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Towards a better understanding of the dynamics of value creation in R&D intensive small firms

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Standard financial and economic theories suggest that the stock value of R&D intensive High Technology Small Firms (HTSF) undergo a geometric random walk. Such a model neglects to account for observed periods where firms experience large fluctuations due to uncertainty related to its R&D activities, external competitive or regulatory environments. Empirical evidence also shows that the behavior of these firms is difficult to describe – let alone predict – using this Gaussian process. With ambidexterity as a theoretical basis, we show that the value of HTSF can be statistically described as the result of a combination of two distinct random walks: an exploitative steady state component characterized by Neo-Marshallian equilibrium and low volatility; and a more dynamic component with high volatility reflecting bursts of large and rapid changes associated with Schumpeterian outcomes of explorative processes. A mixture of two normal distributions provides an overall function that is more reflective of the empirical evidence and provides a quantitative measure for the theory that firms engage in concurrent exploration/exploitation activities. A linear relationship between the two components of the mixture distribution that describe the stock value of these firms also emerges. By understanding this dual nature and its impact on stock value, firms can better manage resources and prepare for the increase in variability that are associated with exploration activities. A more accurate financial description of HTSF that reduces or that anticipates uncertainty may lead to financial tools and option pricing methods that put a premium on the value of HTSF markets, incentivizing investors to invest more in such firms.

1. Introduction

Using a mixture distribution to describe the stock returns of R&D-intensive High Technology Small Firms (HTSF) provides greater accuracy than the traditional Gaussian distribution that real options models use (Jacob and Kwak, 2003; Schneider et al., 2008; Avadikyan and Llerena, 2010; Cassimon et al., 2011; Verdu et al., 2012; Wang et al., 2015). This approach provides management with greater insight into value creation caused by R&D, supporting decision-making on management of and investment in R&D. A mixture of two Gaussian functions provides a quantitative model that complements ambidexterity theory (McCarthy and Gordon, 2011; Wei et al., 2014) – suggesting firms operate in concurrent exploration (high volatility) and exploitation (low volatility) states (Williams and Lee, 2009; Gobbo and Olsson, 2010; Bauer and Leker, 2013; Hoppmann et al., 2013; Mäkinen and Vilkkö, 2014; Costantini et al., 2015).

Success in capitalizing R&D is needed for continued growth. Firms commit resources to R&D to increase financial gains directly and/or indirectly. For example, firms engage in R&D activities to support the core business by increasing efficiency, gaining competitive advantage, or maintaining internal capacity to mitigate competitive risk. Consequently, R&D intensive firms have higher growth rates (Del Monte and Papagni, 2003; Thornhill, 2006) and greater profitability (Chan et al., 2001; Chambers et al., 2002). The challenge is deciding on what is the appropriate level of resources to commit to R&D.

Achieving the appropriate level of R&D investment is difficult. Abernathy and Utterback (1978) suggested that a firm's focus on productivity maximization inhibited flexibility and the ability to innovate. Organizational learning theory (March, 1991) suggested that firms operate in either an exploitation or exploration state. These states (exploration and exploitation) can coexist within the same organization – ambidexterity (Levinthal and March, 1993). This concept – ambidexterity – has been studied from the perspective of: organizational learning, strategic management, leadership theory, and organizational design; this offers opportunities for advancing with a cross-disciplinary perspective (Raisch and Birkinshaw, 2008). However, few quantitative studies consider how this process evolves over time within firms and how balance is achieved between the two states (Ancona et al., 2001; He and Wong, 2004).

Uotila et al. (2009) used media analyses of firms to show that an optimal balance between exploration and exploitation can be achieved through studying

financial performance versus relative exploration intensity. The relationship between the two states appears to be dependent on the average R&D intensity of the firm's sector. Groen et al. (2008) shows that balancing exploration and exploitation is particularly difficult to manage in HTSF. Jansen et al. (2006) provide an overview of how firms coordinate balancing between the two states by using organizational structure to respond to the competitive environment. A better understanding of the appropriate balance provides managers and investors with better decision support (Perlitz et al., 1999; McNamara and Baden-Fuller, 2007; Wu and Yen, 2007; Mudambi and Swift, 2011). Understanding is helpful to managers who plan R&D projects with highly uncertain outcomes and risk (Hartmann and Hassan, 2006).

The variability observed in firms' stock returns are explored. A data-driven methodology for statistically measuring the impact of exploration and exploitation activities on the stock value of firms is offered. A sample of relatively small R&D intensive firms (market capitalization of under \$100 million) listed in the United States is used. A mixture distribution is found to be more accurate than a simple Gaussian process and mathematically simpler than time-dependent processes (e.g., GARCH models). The method allows for quantitative measurement of firms' exploration and exploitation states.

2. Background

R&D activities are critical to growth and profitability (Sahaym et al., 2010). Without the R&D (exploration) activities, companies remain in a suboptimal state and do not grow. Exploration considers new opportunities for change and growth.

R&D objectives differ within firms. Exploration activities compete for scarce resources and offer neither immediate gain nor a measureable link between resource utilization and resulting financial returns. Traditional accounting, economic and financial tools do not place a monetary value on R&D – or estimate the amount that should be spent on R&D (Behr and Pötter, 2007). R&D knowledge is a non-rival good that is difficult to appropriate (Hall, 2002), making it difficult to justify. It is, therefore, unsurprising that there is a lack of quantitative tools to model the returns from R&D activities and that investment in R&D is sub-optimal.

The challenge of funding R&D activities is even more apparent in small firms, as they lack the ability to sustain costly investments. Most HTSFs are at a disadvantage because of restricted access to external capital and lack of slack resources relative to larger

firms (Jarillo, 1989). Information asymmetries between investors and investees further exacerbate this issue. Finally, small firms lack tangible collateral that is often required by investors funding pre-commercial R&D (Binks and Ennew, 1996; Hall, 2002; Czarnitzki and Hottenrott, 2009).

HTSFs face the complexities of foreign markets with little internal resources and expertise (Preece et al., 1999). Consequently, small firms are highly dependent on strong networks (Harryson, 2008; Hernández-Espallardo et al., 2011; Clausen et al., 2013) to overcome a lack of experience, customers and reputation (Zhao and Aram, 1995; Heuven and Groen, 2012). Social networks coordinate quickly horizontally, exhibit long-term persistence, and have emergent collective behavior (Rybski et al., 2012). These networks offer small firms more flexibility than large firms to rapidly capture market share resulting in advantage if markets require speed, flexibility, and niche targeting (Jarillo, 1989; Dean et al., 1998).

The value of a smaller firm's R&D activities is, therefore, sensitive to recognizing and developing entrepreneurial opportunities (Ardichvili et al., 2003; Park, 2005; Companys and McMullen, 2007), which happens in discrete steps as information on the potential and outcome of the R&D becomes available (Figueroa-Lopez, 2009). The nature of the opportunity (e.g., radicalness and importance) can even result in the formation of a new HTSF (Shane, 2001; Smith et al., 2009). HTSFs may also face policies and regulations based on the assumption of the breakdown of efficient markets (Brock and Evans, 1989). Regulatory requirements such as the number, length, and compliance cost deter opportunity driven entrepreneurship (Ho and Wong, 2007), that is frequently undertaken by HTSFs. Government can have a positive impact on HTSFs by alleviating this burden (Craig et al., 2007; van Stel et al., 2007; Revest and Sapiro, 2012) through interventions, including: R&D tax incentives, small firm loan guarantees and easing of regulatory requirements. Such differences cause HTSF return profiles to behave differently than larger firms; HTSF value profiles are susceptible to dramatic fluctuations (i.e., prices deviating far from mean value).

Economic theory suggest that firms' investment return profiles can be modeled by a Gaussian distribution (i.e., expected returns rarely go beyond two units of the standard deviation from the mean) or by using a random walk with a complex time-dependent volatility profile. Gaussian return profiles are modeled using a simple normal random walk. The value of the investment has an equal chance of going up or down at each time step. Most models assume that the return profile is composed of independent and identically

distributed random variables (Campbell and Zhou, 1993). Central limit theorem is used to explain how return profiles are described by a Gaussian distribution allowing R&D decisions to be easily solved using real options techniques (e.g., the Black-Scholes model).

HTSFs competing in volatile environments with short product cycles and complex network interactions have value extraction mechanisms that are fundamentally different than larger firms with large diversified portfolios of activities. These HTSFs have highly-skewed return profiles (Mason and Harrison, 2002); that is non-Gaussian processes as the likelihood of price going up or down is unequal. As new information on the potential outcome of R&D becomes available, management adjusts its strategy accordingly. This flexibility enhances the R&D's value by reducing potential downside loss and preferentially selecting positive outcomes – the resulting asymmetric returns favors the initial investment. Interestingly, prospect theory (Kahneman and Tversky, 1979; Barberis et al., 2001) suggests that investors are likely to over estimate downside loss and underestimate gain. Net present value, however, does not account for uncertainty reduction over time and the benefits of managerial flexibility. In reality, some uncertainty is resolved simply through gathering information on the R&D investment strategy (Childs and Triantis, 1999).

This process involving multiple management decisions is analogous to options used in financial markets and can significantly increase the investment value. Specifically, in the case of R&D uncertainty in commercial value, budget, and schedule (Huchzermeier and Loch, 2001) is modeled. Asset-pricing models (and the efficient market hypothesis) depends on assumptions of how underlying uncertainty and returns are distributed (Kon, 1984). Therefore, it is critical to accurately describe the value extraction process of R&D activities to allow for a better understanding of the value of HTSFs. The challenge is one of adequately accounting for sudden shifts in value (stock price) that are akin to the black swan phenomena (Taleb, 2007).

Alternative models better describe highly volatile and correlated processes. Incorporating a dynamic factor into a random walk process introduces occasional 'jumps' in price fluctuation. The jump-diffusion model considers how underlying assets undergoes a random walk punctuated by large jumps (Kou, 2002). A Poisson distribution is typically used to describe the frequency and amplitude of these jumps (Merton, 1976; Newton et al., 2004).

Alternatively, price dynamics are modeled by considering time changes in the volatility parameter.

ARCH or GARCH models can account for time-varying volatility cluster in a firm's price over time (Engle, 1982, 2001; Bollerslev, 1986; Mills, 1999; Spanos, 1999). However, such processes are impractical for large datasets and do not offer a link to ambidexterity or other theories. Kou (2002) proposes a double-exponential jump diffusion model to avoid the impracticality of analytical complexity. The jumps can be characterized as Lévy flights. However, in practice empirical data may exhibit kurtosis and skew that deviate from the central limit theorem. Stock traders *correct* for this by introducing an ad hoc *implied* volatility term to the option price (e.g., Black-Scholes equation) to account for skew and kurtosis.

One approach is to describe the static properties of an asset as a fat-tailed power law distribution (Casault et al., 2013). Instead of trying to predict complex market moves as one calculates real option value by using numerical methods and a statistical approximation of the value with a 'Bachelier'-like option pricing formula (Bouchaud and Potters, 2003). This paper offers a novel statistical description of the underlying value of HTSFs for use in option pricing methodologies that is grounded in ambidexterity theory. A quantitative characterization of ambidexterity is accompanied by a methodology to measure the relative impacts of ambidextrous activities on a firm's stock value.

3. Research hypotheses

It is proposed that the R&D value extraction process does not follow standard economic principles (i.e., cannot be modelled using a normal random walk). Small firms performing R&D operate in a regime of punctuated equilibrium, that is a mixed state composed of two Gaussians, with different volatility parameters. This extends economic theory by capturing the dynamics of both the R&D state and non-R&D steady state of firms. This concept of ambidexterity – exploration and exploitation – is well known (Benner and Tushman, 2003). However, it is unclear how these two different types of activities influence stock valuation and whether or not their relative importance in firms can be identified.

This study considers exploitation as market price stability; whereas exploration leads to larger market volatility and variance (March, 1991; He and Wong, 2004; Mudambi and Swift, 2011). Quantitative evidence is presented to test the hypothesis that HTSFs operate in a mixed or ambidextrous state described by mixing two Gaussian distributions. The mixing parameter allows identification of the relative importance of the two states on the firm's resulting stock value.

The value of the HTSF is assumed to be directly linked with a main product and is not moderated by the presence of a portfolio of many products. As the main product is directly linked with R&D efforts, the value is subject to large and frequent fluctuations based on internal and external factors that influence the product's commercial viability. For example, an unexpected new product application will rapidly increase the value of R&D activities. The opposite is true if R&D activities fail in some manner.

If the standard economic model does not accurately represent HTSFs, a single Gaussian distribution may not offer an accurate fit of the static distribution of commercial returns. Consequently, the statistical fit of change in share price with a single Gaussian distribution will be considered for the candidate firms.

H1. P-value statistics will show that the Gaussian distribution is inadequate to describe small firms heavily engaged in R&D activities.

However, if these firms exist in a mixture of two Gaussian states, a similar statistical analysis should show that these firms are more accurately described using a distribution composed of a mixture of two Gaussian distributions.

H2. P-value statistics will show that a mixture of Gaussian distributions is appropriate to describe small firms heavily engaged in R&D activities.

Using rigorous statistical analysis the goodness of fit statistics for fitting specific distributions is tested (Clauset et al., 2009).

4. Research method

The static description of changes in the value of the underlying asset is well described using a Cauchy distribution function (Casault et al., 2013; Casault et al., 2014). However, this static description is unfamiliar and creates analytical challenges (e.g., non-converging distribution with infinite moments). This model does not directly explain the dynamic behavior of the asset (i.e., what mechanism drives the observed changes in the returns of the underlying asset). Models that simulate the dynamic behavior of agents obeying simple rules are sometimes used to explain observed characteristics of returns for underlying assets (Lux, 1998; Bouchaud, 2013). In the absence of a dynamic model, a better static representation of the return profile is desirable (Malevergne et al., 2005).

Modeling the static properties of an HTSF using a mixture of two Gaussian distributions is proposed. This approach is better to describe stock returns with

Figure 1. (a) Illustration of a histogram for a hypothetical data distribution based on a mixture of two Gaussian distributions with different variances. (b) The Probability Distribution Function (PDF) for the data is shown as a solid black curve. The two components of the mixture model (grey curves) are also shown. The overall result is a thick-tailed distribution.

fat tails, high skew, or kurtosis (Kon, 1984; Bhat and Kumar, 2012; Tan and Chu, 2012). Such an approach explains an entrepreneurial firm operating in two distinct states: steady state (similar to other firms); and dynamic state (bursts of large change resulting from engagement in and commercialization of R&D activities). Figure 1 illustrates how a Gaussian distribution with low variability is used to describe a firm's steady state return profile and a second Gaussian distribution with high variability is used to capture the hypothesized high variability portion of the value return profile.

The resulting distribution (mixture of two Gaussian distributions) is better suited for describing the ambidextrous value creation process and other features, such as thick tails that indicate large rapid fluctuations in the firm's value. The main advantages of the mixture distribution are simplicity, stability, and familiarity. The concepts of punctuated equilibrium and jump diffusion (Abernathy and Utterback, 1978; Tushman and Anderson, 1986; Kullman et al., 1999; Mudambi and Swift, 2011; Bouchaud, 2013) both support this model.

5. Empirical analysis and results

5.1. Selecting and analyzing R&D-intensive small firms

Small firms are defined here as firms listed in the United States with market capitalization of less than

\$100 million (average for 2012). Small firms were ranked according to R&D intensity using CapitalIQ. The top 650 were selected. R&D intensity is the ratio of a firm's R&D expenditures to firm revenue. Therefore, firms with R&D activity and no revenue (pre-commercial R&D) were first on the list. The 650 HTSFs from this query represent 10 industrial sectors: 40% information technology; 31% healthcare; 12% industrials; and the remaining 17% from other areas. Table 1 offers a summary of the 605 firms.

Daily Stock prices were obtained using QuoteMedia's online stock quotes for the time period 2002–2012. Firms were then screened to ensure that prices were available for at least 1 year of trading (251 days) during the specified time. Firms failing to meet this criterion were eliminated. Only 512 firms were retained for further analysis (79% of the initial sample).

Previous studies show a persistent positive correlation between a firm's R&D investment levels and excess stock returns (Chan et al., 2001; Chambers et al., 2002). This suggests that conventional quantitative tools do not appropriately account for the risk profile of these firms. This study assumes that the stock price is a good proxy for the commercial value of R&D in HTSFs. A reasonable assumption as small firms have a limited R&D portfolio – usually a single project – making stock value highly correlated to the outcome of the R&D.

The log-returns, η , of stock prices were calculated for the 512 firms. The log-returns are a first order approximation of the arithmetic returns:

Table 1. Financial and structural information on 605 firms in the sample

Indicator	Market capitalization (\$million)	R&D expenditures (\$million)	Revenues (\$million)
Average	29.8	2.97	23.0
Minimum	1.56	–	(0.295)
Maximum	100	73.8	324
Standard deviation	26.7	5.81	41.3

$$\eta(t) = \frac{S(t+1) - S(t)}{S(t)} \quad (1)$$

$$\simeq \log S(t+1) - \log S(t)$$

where $S(t)$ and $S(t+1)$ are the stock prices for consecutive time intervals. In this case the returns consider two consecutive trading days. In total 512 firm time series containing at least 251 data points in each series describe the daily returns of each firm. That is, the daily relative value fluctuations of the future commercial value of firms' R&D activities are captured. The time series are transformed into static histograms describing each firm's distribution profile.

5.2. Research goal

A more accurate static description of the value return profile of R&D intensive small firms (HTSFs) is provided by showing these firms to oscillate between two Gaussian regimes. A fit of the return profiles of these firms along with a "fitness parameter" describing the goodness of fit between the double Gaussian and standard single Gaussian distribution model is obtained.

The time series of returns were assessed using maximum likelihood estimation (MLE) on two probability distribution functions: (1) A Gaussian distribution, and (2) A double Gaussian distribution – a five-parameter stable distribution function comprised of two normal distributions. The distribution of returns, η , is:

$$f(\eta; p, \sigma_1, \sigma_2, \mu_1, \mu_2) = p \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(\eta-\mu_1)^2}{2\sigma_1^2}} + (1-p) \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(\eta-\mu_2)^2}{2\sigma_2^2}} \quad (2)$$

with means μ_1 and μ_2 and variances σ_1 and σ_2 . A mixing parameter $0 \leq p \leq 1$ implicitly acts as an amplitude parameter for each of the two Gaussian components. We make the simplifying assumption that p is fixed over our period of analysis.¹

This results in a simple Gaussian and a mixture of two Gaussian fits for each of the 512 firms under evaluation. To measure goodness of fit, the Kolmogorov-Smirnov (KS) test was used. KS was chosen as it is simple to calculate and relatively accurate compared to other goodness of fit tests (Clauset et al., 2009).

The resulting KS distance describes the appropriateness of using a single Gaussian distribution versus the proposed mixture distribution. The empirical P -value for each fit was determined by generating bootstrap datasets using the fitting parameters obtained in

in the MLE step. The P -value is calculated as the ratio of the number of times that KS distance for the empirical data and its corresponding best fit is smaller than between the bootstrap datasets and their corresponding best fits. Normally a P -value > 0.05 is evidence that the tested distribution function has adequate descriptive properties. These two iterative processes were used throughout to estimate goodness of fit parameters.

5.3. Results

Figure 2 offers an example of one of the 512 firms in the sample by showing the histogram of returns of Vringo Inc. NASDAQ:VRNG – and its best one- and two-Gaussian fits. A mixture of two Gaussian distributions is better at describing the firm's return profile (P -value = 0.720).

P -values show that the traditional model used to describe the value extraction process of R&D (single Gaussian) is not a good fit. A single Gaussian distribution tends to neglect both the steady state portion centered on the mean and the high fluctuation events contained in the heavy tails that are observed with R&D intensive small firms.

Vringo Inc. (Figure 2) has a mixing parameter value of 0.163. This indicates that the component with higher variance contributes less than 20% of the overall profile. For the 512 firms, the mixing parameter, p , (Equation 2) is distributed log-normally with a mean of 0.315 and a variance of 0.052. The high variability component of the firm contributes to over one third of the overall profile. While it is tempting to disregard high fluctuation events as uncharacteristic or as outliers, for R&D intensive small firms these outliers describe a substantial amount of behavior that is critical for the firm. These outliers describe events where the firm successfully or unsuccessfully extracted commercial value from R&D efforts (e.g., product testing or development milestones).

In the sample of 512 firms, the overall best fit using a mixture distribution contains both low variability $\sigma_1 = 0.156$ and high variability $\sigma_2 = 0.045$ components. This supports the hypothesis that HTSFs exist in a combination of two distinct phases, characterized by magnitude of variance. Both Gaussian components of the mixture model have similar location parameters, μ . This further supports the R&D intensive small firms existing in two states: steady and large fluctuation state.

The stock price return fluctuations of the top 30 global R&D spenders ('EU Industrial R&D Scoreboard' 2013) were considered for comparison. These firms have large portfolios of R&D activities and consequently have less variation between the two

Figure 2. Histogram of Vringo Inc.'s stock returns shown as a grey bar chart. A simple Gaussian distribution, the dashed line (P -value 0.000, $\mu = 2.00\text{e-}4$, $\sigma = 0.079$), does not appropriately capture the full behavior of this firm because it overcompensates on the variance at the expense of the central portion of the returns. The mixture of two Gaussian, the black line with its two Gaussian components (P -value = 0.720, $P = 0.163$, $\mu_1 = 0.054$, $\sigma_1 = 0.156$, $\mu_2 = -0.010$, $\sigma_2 = 0.045$) shown as light grey lines, provide a better fit for Vringo Inc.'s return profile.

Gaussian components of the best mixture model fit. That is they are more accurately described with a single Gaussian distribution. On average, the top 30 large R&D spenders have a best mixture model fit with variability parameters of $\sigma_1 = 0.02$ and $\sigma_2 = 0.06$.

Only one of the 512 firms had a P -value indicating that returns have a Gaussian distribution. In contrast, 29 firms (6%) have P -values >0.5 when fitted with a mixture distribution. Furthermore, KS statistics indicate that 420 firms (82%) are better described using a mixture of two Gaussian distributions. In summary the mixture distribution is a great improvement for modeling the static properties of return profiles for HTSFs. The model better captures the two-state features of firms and provides quantitative evidence of ambidexterity.

H1: P -value statistics reveals that one firm has R&D returns that can be adequately modelled using a Gaussian distribution.

H2: P -value statistics also reveals that 6% of firms are described using a mixture of Gaussian distribution. While 82% of firms are better described by a mixture distribution than by a single Gaussian distribution.

The findings substantiate that firms engaged in R&D activities have stock profiles that are a mixture

of two states. (1) Exploitation (steady state) the profile of a firm's returns due to processes associated with low uncertainty. (2) Exploration (high volatility) the profile of a firm's returns due to processes associated with high uncertainty – appropriate to describe a firm's R&D-related activities.

Firms that are better described with a mixture of Gaussian distribution offer a surprisingly linear relationship between the two σ values specified by the MLE algorithm. The higher volatility distribution is almost an order of magnitude above the lower volatility distribution (Figure 3). By removing only 24 (5%) of the outlying data points using a robust bi-square regression, a linear relationship is shown between the two variability components:

$$\sigma_2 = 0.12\sigma_1 + 0.02 \quad (3)$$

This relationship is consistent with the earlier illustrative example (Figure 2). However, this is a persistent characteristic of the overall set of HTSFs further supporting the theory that firms operate in a linked dual-state governed by similar Gaussian mechanisms. *Exploration* characterized by larger fluctuations and higher variability and *exploitation* a steady state mode characterized by smaller fluctuations with a consistent relationship between the two modes (Equation 3).

Figure 3. Shows the relationship between the variance of the two curves that comprise the mixture distribution that best describes the empirical data. A ratio of approximately 10 to one exists between the two normal distributions. The firms exist in a mixture of two normal states where one state is characterized by variability one order of magnitude larger than the steady state. The line of best fit was obtained by excluding data points considered outliers using a bi-square robust regression.

A useful consequence of this finding is that managers of R&D intensive small firms and financial investors have an estimate of the expected increase in variability during periods of high volatility in relation to the variability during periods in which the firm's price is relatively stable. This offers insights into the financial impact of uncertainty related to R&D investments. That is, firms can anticipate variability almost an order of magnitude greater than normal when substantial resources are diverted to R&D investments. This information is valuable for making financial preparations in advance of significant R&D investments. Awareness of the extent of the change in volatility is also of valuable for assessing firm financial health by the management team and other stakeholder – such as stockowners, analysts, and media.

This study leads to some interesting additional questions. A two Gaussian model offers helpful insights. However, would the results be even more favorable through the use of different distributions. For example, a combination of Gaussian for steady state and a *t* or Cauchy distribution for the more volatile exploration (R&D) related behaviors. A further concern is the assumption of static volatility over time. That is, the results have not been able to offer insights into time-dependent variation as could be offered by ARCH and GARCH. To better understand differences in time dependency mature technology

firms such as General Electric, IBM, and Microsoft should be studied to understand the different phases of volatility that occur from initial listing to being a mature S&P 500 firm. Having considered areas of further research, concluding notes are now offered.

6. Conclusion

HTSFs have return profiles that are not adequately explained using traditional economic models. More specifically HTSFs have return profiles with distinct periods of rapid and large fluctuation in stock value. These R&D intensive small firms differ from other firms in that their stock value is highly correlated to the value of their exploration efforts.

A mixture of two Gaussian distribution more accurately describes the return profiles of R&D intensive small firms over time – as they operate in two distinct states: exploration and exploitation. Most HTSFs (82%) were better described by a Gaussian mixture distribution. While *P*-value statistics indicate that the mixture distribution is valid for only 6% of the firms, it is an improvement over traditional models and is theoretically based (ambidexterity theory).

The Gaussian mixture distribution provides a better explanation because the value profile of these firms is thick-tailed. The mixture model allows for a

component to capture low probability, high fluctuation events that result in large value changes. The resulting thick tail component of the firms' profile contributes to over a third of the overall return profile for most firms studied. A quasi-linear relationship between the two Gaussian components of the mixture distribution was found. This linear relationship provides insight to decision makers about investing in R&D. That is, managers can expect firm volatility to undergo fluctuations of an order of magnitude greater than experienced in steady state periods. R&D-intensive small firms can expect to undergo periods of high volatility about one third of the time – with a high increase in volatility is important to all stakeholders – managers, investors, and policy makers.

This study extends the body of knowledge on the effect of R&D on the value of R&D intensive small firms. A novel statistical methodology allowing the measurement of transition between a steady exploitative state and a volatile exploration state is provided. The study assists in better modeling the R&D driven value extraction process of firms. Thereby improving the foundation from which to more accurately value the commercial opportunities generated by R&D and assist in placing an appropriate premium on such firms.

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Note

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