional form,

\[ Y_t = [\theta C_t]^{1-\alpha-\beta} M_t^\alpha R_t^\beta, \]  

(3)

where \( C_t \) is COGS at time period \( t \), \( 1-\alpha-\beta \in (0,1) \) that cost’s elasticity, and \( \theta (>0) \) the productivity of production expenditure. Clearly, \( \alpha \) represents the elasticity of SG&A stock and \( \beta \) the elasticity of R&D stock. The production function in Eq. (3) reflects the roles of three factors of revenue generation reported by real firms: SG&A, R&D and COGS expenses. As portrayed by Eq. (1) and Eq. (2), the effects of SG&A and R&D accumulate in a manner that is analogous to marketing and human capital in the marketing literature and in the economics literature, respectively (e.g., Kamien and Schwartz 1978). Based on accounting rules, COGS covers a period of production costs (including variable material and labor costs) that do not accumulate. We also define

\[ a_t \frac{\dot{M}_t}{M_t} = b_t \frac{\dot{R}_t}{R_t} = \frac{\dot{Y}_t}{Y_t} = g_t, \]  

(4)

to study the effect of rates of growth in SG&A and in R&D stocks on a firm’s revenue. We note that neither \( a_t, b_t \) nor \( g_t \) is restricted to be positive. The parameter \( a_t \) represents the controls that allow adjustments to be made on the rate of growth in SG&A stock to equate the firm’s actual rate of growth \( g_t \) in revenue. Since firm performance gets compared by industry analysts, we
argue that firms aspire to have \( g_t \) reach or exceed their particular industry’s average growth rate in revenue. Then, such firms can make decisions on whether the corresponding growth rate in its SG&A and R&D investments should match that average growth rate. When “\( a_t \)” equals 1, the firm elects to invest in SG&A in the same proportion as its actual revenue growth rate. A value less (more) than unity indicates that the firm is investing more (less) in SG&A growth than it actually invest in its revenue. Similar interpretation also applies to the control variable “\( b_t \),” a.k.a. R&D investment adjustment.

3.2. Normalizing the Production Function

The above equations allow us to first characterize the firm’s revenue per unit of COGS, which we label \( COGS \) productivity. Recall that this construct is a proxy for the inverse of the gross margin ratio, commonly reported in the accounting literature. Formally, the COGS productivity is given by (mathematical derivations are relegated to an appendix)

\[
\ln \frac{Y_t}{C_t} = \ln \theta + \frac{\alpha}{1 - \alpha - \beta} \ln s_{M,t} - \frac{\alpha}{1 - \alpha - \beta} \ln \left[ \frac{\theta_a}{a_t} + \theta \right] + \frac{\beta}{1 - \alpha - \beta} \ln s_{R,t} - \frac{\beta}{1 - \alpha - \beta} \ln \left[ \frac{\theta_e}{e_t} + \theta \right].
\]

In addition to providing an econometric equation for estimating the production function, Eq. (5) can be used to characterize the COGS productivity when changes occur in key model parameters, including the exponential rate \( d \) at which the firm’s SG&A stock decreases over time and the exponential rate \( e \) at which its R&D stock decreases over time – two obsolescence rates. Sensitivity analysis with respect to these two parameters is especially important for our empirical tests because these parameters cannot be easily estimated. We will check the robustness of the hypotheses formulated in the next section with respect to changes in these two obsolescence rates.
3.3. Hypotheses

From the above formal analysis, we put forward a set of empirically testable hypotheses. The first set of hypotheses focus on the elasticity parameters $\alpha$ and $\beta$ in Eq. (3) (specifically their signs) and is motivated by findings in prior studies that have examined the standalone impact of either marketing or R&D efforts on productivity (e.g., Hall et al. 2005). In these studies, the presence of either SG&A activities or R&D effort is seen to enhance revenue generation, *ceteris paribus*. The SG&A effort is aimed at generating and closing on sales leads, building brand and facilitation of administrative effort that will enhance demand (Ailawadi et al. 2003), while decreasing the associated variable – i.e., production costs. While scholars have argued that R&D expense enhances revenue, it is unclear if R&D brings down the COGS. Theoretical rationale suggests that the type of R&D dictates its linkage into the cost structure (Utterback 1996): product R&D may increase the costs, whereas process R&D will reduce the unit costs. Recent-IPO firms tend to focus on product rather than process R&D (Jain and Kini 1995). Hence, we argue that while an increase in R&D stock will increase the demand, it may also require larger COGS. Formally,

H1A: *A firm’s investment in SG&A stock substitutes its allocation towards COGS in generating revenue.*

H1B: *A firm’s investment in R&D stock complements its allocation towards COGS in generating revenue.*

The COGS elasticity (i.e., substitute versus complement) hypotheses affect firms margins because the relationships between R&D, SG&A and COGS determine the margin, for a fixed level of revenue. However, focusing on the COGS elasticity measure alone may not be sufficient to explain aggregate firm-level decisions on growth because managers are concerned about raising *both* revenue and margins (Baumol et al. 1970). Hence, we offer a second set of
hypotheses centered on the adjustments $a_i$ and $b_i$ selected by managers. Financial accounting research incorporates both SG&A and R&D as levers for adjustments in growth and earnings (Bange and De Bondt 1998). Marketing and R&D productivities have been shown to be relevant while making growth related resource allocation decision (Joglekar and Lévesque 2009). Hence, we argue that a firm’s investment adjustments in both R&D and SG&A are such that they increase COGS productivity (i.e., revenue per unit of COGS). Formally,

H2A: A firm’s growth rate adjustment while making SG&A investment is positively associated with its COGS productivity.

H2B: A firm’s growth rate adjustment while making R&D investment is positively associated with its COGS productivity.

The next two hypotheses concern the productivity parameter $\theta$ in the production function (i.e., Eq. 3) and the magnitudes (as opposed to the signs) of the elasticity parameters $\alpha$ and $\beta$. As per Eq. (5), the focus here is on comparing the magnitude of these parameters (and hence their impacts on COGS productivity) for recent-IPO firms to their magnitude for the established firms. Based on Davidsson et al.’s (2009) evidence, high profitability and low growth are preferable in the early stages to sustain both later growth and later profitability. Since they are in their early stages of growth, recent-IPO firms would thus be expected to grow at a slower rate than their established counterparts, yet be more profitable. But because recent-IPO firms likely exhibit lower volumes of revenues, they need to be more efficient in transferring each unit of marketing, innovation and production efforts into revenue in order to be profitable. Consequently, not only is a unit of COGS expected to yield more revenue in recent-IPO firms than in their established counterparts, but the elasticity of SG&A investment and the elasticity of R&D investment are both expected to be higher in recent-IPO firms.
These comparative observations are also supported by Wiklund and Shepherd (2003) who argue that “the willingness to be innovative, proactive, and take risks [i.e., to possess an entrepreneurial orientation] enhances the positive impact that a firm’s bundle of knowledge-based resources [i.e., those pertinent to opportunity discovery and exploitation] has on performance” (p. 1312). Recent-IPO firms are likely to possess a higher entrepreneurial orientation because they are just coming out of their entrepreneurial phase and starting their growth phase. This higher entrepreneurial orientation, according to Wiklund and Shepherd, enhances the relationship between the firm’s performance and resources (mostly knowledge-based and abundant in high-tech industries in either the form of marketing, R&D and production investments). Formally,

H3: The COGS productivity for recent-IPO firms is larger than that for established firms, ceteris paribus.

H4A: Investments in SG&A at recent-IPO firms have a larger elasticity with respect to COGS in generating revenue than at their established counterparts.

H4B: Investments in R&D at recent-IPO firms have a larger elasticity with respect to COGS in generating revenue than at their established counterparts.

We introduce in the next section an appropriate set of controls used for the empirical testing of these hypotheses, and identify directional relationships around the impacts of these controls on the outcome variable.

4. Empirical Analysis

4.1. Operationalization

A relevant issue in our analysis is firm growth and the influence of age and the industry sector where the firm operates. The literature on the theory of the firm routinely argues for

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1 Their performance measures include growth in sales, growth in revenue, growth in number of employees, and net profit margin, among others.
managers to pay attention to industry effects (Rumelt 1991). In addition, adjusting for industry sector effects and for period lags is an established practice in the financial economics and accounting literature (Kothari et al. 2002, Petersen 2009). McGahan and Porter (2002) also examine variance in accounting profitability and indicate that “industry and corporate-parent effects are important and related to one another. As expected, business-specific effects, which arise from competitive positioning and other factors, have a large influence on performance” (p. 834). Hence, we account for the influence of industry sector effects (including industry sector growth rate) and the firm’s choices towards profitable growth and operationalize Eq. (5) as

\[
\ln \frac{Y_t}{C_t} = \gamma_0 + \gamma_1 \ln s_{M,t} + \gamma_2 \ln s_{R,t} + \gamma_3 \ln \left[ \frac{\bar{K}}{\bar{L}} + d \right] + \gamma_4 \ln \left[ \frac{\bar{K}}{\bar{L}} + e \right] + \gamma_5 ghat_{i,t} \\
+ \gamma_6 Industry_{i,t} + \gamma_7 EST_{Firm} + \gamma_8 Age + \epsilon.
\]  

(6)

ghat_{i,t} is the average growth rate in revenue for industry segment i at year t, Industry_{i,t} is a dummy variable for industry segment i, EST_{Firm} is a dummy variable for firm type (recent-IPO versus established), and Age tracks the age of the firm (and its comparable pair) at IPO. The left-hand side tracks the revenue per unit of COGS, which we have labeled COGS productivity and which also represents the amount of gross profit added to the amount of COGS divided by the amount of COGS. The left-hand side is thus a good proxy for profitable revenue acquisition.

From Eq. (5) and Eq. (6), \( \gamma_1 = \frac{\alpha}{1-\alpha-\beta} \) and \( \gamma_2 = \frac{\beta}{1-\alpha-\beta} \). Consequently, to test the elasticity-related hypotheses (i.e., H1 and H4) we use the estimated values for \( \gamma_1 \) and \( \gamma_2 \) to impute the values for \( \alpha \) and \( \beta \) numerically by solving for them simultaneously. On the other hand, we have scaled up the adjustments to growth rates. That is, the regressions use \( \ln [ \frac{\bar{K}}{\bar{L}} + d + k ] \) and \( \ln [ \frac{\bar{K}}{\bar{L}} + e + k ] \), where \( k \) is a scaling constant to avoid negativity. Since this scaling is specified within a logarithmic function, coefficients \( \gamma_3 \) and \( \gamma_4 \) cannot be used to estimate \( \alpha \) and \( \beta \) in an
analogous manner to $\gamma_1$ and $\gamma_2$. However, these coefficients can be used for a relative assessment of the impact of growth rates. Accordingly, we use $\gamma_3$ and $\gamma_4$ to test H2, that is, the association between growth rate adjustments and COGS productivity. The estimated parameter $\gamma_0$ reflects aggregate productivity of the data and is thus used to test H3.

4.2. Sample Selection and Descriptive Statistics

We focus on four industry sectors to obtain a reasonable variation in industry growth rate, a key control variable in our specification: electronics, energy, medical devices and software. Industry sectors were established based on SIC codes. We searched and randomly selected 16 firms within each industry, yielding a total of 64 firms that underwent an IPO in the United States during the period 1994-2002. For each firm, we collected annual data from the COMPUSTAT/CRSP database for one year prior and five years post IPO providing 7 contiguous years of information. We label these data as the recent-IPO set. We also created a comparable sample for 64 established firms, labeled as the EST set, by randomly selecting these firms while drawing from identical industry sectors and years as the recent-IPO set. We also ensured that these established firms had their IPO at least 8 years prior to the initial year in which their annual data was collected. Thus, the dataset set reports 5 years of growth for each recent-IPO and EST firm, because the sixth contiguous year of data are required to establish annual growth rates. Data for additional seventh year have been used to compute lagged corrections, both for the IPO and the EST samples. By pooling the recent-IPO and EST sets, we have created a panel data set with a sample size of 768 firm-years.

We examined the annual 10-K statements and websites of the sampled firms to explore if there were any extraordinary events, such as special changes from mergers and acquisitions, in the firm-years where the data has been gathered. In addition, we used primary data for the
following variables, for each firm and accounting year (note that the time index \( t \) has been removed on these variables for simplicity of exposition):

- \( Y \): revenue
- \( C \): COGS
- \( \text{SG&A} \): sales, general and administrative expenses
- \( \text{R&D} \): research and development expenses
- \( \text{Age} \): at IPO and for a comparable firm in years
- \( \text{Liquidity} \): cash on hand

and constructed these variables from the primary data:

- \( a \): SG&A growth rate adjustment defined in Eq. (4)
- \( b \): R&D growth rate adjustment defined in Eq. (4)
- \( g \): revenue growth rate for the firm
- \( \hat{g}_i \): average revenue growth rate by industry sector \( i \)
- \( \ln(Y) \): natural log of \( Y/C \)
- \( \ln(S_{MG}) \): natural log of the ratio of SG&A and revenue
- \( \ln(S_R) \): natural log of the ratio of R&D and revenue
- \( \ln(d+g/a) \): natural log of adjusted SG&A growth rate
- \( \ln(e+g/b) \): natural log of adjusted R&D growth rate

Tables 1, 2 and 3 offer the statistics on the aggregate data, key measures by industry and the correlations, respectively. The aggregate statistics in Table 1 indicate that on average the revenue and the gross profit of the established firms are more than 5 times the averages for the recent-IPO firms. On the other hand, there is a wider dispersion in terms of the minimum and maximum values of SG&A, R&D, COGS expenses and age, particularly for established firms. Table 2 provides the comparison of these data in terms of industry sectors. The average annual growth rate \( \hat{g}_i \) in the energy and software sectors is higher than for electronics and medical devices sectors. High values for \( a \) and \( b \) imply that firms in that sector tend to move their allocation for SG&A and R&D at a rate that is relatively lower than their actual growth rate in revenue. In all four industry sectors, the recent-IPO firms invested in both SG&A and R&D at a higher rate, on average, than they invested in their revenue \((a < 1 \text{ and } b < 1)\), but the established
firms invested at a lesser rate. Correlation coefficients are shown in Table 3 for transformed variables based on Eq. (6). Items 4 and 5 (the adjusted growth rate) have been computed by setting the values of \( d \) and \( e \) at 0.15. We set these obsolescence rates for R&D and SG&A stock in the base case at 15% as previously determined within the literature as realistic rates for firms (Cockburn and Griliches 1988, Berndt et al. 1995). In the next section, we explore the sensitivity of the results to the magnitude of \( d \) and \( e \). We have also adjusted the growth corrections by a constant shift parameter \( (k) \), set at 10, so as to overcome the non-negativity constraint associated with a logarithmic function.

------- Insert Tables 1, 2 and 3 about here -------

5. Results

5.1. Specification Checks

There are several econometric issues that need to be considered in testing Eq. (6). Firm characteristics (fixed effects) such as strategy may be correlated with the independent variables, there may be autocorrelation in the panel data set, and because causality may run in both directions – from revenue to expenditure and vice versa – the independent variables may be correlated with the error term. As neither a fixed effects regression nor autoregressive lag model addressed the endogeneity issue, we conducted a two-stage least squares regression using liquidity, average revenue growth rate by industry sector \( (ghat_t) \) and lag of the natural log of COGS productivity, \( \ln(\gamma) \), as instrumental variables. From the post-estimation analysis, these three instruments proved to be strong and exogenous. The first-stage test statistics for the suspected endogenous variables \( \ln(s_M) \) and \( \ln(s_R) \) were 21.85 and 29.16, which comfortably pass the Stock and Yogo (2004) test for weak instruments. The Sargan test also supported the exogeneity of liquidity, average revenue growth rate by industry sector and lag of \( \ln(\gamma) \). Fixed
assets were also considered as instrumental variables but were shown to be a poor instrument. The dummy variables for sectors were dropped from the base and subsequent models because of collinearity with the average revenue growth rate by industry sector. Age was also excluded because of its collinearity with the established firm dummy.

The Pagan and Hall (1983) test did not indicate that heteroskedasticity was present. However, the Arellano and Bond (1991) test did reveal evidence of autocorrelation. Further, we ran additional models including terms for the interaction between each of the independent variables and the established firm dummy to identify the validity in separately comparing the recent-IPO and established firms. All the interactions were significant, confirming the difference in the coefficients for recent-IPO and established firms. The results presented in Tables 4 and 5 are from the two-stage least squares regression with autocorrelation consistent statistics.

5.2. Regression Analysis

The regression results for the base case are presented in Table 4. The dependent variable is the natural log of COGS productivity; recall that this is a proxy for the inverse of gross margin and measures the revenue per unit of COGS. The results for the base case, with obsolescence rates $d = e = 0.15$, are presented as a set of three models: pooled data, established firms only, and recent-IPO firms only. The results for hypotheses H1 and H2 are presented first under the heading pooled data analysis, followed by the results for H3 and H4 where the recent-IPO firms are compared to their established counterparts. Model 1 pools the data for recent-IPO firms (labeled as recent-IPO) and established firms (labeled as EST) and is thus used to test H1 and H2. Model 2 (for the EST sample only) and Model 3 (for the recent-IPO sample only) are used to test H3 and H4, that is, to illustrate that segmented (recent-IPO versus EST) results differ.

------- Insert Tables 4 and 5 about here -------
**Pooled Data Analysis.** Model 1 pools the data and includes a dummy for the established firms. We draw four key inferences. First, we note that the regression coefficients $\gamma_1$ and $\gamma_2$ are significant, suggesting that both SG&A and R&D investments are associated with COGS productivity. As articulated earlier, we are able to compute the values of $\alpha$ and $\beta$. Elasticity $\alpha$ is shown to be positive (3.248), thus supporting H1A and allowing us to infer that an increase in SG&A investment can diminish COGS while generating revenue; in other words, they are substitutes in the growth driven environment. On the other hand, $\beta$ is negative (−2.888), again supporting H1B and suggesting that an increase in R&D investments can augment COGS while generating revenue; in other words, they are complements.

Second, we observe that $\gamma_3$ is not significant but $\gamma_4$ is significant and positive. That is, H2A is unsupported but H2B is supported. This suggests that the aggregate population does not adjust its growth rate while making SG&A investment in order to improve its COGS productivity, but it does adjust its growth rate while making R&D investment. We further observe in Model 1 that the overall productivity parameter $\gamma_0$ is significant but $\gamma_7$ (corresponding to the dummy variable for firm type) is not significant.

**Comparing Recent-IPO to Established Firms.** We estimate the production function separately in Model 2 and Model 3, based on the EST and recent-IPO samples, respectively. In order to test H1, we impute the values of $\alpha$ and $\beta$ for Model 2 and Model 3 from their respective regression coefficients $\gamma_1$ and $\gamma_2$. In Model 2, we note that $\gamma_1$ is significant but $\gamma_2$ is not significant, suggesting that SG&A investments are associated with COGS productivity in generating revenues but R&D investments are not for the established firms. In Model 3, however, both $\gamma_1$ and $\gamma_2$ are significant, suggesting that both SG&A and R&D investments are
associated with COGS productivity in generating revenues for the recent-IPO firms. It follows in Model 2 that the imputed value for $\alpha$ is positive (0.706) and $\beta$ equals zero, thus supporting H1A but not H1B. In Model 3, $\alpha$ is positive (1.679) and $\beta$ is negative (–1.103), thus supporting both H1A and H1B. In other words, R&D investments and COGS are complement only for recent-IPO firms, while SG&A substitute COGS for both recent-IPO and established firms.

We also observe that, in Model 2, $\gamma_3$ is not significant but $\gamma_4$ is significant and positive. Hence, H2A is unsupported but H2B is supported. The significance of $\gamma_1$ and $\gamma_4$ for the established firms suggests that both SG&A and R&D investments drive COGS productivity, although only an upward adjustment in the growth rate while making R&D investment improves COGS productivity. In Model 3, on the other hand, both $\gamma_3$ and $\gamma_4$ are significant, but the former is negative whereas the latter is positive. Hence again, H2A is unsupported but H2B is supported. The significance of $\gamma_1$ through $\gamma_4$ for the recent-IPO firms suggests that both SG&A and R&D investments along with their related growth rate adjustments ($a$ and $b$) drive their COGS productivity. The implication of the regression coefficients associated with “$a$” and “$b$” being significant are that managers in recent-IPO firms consider their actual growth rates in revenue and deviate significantly from them while making SG&A and R&D allocations in order to control revenue growth. Tracking and accounting for “$a$,” “$b$,” and allied productivities during a firm’s resources allocation process, and their relevance in that firm’s competitive strategy formulation, are further discussed in the next section.

These findings establish some asymmetry between the choices made by recent-IPO and established firms, especially with respect to SG&A growth adjustments and R&D investments in their association with COGS productivity to generate revenue. We test H3 and H4 by comparing the corresponding regression coefficient of Model 2 to that of Model 3. The overall productivity
parameter ($\gamma_0$) is not significant for Model 2 but it is significant for Model 3, yet negative. Since its value is smaller for the pooled sample than the recent-IPO firms, we conclude that these recent-IPO firms are more productive in converting COGS into revenue, thus supporting H3.

Since the imputed value of $\alpha$ for Model 2 and Model 3 are 0.706 and 1.679, respectively, H4A is supported. Similarly, the imputed values of $\beta$ for Model 2 and Model 3 are 0 and −1.103, respectively, and H4B is also supported. Therefore, SG&A and R&D investments in recent-IPO firms have a larger elasticity with respect to COGS in generating revenue than their established counterparts.

**Sensitivity Analysis.** We can examine the robustness of the findings described above (i.e., for testing H1 through H4) by changing the values of $d$ and $e$ to the extreme values of their range, as shown in Table 5. The 4th, 7th and 10th columns correspond to the base case ($d = e = 0.15$) discussed above. Results from the base case do change to a small extent, but the signs and ranges of the imputed values of elasticity parameters $\alpha$ and $\beta$ do not change. Consequently, our findings above regarding H1 and H4 (i.e., supporting or not a hypothesis) still hold true. As for H2A, it is still unsupported, and H2B is still supported, except for one out of twelve possible scenarios ($\gamma_4$ is not significant for the established firms when $d = e = .99$). The overall productivity parameter ($\gamma_0$) continues to be significant for recent-IPO firms and not significant for established firms. However, our findings regarding H3 shift with the values of the obsolescence rates. Established firms get to be more productive than the pooled sample at low obsolescence rates, and the reverse is true for the recent-IPO firms, where they become more productive at higher obsolescence rates. Similar conclusions (not reported here) are drawn with other combinations of values for $d$ and $e$ (i.e., where they are unequal) than those in Table 5.
6. Discussion and Concluding Remarks

6.1. Deviating from the Hypotheses

A summary of our findings is provided in Table 6. Our first elasticity-related hypotheses are that a firm’s investment in SG&A stock substitutes, and that in R&D stock complements, its allocation towards COGS. These hypotheses are supported, except for one out of the six cells in Figure 6: for R&D stock in established firms. A plausible explanation for this deviation may be that established firms spend a considerable amount of their R&D allocation on process innovation, such that COGS are reduced rather than increased through R&D.

------- Insert Table 6 about here -------

Similarly, our hypotheses about adjustments with respect to the firm’s actual growth rate in revenue are supported for R&D, but not for SG&A. That is, firms do not tend to look at COGS productivity while selecting their SG&A investment, but they do consider their COGS productivity while making R&D allocations in aggregate. A plausible alternative explanation in this observation may be organizational: SG&A decisions such as selection branding campaigns by the relevant decision makers (e.g., by the VP of marketing) is not closely coordinated with COGS decisions (e.g., process improvement decisions in order to reduce unit cost by the VP of production) within the firms we have studied.

6.2. Influence of Industry Effects

The industry sectors we have followed are undergoing rapid technological evolution and continue to generate a large number of startups and IPOs (Technology Review 2009). Our study shows that recent-IPO firms tend to be more productive than their established counterparts, when we account for the growth rate of each industry sector. Management theorist (McGahan and Porter 2002) and analysts (Genomeweb 2003) following various industries tend to recognize that
such differences across industry sectors should exist. However, this body of literature does not account for the recent-IPO versus established firm asymmetry. Moreover, our industry sector growth rates are correlated with other sector variables such as age and the sector dummy variables. Hence, it is no surprise that the inclusion of industry growth rate as an instrumental variable drops the sector dummy variables from the base case. However, the managerial adjustments (“a” and “b”) that account for firm strategy above and beyond the firm’s revenue growth rate are significant.

A second construct worth examining is liquidity, that is, the amount of cash carried by these firms. Table 2 shows that, in all four industry sectors, recent-IPO firms have more liquidity on average than their established counterparts, even though the established firms have a much larger scale of revenue. Arguably, this could imply that recent-IPO firms are hedging their risks by carrying larger amount of cash because their revenues are smaller and presumably more volatile.

Some post hoc analysis of the outlier firms underscores this fact. For instance, between 1997 and 2001 Angeion Corporation, an established medical devices firm and outlier in our dataset, experienced a growth rate that was nearly six times more than its industry average. The reverse can be true for the revenue growth rates of the electronic and software firms. For instance, between 1996 and 2000 Applix, a then recent-IPO firm, showed a growth rate that is nearly six times less than its industry average. Consequently, smallness, which is often associated with recent-IPO firms, does not necessarily mean faster growth.

6.3. Aggregate Allocation: Managerial and Policy Implications

We examined a comparable set of 16 established and 16 recent-IPO firms in four sectors for a period of 7 years each. While we do not observe the articulation of firm strategies and their
implementation at the level of individual products, the outcomes of such implementations are reflected in the COGS-productivity measure. Hence, we argue that our dataset on SG&A, R&D and COGS reflects the de facto strategies and operational performance of the underlying firms. For instance, a firm such as Walmart (not included in our dataset) or Micron (a major maker of PCs and memory chips, included in our dataset) may be following growth strategy based on low cost. The COGS productivity of such a firm ought to be higher than its industry average.

Growth driven firm, either established or recent-IPO, must make the aggregate resource allocation decision that reflects their strategy. Our results imply that, during growth, firms ought to track not only the industry sector growth rates and their actual growth rate in revenue, but also their own COGS productivity and adjustments \( a \) and \( b \), along with the obsolescence rates \( d \) and \( e \) during their annual planning and strategy formation process. A longitudinal view of these parameters will allow these firms to test if their strategy is on course, when compared to their peers. These firms could also look for opportunities by examining their R&D and/or SG&A elasticity with respect to COGS, and look for biases or myopic choices that may get built into their aggregate resource allocation processes.

Our analysis also contributes to the policy debate on R&D tax credit for growth oriented firms, especially immediately following IPOs (Atkinson 2007). Empirical evidence on claimed R&D tax credits indicates that “as a percentage of average assets, the average amount of (R&D) tax credit claimed per company is a decreasing function of size” (Ernst & Young 2008). Our findings for the established firms appear to be in sync with this evidence. More interestingly, our findings also indicate that, during the growth of recent-IPO firms, SG&A investments play a key role as substitutes to COGS. That is, it is difficult for recent-IPO firms to foster growth through R&D alone, and they could use complementary tax incentive to invest in SG&A (e.g., for
marketing programs). A second policy implication is based on the importance of liquidity in the lifecycle of these firms. Supporting the liquidity needs (e.g., though loan guarantees for certain technology sectors such as energy firms engaged in clean technologies) may make more resources available for SG&A and R&D to foster growth. Findings from our current analyses could be used to develop a follow on study to look closely into these policy implications for both pre-IPO and recent-IPO firms.

Our study comes with limitations and opens doors for additional research. Some of the firms in our sample have gone through acquisitions, while others showed negative profits for a few quarters, but we did not need to censure any firm because it failed during or after the period of observation. To that extent, our work suffers from survival bias. Also, we do not allow for the elasticity terms to vary over time. Such adjustments would enable us to characterize the time period when the decision of recent-IPO firms can converge with the growth related allocation choices being made by their established counterparts. A third shortcoming, especially for the established firms, is that financial data typically aggregate a portfolio of business units that offer a diversification of products (Wernerfelt and Montgomery 1988) and the results of our analysis could be confounded by such diversification effects. Similarly, our empirical study is restricted to a time horizon and industry sectors where the average growth rates (as shown in Table 2) are positive. Application of the framework to firms in a declining economy or with capital constraints may yield another set of findings. Our results on asymmetries could be exploited to set up managerial incentives in settings where growth and profitability are central concerns (Chao et al. 2009). We leave these as issues that need further scrutiny in the realm of growth-adjusted dynamics associated with business venturing.
Appendix: Characterizing Firm Revenue per Unit of COGS

From Eq. (1) and Eq. (4),
\[ Y_t = \frac{g_t}{s_{M,t}} + d \left[ M_t \right], \quad (A1) \]

and similarly from Eq. (2) and Eq. (4),
\[ Y_t = \frac{g_t}{s_{R,t}} + e \left[ R_t \right]. \quad (A2) \]

From Eq. (3) and Eq. (A1),
\[ M_t = \left[ \frac{s_{M,t}}{\frac{g_t}{s_{M,t}} + d} \right]^{\frac{1}{1-a}} \left[ \theta C_t \right]^{\frac{1-a-\beta}{1-a}} R_t^{\frac{\beta}{1-a}}, \quad (A3) \]

and similarly from Eq. (A1) and Eq. (A2),
\[ R_t = \left[ \frac{s_{R,t}}{\frac{g_t}{s_{R,t}} + e} \right]^{\frac{1}{1-a-\beta}} M_t. \quad (A4) \]

Consequently, from Eq. (A3) and Eq. (A4),
\[ R_t = \left[ \frac{s_{M,t}}{\frac{g_t}{s_{M,t}} + d} \right]^{\frac{1}{1-a-\beta}} \left[ \frac{s_{R,t}}{\frac{g_t}{s_{R,t}} + e} \right]^{\frac{1}{1-a-\beta}} \theta C_t, \quad (A5) \]

and from Eq. (A2) and Eq. (A5),
\[ Y_t = \left[ \frac{s_{M,t}}{\frac{g_t}{s_{M,t}} + d} \right]^{\frac{1}{1-a-\beta}} \left[ \frac{s_{R,t}}{\frac{g_t}{s_{R,t}} + e} \right]^{\frac{1}{1-a-\beta}} \theta C_t. \quad (A6) \]

Therefore, from Eq. (A6),
\[ \frac{Y_t}{C_t} = \left[ \frac{s_{M,t}}{\frac{g_t}{s_{M,t}} + d} \right]^{\frac{1}{1-a-\beta}} \left[ \frac{s_{R,t}}{\frac{g_t}{s_{R,t}} + e} \right]^{\frac{1}{1-a-\beta}} \theta, \quad \text{and Eq. (5) follows.} \]
References


Table 1. Aggregate Data*

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*All values in million $, except for age in years

Table 2. Average Sector Statistics

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Table 3. Correlations

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*significant at 0.05
Table 4. Regression Model  
(*** significant at 0.01; ** 0.05; * 0.10)

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<td>adjusted ln(d+g/a)</td>
<td>γ_3</td>
</tr>
<tr>
<td>adjusted ln(e+g/b)</td>
<td>γ_4</td>
</tr>
<tr>
<td>Industry growth average</td>
<td>γ_5</td>
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<tr>
<td>Energy Sector Dummy</td>
<td>γ_6.1</td>
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<tr>
<td>Med Dev Sector Dummy</td>
<td>γ_6.2</td>
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<td>Software Sector Dummy</td>
<td>γ_6.3</td>
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<tr>
<td>Established Firm Dummy</td>
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<td>Observations</td>
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</tr>
<tr>
<td>F Statistic</td>
<td>3.35</td>
</tr>
<tr>
<td>P Value</td>
<td>0.01</td>
</tr>
<tr>
<td>Imputed α</td>
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</tr>
<tr>
<td>Imputed β</td>
<td>-2.888</td>
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</table>

† Variables dropped from the analysis due to collinearity.

Table 5: Sensitivity Analyses  
(*** significant at 0.01; ** 0.05; * 0.10)

<table>
<thead>
<tr>
<th>Model</th>
<th>Condition</th>
<th>1-Low</th>
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<th>1-High</th>
<th>2-Low</th>
<th>2</th>
<th>2-High</th>
<th>3-Low</th>
<th>3</th>
<th>3-High</th>
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</thead>
<tbody>
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<td>384</td>
<td>384</td>
<td>384</td>
<td>384</td>
<td>384</td>
</tr>
</tbody>
</table>

Observations | 768 | 768 | 768 | 384 | 384 | 384 | 384 | 384 | 384 | 384 |
F statistic  | 4.08 | 3.35 | 1.91 | 11.77 | 11.50 | 15.24 | 3.20 | 3.15 | 1.93 |
P Value      | 0.00 | 0.01 | 0.09 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.10 |
Imputed α    | 0.818 | 3.248 | 0.871 | 0.701 | 0.706 | 0.705 | 1.674 | 1.679 | 5.336 |
Imputed β    | 0 | -2.888 | 0 | 0 | 0 | 0 | -1.117 | -1.103 | -1.129 |
## Table 6. Result Summary

<table>
<thead>
<tr>
<th>Hypotheses for the Aggregate Population</th>
<th>Model 1 (all firms)</th>
<th>Model 2 (established firms)</th>
<th>Model 3 (recent-IPO firms)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H1A</strong>: A firm’s investment in SG&amp;A stock substitutes its allocation towards COGS in generating revenue.</td>
<td>Supported</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H1B</strong>: A firm’s investment in R&amp;D stock complements its allocation towards COGS in generating revenue.</td>
<td>Supported</td>
<td>Unsupported</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H2A</strong>: A firm’s growth rate adjustment while making SG&amp;A investment is positively associated with its COGS productivity.</td>
<td>Unsupported</td>
<td>Unsupported</td>
<td>Unsupported</td>
</tr>
<tr>
<td><strong>H2B</strong>: A firm’s growth rate adjustment while making R&amp;D investment is positively associated with its COGS productivity.</td>
<td>Supported</td>
<td>Supported</td>
<td>Supported</td>
</tr>
</tbody>
</table>

### Hypotheses Comparing Established and Recent-IPO Firms

<table>
<thead>
<tr>
<th>Hypotheses Comparing Established and Recent-IPO Firms</th>
<th>Model 2 (established firms) versus Model 3 (recent-IPO firms)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H3</strong>: The COGS productivity for recent-IPO firms is larger than that for established firms, ceteris paribus.</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H4A</strong>: Investments in SG&amp;A at recent-IPO firms have a larger elasticity with respect to COGS in generating revenue than at their established counterparts.</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H4B</strong>: Investments in R&amp;D at recent-IPO firms have a larger elasticity with respect to COGS in generating revenue than at their established counterparts.</td>
<td>Supported</td>
</tr>
</tbody>
</table>