Spring 5-22-2020

Innovation, Firm Life Cycle and the Dividend Payout Scale Effects on ETF Performance

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Scale Effects on ETF Performance

A Dissertation

Submitted to the Graduate Faculty of the
University of New Orleans
in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
in
Financial Economics

by

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May, 2020

DEDICATION

I wish to dedicate this dissertation in memory of my late grandfather Harinath Upadyaya.

ACKNOWLEDGMENTS

I would like to thank my advisors, Prof. Tarun K. Mukherjee and Prof. Atsuyuki Naka for their invaluable guidance and continuous support from the inception of the idea to the completion of this dissertation. This dissertation would not have been possible without their support and hard work. I gratefully acknowledge all their supports and valuable insights for this dissertation.

I would also like to thank Professor Sudha Krishnaswami and Assistant Professor Ramesh Adhikari for serving as members of my dissertation committee and providing many useful suggestions that helped me to improve this research.

I also take this moment to express my sincere thanks to Professor and chair of the department, Walter J. Lane, for the continuous support during my time as a Ph.D. student at the University of New Orleans. Further, I would like to thank Prof. Hassan, Prof. Maroney, and Prof. Zirek, whose support and time have been instrumental in my success in this program.

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ABSTRACT

This dissertation consists of two essays. In the first essay, I introduce a new measure of the firm life cycle and compare its efficacy with the three existing life cycle proxies: ‘cashflow patterns’, ‘earned contributed capital mix’, and the firm’s public ‘age’. More specifically, I show that two groups of firms, similar in all respects except in their innovations efficiencies, will adopt different dividend policies regardless of their calendar age, earned income, or the cash flow patterns. I employ a large sample of US manufacturing firms spanning from 1973 to 2017. I find that more innovative firms pay lower dividends than the less innovative firms, irrespective of how we describe the life cycle stages. Besides, I perform a comprehensive cross-sectional look at the interrelations among various factors, including innovation output, growth, firm life cycle, and the dividend payout. I conclude that the intensity of innovation outputs has a direct relation with the firm's growth rate, and that, in turn, affects the firm’s life cycle, and thereby its dividend policy.

In the second essay, I evaluate the returns to scale, tracking error, and the role of fund characteristics on the ETFs risk-return performance. I investigate the impact of asset base size growth on the risk-adjusted performance and on the tracking ability of ETFs to their benchmark indices. I use the quantile regression approach with survivorship biased free non-leveraged, non-active, equity-only ETFs sample for ten years. I find that the ‘universe of equity ETFs’ do not provide increasing returns to scale. The results show that the size has a more substantial negative impact on the highest performing quantiles of the ETF cluster. I also observe that the ‘illiquidity,’ ‘expense ratio,’ the ‘equal-weighted index composition’ among others are the main key drivers that exacerbate the inverse relationship between the size and the performance. However, the core blend style and the capitalization-weighted index composition have a positive effect. Finally, I conclude a negative relationship between the size and the tracking error. I document that the ‘illiquidity,’ ‘expense ratio,’ and ‘volatility’ have a positive relationship with the tracking error.

Keywords: Firm life cycle, Innovation, Growth, Dividend Policy, ETFs, Tracking Error, Performance

CHAPTER 1

INNOVATION, FIRM LIFE CYCLE, AND THE DIVIDEND PAYOUT

1. INTRODUCTION

Researchers have long embraced the linkage between a firm's life cycle and its growth rate. According to Mueller (1972), a business firm has an 'S' shaped growth pattern, with a period of slow growth at start-up followed by a period of more robust growth and eventually to maturity and stagnation. As the firm progresses through its lifecycle towards maturity, its ability to process information deteriorates. Moreover, the risk-taking incentives of the average manager diminish. Consequently, net investment in tangible assets decreases. The firm is not able to generate innovations to maintain continuous growth, and ultimately, it reaches a point at which the firm lacks profitable investment opportunities. This view has almost universally accepted in the academic and business communities. For example, Hubbard (2018), among others, suggests that in the early stage, the firm invests more to capitalize on its growth opportunities, while during the maturity stage, it invests in maintaining the assets in place. Faff et al. (2016) argue that the firm's cash holdings go up in the introduction and growth stages but decrease in the mature and shake-out/decline stages as its financing need subsides.

Mueller (1972) extends the linkage between the life cycle and growth of the firm to its dividend payout decision by proposing that at the mature stage, a value-maximizing firm would begin distributing its earnings in dividends. The literature, in general, agrees on the notion that the dividend payout follows a life cycle pattern, and the likelihood of dividend payments is positively related to the maturity of the firm (Fama and French, 2001, Grullon et al., 2002, and DeAngelo et al. 2006). Consistent with the view, Bulan, and Subramanian (2007) document that firms initiate/increase dividends after reaching maturity in their life cycles. According to Flavin and O’Connor (2017), the degree of dividend payouts increases over the life cycle of the firm, but peaks during the maturity stage.

Although the life cycle theory of dividends is a broadly accepted notion, the debate continues about the right proxy to demarcate the stages of a firm’s life cycle, especially its maturity stage. The most popular empirical proxy appears to be the firm’s age. However, equating the life cycle to the 'calendar age' has been challenged by researchers who offer alternative proxies. For example, DeAngelo, et al. (2006) suggest ‘the contributed capital mix’, whereas Dickinson (2011) recommends ‘the cash flow patterns’ as an alternative to measure the life cycle stages. Despite the extensive coverage of the firm lifecycle in the existing literature, a clear demarcation of the stages, especially the maturity stage, is yet to emerge. I argue that growth induced by innovation output has a crucial role in dictating the length of each stage and the corresponding dividend payout.

The evidence is aplenty in the literature that links innovations to growth. Chan et al. (1990), Doukas and Switzer (1992), Blundell et al. (1999), Toivanen, et al. (2002), and Yang and Chen (2003) among others, present evidence that the innovative, small and medium-size firms have higher future growth opportunities and profitability than the non-innovative ones. Deschryvere (2014) finds that continuous product and process innovators show positive associations between R&D growth and sales growth. Coad et al. (2016) find that innovative firms grow more than non-innovative ones. Their quantile regression results show that the coefficient of innovation is higher for firms with the highest growth rates. Faff et al. (2016) opine that innovative firms may continue to grow in a given lifecycle stage longer than less innovative firms. Spescha & Woerter (2019) suggest that innovative firms based on R&D activities have higher sales growth rates than non-innovative firms.

At least theoretically, a persistently innovative firm should be able to produce sustainable growth and, therefore, avoid paying dividends forever. Realistically, we should expect a highly innovative firm to stretch its life far beyond the “maturity” stage, irrespective of what proxy (age, contributed capital, or cash flow pattern) we use to measure it. For example, suppose there are two firms that are similar in all respects except their innovation efficiency, the one with demonstrably high innovation efficiency would pay significantly lower dividends than the one that exhibits poor innovation performance.

When using innovation efficiency as a proxy for the life cycle, a firm reaches its maturity once its innovation performance decreases to the level of the industry average. On the other hand, a poor performer in the innovation contest reaches the maturity stage much sooner than their counterparts in the same stage of the life cycle regardless of the proxies used. These are the issues I address in this paper and hypothesize the most appropriate proxy for a firm's life cycle. I contribute to the literature by first defining a firm's life cycle based on its innovation efficiency and then demonstrating how innovation might explain cross-sectional differences in dividend payments between two firms that are otherwise similar in all respects. Besides, I re-examine and perform a comparative study of the most popular life cycle proxies in the extant literature.

The results show that innovation superiority prevails in measuring "maturity" irrespective of how it is defined. I find that there is no defined life cycle for all firms. Instead, the innovation-based criteria define each firm's life cycle individually. A young firm may fall in the declining stage if the firm loses its creativity, while an old firm that may otherwise qualify for the maturity stage based on age may continue to function as a growth firm and might decide not to pay (or raise) dividends. Using innovation measure, I can see the life cycle occurring in three stages; first, when a firm's innovation efficiency is higher than the industry average, the firm is at the growth cycle. It is likely to follow a low-dividend policy. Second, when the firm's efficiency level mirrors the industry, the firm is in the maturity stage and may pay higher dividends. Finally, a firm with a below-industry level of efficiency is expected to be at the declining phase, but its dividend decision would likely depend on the management quality.

Thus, I claim that the maturity hypothesis (as explained by the dividend payout) is better defined by innovation output intensity. The existing studies lack sufficient empirical researches that connect the innovation outputs or innovation success with the firm's business life cycle, and I attempt to fill the gap.

Likewise, Dickinson (2011) study cashflow patterns during a corporate life and defines life-cycle stages in terms of a firm's cash flow pattern. However, to the best of my knowledge, cashflow maturity as proposed by Dickinson has not been tested for the dividend payout. In this research, I put it in perspective and investigate whether the cashflow maturity of a firm is aligned with the maturity hypothesis associated with the dividend payouts. I claim that this is an added contribution to the literature.

The paper proceeds as follows. In section 2, I provide the literature review. Section 3 introduces the main hypotheses. Section 4 presents the data and univariate analysis and empirical methodologies. Section 5 contains the discussion and presentation of the findings, theoretical underpinnings, and the policy implications, and finally, Section 6 concludes the paper.

2. LITERATURE SURVEY

2.1. Debate on the Life Cycle Measurement

As discussed, there is no consensus yet in the literature on the definition of the life cycle[1], although the 'firm age' has been the most popular proxy.[2] In sharp contrast to the abundant empirical supports for 'age' to measure the life cycle, a few recent papers repudiate 'age' as a useful life cycle proxy. DeAngelo et al. (2006) argue that it is not the 'age' but the 'earned to contributed capital ratio (RE/TA)' is an excellent proxy to measure the firm life cycle. In contrast to DeAngelo's findings, Megginson and Von Eije (2008) find no relationship between retained earnings to total equity ratios and the propensity to pay dividends in their study listed in EU

[1]see Yan, Zhipeng and Zhao, Yan, A New Methodology of Measuring Firm Life-Cycle Stages (2010). International Journal of Economic Perspectives, 2010, Volume 4, Issue 4, 579-587.

[2] A debate, however, exists among scholars about the type of relation between age and the life cycle. Some scholars (see Anthony, J. H. & Ramesh, K., 1992; Bhattacharya et al., 2004; DeAngelo et al., 2010; Seifert and Gonenc, 2012; Chincarini et al., 2016; Kieschnick and Moussawi, 2018) believe that the relationship is linear, while others (e.g., Freeman, Carroll, Hannan (1983), argue that the firm age follows 'non-linear' 'U shape' relation across life-cycle stages as the new firms grow faster but are more likely to fade out.

countries. However, they do find that age, size, and past profitability are positively related to the propensity to pay dividends. Dickenson (2011), on the other hand, discover that it is the cash flow pattern that accurately defines the firm life cycle. Faff et al. (2016) further claims that while these variables ('earned to contributed capital ratio,' 'firm size' and 'age') do provide some indication of a firm's life cycle progression, they have limitations and hence are unlikely to be the reliable life cycle proxies on their own. The paper attempt to address the issue with a new method called multiclass linear discriminant analysis (MLDA) to generate the main life-cycle proxy, as a function of age, earned to contributed capital ratio, profitability, and asset size. The debate goes on for over two decades now, and the search for better life cycle measurement also continues on. In this context, I intend to extend the discussion from a new perspective that an 'innovation output intensity' plays a crucial role in the formation of the firm life cycle stages.

2.2 Life Cycle Patterns, and the Dividend Policy:

Following the dividend irrelevancy theory of Miller and Modigliani (1961) under the assumption of the perfect capital market, earlier studies devoted their attention to explaining firms' dividend decisions by introducing market imperfections (e.g., information asymmetry). In more recent years, the focus has turned on market variables and firm characteristics. Fama and French (2001) investigate the patterns and the determinants of dividend payout policy over the period 1926-1999 and point to life cycle factors playing an essential role in the cash dividends payout decisions. Fama and French (2001) documents that dividend-paying firms are large and highly profitable and the firms that never paid dividends are small and unprofitable. The small firms have many investment opportunities that require external financing because their capital spending is far higher than their earnings. Fama and French (2001) concluded that dividend payers have the characteristics of mature firms, while firms that have never paid dividends have the features of young, fast-growing firms. In sum, the Fama-French (2001) study confirms a strong association between the patterns of dividend payment and firm characteristics that govern a firm's life cycle stage. While Fama-French(2001) concludes the decreasing propensity to pay dividends during their sample duration, Amin et al. (2015) and Floyd et al. (2015) find that for US industrial firms, the declining propensity to pay dividends reverses after 2002. They present evidence of a consistent and steady surge in the percentage of dividend-paying firms from 2002 to 2012. DeAngelo et al. (2004) also show that while the number of firms paying dividends have fallen, the total amount of cash dividends by US industrial firms has increased over time.

Another major line of research is to analyze whether firms vary their dividend payments according to the stages of their life cycle in which they find themselves. Mueller (1972) proposed the life cycle hypothesis of dividends suggesting that a firm's dividend policy should be determined based on where it is in its life cycle. On Mueller's foundation work, Grullon et al.(2002) come up with the maturity hypothesis, saying that dividend payout signals the maturity of the firm. Julio and Ikenbeery (2004) test the maturity hypothesis and explain disappearing and reappearing dividends in which they use firm age as the variable to define the firm maturity. Likewise, DeAngelo et al. (2006) show that the likelihood of dividend payment is related positively to the maturity of the firm measured by RE/TA or RE/TE. Their findings are in alignment with the view that younger firms are in the capital infusion stage, which limits their ability to pay dividends. In contrast, mature firms are profitable with few investment opportunities, which allows them to pay dividends in the stockholders.[3]

Bulan et al. (2007) examine whether the firm life cycle affects firms' decisions to initiate dividends. They find that mature firms with a larger size, profitability, and cash reserves, fewer growth options, tend to start dividend payout. The argument is that as a firm becomes mature, the management has less incentive to preserve cash for future projects, and is, therefore, in a better position to make dividend payments. Thus, dividend payout is an integral part of the firm life cycle, and in most literature, it represents the maturity of the firm.

[3] See illustrations in Habib, Ahsan, and Hasan, Mostafa Monzur, Corporate Life Cycle Research in Accounting, Finance, and Corporate Governance: A Survey and Directions for Future Research (August 20, 2018).

2.3. Life Cycle Proxies and Their Limitation

The Anthony & Ramesh (1992) paper is perhaps one of the earliest empirical work on accounting-based measures for classifying life cycle stages. The paper uses four variables: age, sales growth, dividend yield, and capital expenditure. They provide strong empirical supports for ‘age’ as a lifecycle determinant. Bhattacharya et. (2004) uses 'firm age' to study the trends in pro forma reporting. They find that "young" firms are significantly less profitable, more liquid, higher P/E, and book-to-market than older firms in their industry. The univariate measures such as firm size and age assume that the firm progresses linearly over the life cycle; however, some of the recent studies suggest that a firm’s movement over the life cycle is dynamic (Helfat and Peteraf, 2003). In a recent study, Dickinson (2011) shows that the classification of firms into different life cycle stages based on Anthony and Ramesh (1992) is mostly erroneous because the underlying variables fail to capture the attributes of the firm life cycle. The paper argues that firms of the same age can learn at different rates because of imperfections in their feedback mechanism. Likewise, Faff et al. (2016) discuss that extant studies mostly use the listing year to measure firm age; however, many firms continue as unlisted private firms for an extended period. They argue that this introduces noise into the measurement of firm age. The paper study whether the corporate decision-making process is interdependent over the firm’s life-cycle, and it uses the ‘age of the firm’ as one of the life cycles proxies in the multivariate measurement methods. The empirical research finds that firm age is not an appropriate proxy for the firm life cycle measurement. The authors make the point that while univariate proxies such as age and firm size do provide some indications about firm maturity, they are unlikely to capture a firm's life cycle on their own to their inherent limitation. To address the problem, they employ a new method (multi-class linear discriminant) as a function of multiple relevant variables and study the corporate decision makings. They find that their new measure is more effective in comparison to the cash flow pattern proxies, as mentioned by Dickinson (2011) and the traditional proxy of ‘firm age’ (adjusted for industry and size effects) to study the corporate policy makings. The paper explains, like firm age, cash flow pattern, and size can also evolve non-monotonically across life-cycle stages and hence are not a good life cycle proxy.

The interesting observation is that despite repudiation, a firm's age continues to be broadly used in studies linking the life cycle to financial decisions other than dividends. DeAngelo et al. (2010) examine the effect of the life cycle on the likelihood of conducting SEOs. Using the number of years since listing (firm age), and dividend history, as proxies for the firm life cycle, the authors show that corporate life cycle stages have statistically and economically meaningful influences on the decision to conduct an SEO. Seifert and Gonenc (2012) examine the impact of a firm life cycle on firms' decisions to issue or repurchase equity or debt. They provide evidence in support of the life cycle theory of financing choices using 'age' as a life cycle proxy. They show that firms in the earlier stage of the life cycle (proxied by age) issue (repurchase) more (less) equity than do older firms. Keasey et al. (2015) introduce family firms in the life cycle literature and examine whether the life cycle of family firms influence the association between leverage and ownership. Their sample consists of European listed firms over the period 2000 thru 2009. They use firm age as the proxy for the life cycle and find that the relationship between ownership and leverage is positive (negative) for mature (growth) stage firms. Chincarini et al. (2016) find that firm age (a proxy for firm life cycle) captures the time-variation of beta (systematic risk) and its relation to the cost of equity capital. Kieschnick and Moussawi (2018) use firm-age (since IPO) as a life cycle proxy and show that the level of debt a firm uses has a negative association with the age. They also show that this relation is driven primarily by the interaction between a firm's age and its governance features.

To sum up, new firms are young but are also more likely to fail, which means that young firms can occupy both the introduction and the decline stages of the life cycle. An old firm can keep growing if they are inventing the new products and process aligning with the market demand. Therefore, the old firm is not necessarily mature, and similarly, a young firm may not be a growth firm either. I argue that 'growth,' induced by innovation output, can indeed shape the lifecycle patterns more appropriately. As Dickinson (2011) argues, the firm life cycle differs from firm age because firms of the same age can learn at different rates due to imperfections in their feedback mechanisms. She also highlights the fact that prior literature such as Anthony and Ramesh (1992) and Black (1998) rely on the development of the monotonic patterns on variables such as - age, sales growth, dividend payout, or some composite of these variables to assess life cycle. However, according to Dickinson, the drawback in those researches is that a uniform monotonic distribution of life cycle stages across firms is inherently assumed. The assumption that a firm moves monotonically through its life cycle is an apparent fallacy because a business firm is a portfolio of multiple products, each at potentially in different product life cycle stages.

I summarize the table below with the major life cycle proxies in use in the current literature. In this list, I introduce a new life cycle proxy ‘the innovation intensity.’ I claim that the new proxy is proven more accurate and economically meaningful than any other existing proxies currently in use because the innovation success of a firm is accountable for much of the firm growth that better explains the dividend life cycle.

No.	Paper	Proxy	Life Cycle Stages
1	Miller and Friesen (1984)	Age and sales growth	Identify five life cycle stages – birth, growth, maturity, revival, and decline. Show each stage on average lasts for six years.
2	Anthony and Ramesh (1992)	The dividend, sales, capital expenditure, and firm age	First accounting study to document the relationship between the life cycle and the stock returns. Identify three stages – growth, mature, stagnant
3	Bhattacharya et al. (2004)	Univariate measures – age, size, and profitability	
4	DeAngelo et al. (2006)	Earned(internal) Contributed(external) Capital Mix, Retained Earnings to Total Assets or Retained Earnings to Total Equity	Young, Mature, and Old. The underlying premise is that young firms have little or no retained equity and rely on contributed(external) equity, resulting in low RE/TE ratios. Mature firms, on the other hand, have greater access to internal funds (retained equity) and less need for contributed equity; hence they have larger RE/TE ratios.
5	Dickinson (2010)	Cash flow patterns from operating, investing and financing	Five stages – introductory, growth, maturity, shakeout, and decline stages based on cash flow pattern classification; however, they do not

			relate their life cycle stages with the dividend payout.
6	Faff et al. (2016)	MLDA (multiclass linear discriminant as a function of age, RE/TE, profit(EBIT/asset), and sales per year)	They enhanced the Dickinson methodology by performing linear discriminant analysis. They classify life cycle into four stages - introductory, growth, maturity, shakeout/decline stages
7	This study (my dissertation)	Innovation Intensity (degree of innovation success of a firm based on citation weighted patents output and dollar value-based patent output for firm 'f' on year 't')	The idea is that life cycle patterns are driven by growth, which, in turn, is driven by the degree of innovation success of the firm. Persistent innovators can push the maturity phase longer in comparison to the less innovative firms. I propose three phases - introductory, growth, and mature. I use Kogan et al. (2017) innovation output measures as an innovation index.

2.4. Factors Affecting Firm Growth

Is there a relation between growth and life cycle?

The traditional determinants of firm growth are firm-specific characteristics such as age, size, legal structure, and innovation. These papers have demonstrated that small, young, and independent businesses grow at the fastest rate (Almus and Nerlinger, 1999). Some papers have entirely different views on growth, such as Geroski and Gugler's (2004) document that growth is mostly random, and there is little correlation in growth rates over time. It argues that there is more variation in growth rates within firms than across firms over time. Benartzi, Michaely, and Thaler (1997) states that dividend reductions are associated with an improvement in the growth rate, while an increase in the earnings growth rate does not follow the dividend increases.

How does age affect firm growth?

Herriott et al., (1984) and Levitt and March (1988) find a positive impact of age and explains that new firms face up to difficulties associated with lack of market recognition and economies of scale, and lack of alliances with partners. However, over time, these firms can strengthen their available resources, managerial knowledge, and the ability to handle uncertainty. Loderer et al. (2016) show that as firms mature, they become more rigid in exploiting benefits from the assets in place. They do not consider renewing their growth opportunities and hence, suffer a decline in firm value. Grullon et al. (2002) established the "maturity hypothesis" that argues that as firms mature, the investment and growth opportunities diminish. As a result, the expectations for return on their investments will fall. As the expected return deteriorates, companies dispense cash from their prior investments to the shareholders as dividends instead of turning the reserve cash into new ventures.

How does r&d affect firm growth?

The literature extensively discusses the effect of R&D investment on firm growth. Concerning future performance, many studies provide evidence showing that R&D investment is positively associated with future performance[4]. Grabowski and Muller (1978) assert that R&D expenditure plays an essential role as the innovative driver to increase the future growth opportunities and profitability of the firms. However, some studies report that R&D investment has no or minimal negative impact on future performance[5]. Chun et al. (2014)[6] report that R&D investment directly affects future profitability as it enables the development of new products and new technologies. R&D investment can reduce costs through efficient production technology, which has a positive impact on future performance.

[4] see extensive discussion in Yoo et al. (2019) that cites the following papers Bublitz, B.; Ettredge, M. The information in discretionary outlays Advertising, research, and development. Account. Rev., 1989, 64, 108–124. 5., Kim, J.K.; Seo, J.S. The effects of R&D expenditures on the firm's value. Korean Int. Account. Rev., 2007, 20, 207–229. 6. and Chung, A.J.; Park, S.B. The effects of business groups on the association between R&D intensity and firm value. Korean Int. Account. Rev. 2014, 57, 38–58

[5] Lee, Y.H.; Lee, H.J. Impact of R&D expenditure size on financial performance focused on the IT service industry. J. Korea Soc. It Serv. 2009, 8, 1–14. 8. and Choi, M.S.; Kim, Y.C. The relation between excess R&D expenditure and future earnings growth of a firm. Korean Account. Inf. Rev. 2011, 29, 1–28

[6] Chun, D.P.; Chung, Y.H.; Bang, S.S. Measuring R&D productivity of the major Korean firms: Using data envelopment analysis. Korean Acad. Soc. Account. 2014, 19, 173–190

However, the effects of R&D investment are not always positive[7]. For example, if R&D investment fails, sunk costs will increase, which can negatively affect the firm value. Amir et al. (2007) provide evidence that in industries with high R&D intensity, R&D investment has considerably more uncertainty than intangible investment assets, while in industries with low R&D intensity, there is no difference between the two. Chauvin and Hirschey (1993) argue that firms pursue technology innovation through R&D investment leading to revenue generation through new product development that positively affects profitability. They also explain that the R&D investment has a positive impact on the profitability of the firm because it improves production efficiency due to cost reduction.

Based on the findings of the papers discussed above, the evidence on the effects of R&D on firms' value is mixed depending on the degree of success of resulting innovations. This prompts us to use patents and citations as measures of success of the R&D investments.

2.5. Innovation, Growth, and the Dividend Policy:

Bulan and Subramanian (2007) extensively discussed the work of Knight (1921), Schumpeter (1934), and Mueller (1972) to explain that in its initial stages, the firm invests all available resources in developing innovation and improving its profitability. Afterward, the enterprise will proliferate as it enters new markets and expands its customer base before any significant competition can arise. While the innovative firms are growing, competitors begin to enter the market, adopting and improving upon the original firm's innovations. As the existing market becomes saturated and new markets are harder to find, the growth of the firm begins to slow down. To maintain growth and profitability, firms need to regenerate innovations.

Anthony and Ramesh (1992) suggest that the capital expenditure is highest for growth firms, while firms in revival and decline have higher cash dividends. Gaver and Gaver (1993) find significantly lower dividend yields for growth firms than for non-growth firms. Fama and French (2001) show that firms with excellent investment opportunities payout substantially less or are

[7] Kay, N.M. The R&D function: Strategy and structure. Tech. Chang. Econ. Theory 1988, 282–294

much more likely to payout nothing. Moreover, the authors find that firms have become less likely to pay dividends, whatever their characteristics (such as size, profitability, or investment opportunities) during the period 1978–99. Huergo and Jaumandreu (2004a, 2004b) and Huergo (2006) find a negative impact of age on the probability to innovate, which shows that the youngest cohorts are conditional on the peculiarities of their activity and size, prone to innovate more than the oldest ones. Segarra and Teruel (2014) results show that investing in R&D increases the likelihood of becoming a high-growth firm. They use the Spanish CIS database to analyze the asymmetries of the innovation phenomenon from two different approaches. The paper considers the heterogeneous impact that R&D effort may exert on the firm growth distribution.

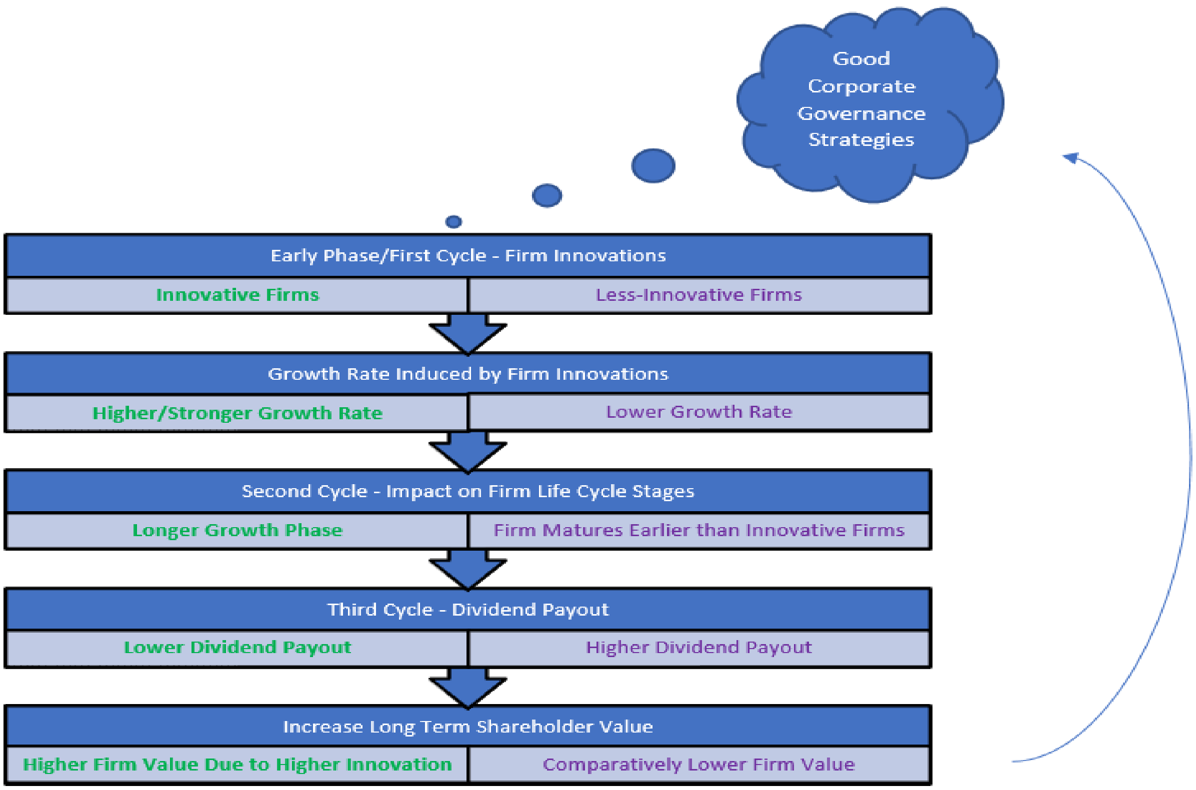
3. HYPOTHESIS DEVELOPMENT

As evidenced from the literature review, the life cycle of a firm is closely related to its expected growth rate. A successful firm goes through an extraordinary growth in the first cycle; a sustainable growth period follows in the second cycle and growth rate subsidies in the final cycle. Theoretically, the growth rate may reach zero if the firm chooses inaction to prevent the growth from falling to that level. The one that is more successful in innovation activities before reaching the final maturity stage is likely to pay lower dividends than the other firms that are less innovative. Innovation output helps firms to gain a competitive advantage over their competitors so that the firms can generate abnormal returns for their shareholders. However, innovation, through R&D, new products, or patent development, is an expensive and risky long-term investment. Firms need to take long-term risks to innovate; this means that only the responsible corporate governance with the right incentive can make such risky but worthy decisions on behalf of shareholders. Good corporate governance involves setting up long term strategies that support economic efficiency, financial stability, and sustainable growth. It ensures companies' access to capital for long-term investment in innovation, which is one of the critical factors to achieve long-run sustainable growth. The interlink between good governance and innovation yields a higher sustainable growth rate that can determine the duration of firm life cycle stages.

Prior research evidence supports the link[8] between sound corporate governance system and the innovation. A stable higher growth backed by great innovation makes it possible for the firm to achieve a more robust growth rate that can extend the growth phases of the firm's life cycle. Besides, the innovative firms have more investment opportunities, and hence they better utilize the firm's assets in comparison to their less innovative counterparts. As a result, during the final stage (the lower growth phase or the maturity phase) of the firm life cycle, the innovative firm is expected to pay a lower dividend. The less innovative firms, on the other hand, will likely run out of investment opportunities and are expected to distribute higher payout in the form of the cash

8 Baysinger et al. (1991) study the link between specific board characteristics and innovation and concluded that there is a definite link between the proportion of internal board members and R&D expenditure per employee. Tylecote and Visintin (2007) states that corporate governance is one of the main determinants of innovation and technological change. Tribó et al. (2007), Wu (2008), Latham & Braum(2009), Zhang et al. (2014), and few other papers claim that corporate interest has grown in the influence of governance mechanisms on innovation decisions in recent years. These papers argue that innovation efforts depend on factors that are influenced by corporate governance, such as ownership structure, shareholder identity, or the functioning of the board of directors. Aghion, van Reenen & Zingales (2013) develop a theoretical model to test the relationship between institutional ownership and innovation. They find a similar result as in previous literature, showing that larger institutional ownership is directly related to more innovation, as measured by cite-weighted patents. Brunninge et al. (2007) and Shapiro et al. (2015) suggests that the external directors on the board have a positive effect on strategic changes, including innovation. Similarly, Balsmeier et al. (2014) find that external directors with experience who sit on the boards of technology companies have a positive and significant effect on applications for patents in the companies which they advise and supervise. Chen (2012) and Lacetera (2001) find that firms that have board members with higher educational level tend to have a more thorough understanding of R&D processes and external environments, so they will be better positioned to implement R&D activities. Chen (2012) also finds that R&D investment is negatively related to board size. Lhullery (2011) indicates that certain board practices that address shareholders, such as duality, may individually have a positive influence on R&D investments, and this is in line with the results as found by Driver and Guedes (2012) for the UK data. However, if R&D does not necessarily boost firm growth as suggested by the mixed empirical evidence, then it does not make sense for the corporate governance to spend money on R&D.

dividend. Thus, based on the discussion, I present a general conceptual framework of empirical research in the figure, as shown below.



As discussed, a feature of a mature company is a higher rate of dividend payout. I argue that if the two groups of firms in the same life cycle stage are pursuing different dividend payouts, say one firm with a lower dividend and another firm with a higher dividend, then Grullon's maturity hypothesis implies that the firm that pays a lower dividend is not in the maturity phase yet, suggesting that the firms (that are paying lower dividends) are the innovative firms that can extend the growth phase. At the same time, while innovative firms keep growing, their non-innovative counterparts are already in maturity as they started paying a higher dividend. As depicted in the figure, I posit that the firm with a sound governance system would, via innovation, be able to extend the growth period, and thereby, avoid increasing the dividend payout ratio during the mature phase of the firm life cycle. This model of corporate governance that promotes innovation will help the firm achieve its long-term goal of increasing shareholder value. Grounded on all these analyses backed by the comprehensive literature review and the research questions that I posed earlier, I attempt to test the working hypothesis that between two groups of firms with similar characteristics (industry affiliation, size, re/te, life span among others) , the one with higher and persistent innovation, will produce more vigorous growth and, therefore, have a lower dividend payout. Further, I investigate which definition of life cycle describes the firm maturity better: is it the firm age or the re/te or the cashflow pattern or the innovation intensity? I examine whether the two firms in the same age group but significantly different innovation success, initiate/increase the dividend payout at the same time? The same question goes to the firms of similar retained earnings ratio (re/te) and the cash flow patterns that demand an investigation. The underlying idea is that if the lifecycle proxies are efficient, then the maturity hypothesis and dividend payout should hold regardless of the life cycle measurements.

4. SAMPLE, VARIABLES, AND THE DATA

I use the data sample starting from 1973 because the disclosure of R&D expenditure is made compulsory for US firms in 1972 (see Hall and Oriani, 2006). I perform the initial analysis of the full sample data in Compustat from 1973 through 2016. I find that the majority of R&D firms in the Compustat database belong to the Manufacturing Industry Sector[9]. My observation is consistent with Autor et al. (2018) and Helper et al. (2012),[10] who indicate that the manufacturing sector creates about two-thirds of U.S. R&D spending and patents even though they account for less than one-tenth of U.S. private non-farm employment. I use the Compustat database and focus on the US manufacturing firms (SIC classes 2000-3399). Consistent with the existing literature, I exclude firms that have average net operating assets, sales revenue, or market value of equity less than $1 million. I also exclude firms with missing values of variables I employ in the analyses.

I cross-reference Kogan et al. (2017), Arora, et al. (2019) and NBER to merge the patent/citation database with the manufacturing sample. Kogan et al.(2017) develop two innovation measures based on innovation output. According to the paper, the first innovation

[9] see appendix on the distribution of data in the full Compustat sample
[10]Helper et al. (2012) claim that a manufacturing share in US R&D spending is more than 68%. They document the fact based on the data from the National Science Foundation's Business R&D Survey.

measure is the dollar value of stock market reaction weighted patents output[11]. The paper explains that authors estimate the total dollar value of innovation produced by a given firm 'f' in year 't' based on stock market reaction after the patent is published. It further illustrates that they sum up all the dollar values of patents 'j' that are granted to a firm 'f' on year 't'.

$\Theta_{f,t}^{sm} = \sum_{j \in P_{f,t}} \varepsilon_j$, *where* $P_{f,t}$ *denotes the set of patents issued to firm* f *in year* t.

The second innovation output measure of Kogan et al.(2017) is the citation-weighted (cw) patents based on the following model:

$$\Theta_{f,t}^{cw} = \sum_{j \in P_{f,t}} \left(1 + \frac{C_j}{\hat{C}_j}\right)$$

Where,

C_j *is number of cites to patent 'j' on year 't' for firm 'f'*

$\hat{C}_j$ *is the mean number of cites to patents granted in the same year*

Kogan's et al. also mention that they normalized the above two measures with the book value of the firm (Compustat variable 'at'). I use both models above and normalized to total firm asset as a citation weighted innovation index to study the impact of innovation output on dividend payout. I also use their patent/citation data that are made available on their paper's online appendix[12] to match with the CRSP merged Compustat firms. I identify the data based on 'lpermno' and 'year'. I confirm the data match with other common Compustat variables that they have in common in the dataset.

I create three subsamples to study the innovation differential impact on the dividend policy. The first one is the 'less innovative' sample consists of the firms that have below-median innovation index, the second one is the 'innovative' sample consists of the firms with above-median innovation index, and the third one 'persistent innovative' sample consists of the firms

[11] Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N., 2017. Technological innovation, resource allocation, and growth. Quarterly Journal of Economics, 132(2), pp. 665-712

[12] data https://paper.dropbox.com/doc/U.S.-Patent-Data-1926-2010-t5nuNWnTH1InM0gyxkizL

with minimum three years of consecutive citation weighted patents. Three subsamples provide a unique opportunity for a comprehensive empirical study on the impact of innovation intensity on the firm's growth, and therefore, on its life cycle. I present the list of all the variables of interest in the Table 'Variable Selection'[13].

5. EMPIRICAL

5.1. Descriptive Statistics and Univariate Analysis:

Table 1 presents the summary statistics of the variables of interest in the research. Panel A provides the mean, median, and standard deviation of all the variables used in the empirical regression models. Panel B includes descriptive information based on the three sub-samples: less innovators, innovators, and persistent innovators. It shows that less innovative firms have higher dividend payout compare to the other higher innovators. The persistent innovators have the lowest dividend payout among the three sub-groups. The pattern is opposite for innovation-related ratios such as R&D, amortization intangible, and the innovation index.

[13] Please, see in the appendix

Table 1-Summary Statistics

This table presents the summary statistics of the variables of interest. On the left side, I report the summary statistics of the sample. On the right side, I present the descriptive statistics for three sub-samples: Below Median Innovators, Above Median Innovators, and the Persistent Innovators. I exclude the data with missing values for total assets, sales, and retained earnings. I also exclude the data with total assets and sales revenue of less than one million. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017. All the ratios are normalized with total assets except for retained earnings, which normalized with total equity.

	Summary Statistics					Descriptive Statistics		
Variable	Obs	Mean	Std. Dev.	Min	Max	Mean (Less Innovator)	Mean (Above Avrg Innovators)	Mean (Pers. Innovators)
divratio	97,586	0.0102532	0.0179087	0	0.1036962	0.0127192	0.009604	0.0084059
rdratio	69,615	0.0794518	0.1178053	0	0.8913236	0.0159702	0.0897263	0.2328962
amratio	70,646	0.0041438	0.0082118	0	0.0497061	0.0036278	0.0051674	0.0039582
lagRDint	65,025	0.3971088	2.341973	0	32.48936	0.0188546	0.3660818	1.520077
k_index	34,804	0.278142	0.8028689	0	59.83537	0.1343905	0.2415297	0.9198633
tsm	34,804	0.1241707	0.3198766	0	12.66584	0.0553538	0.1385747	0.3025869
CitWtedIndx	34,804	0.1539713	0.7020182	0	59.10666	0.0790367	0.1029549	0.6172764
k_npatratio	34,804	0.0576313	0.1651519	4.41E-06	9.948834	0.0348008	0.0429479	0.1953191
growth	91,496	0.0168501	0.2909636	-1.138524	1.372723	-0.0061366	0.0089629	0.044308
saleratio	98,030	1.198443	0.6191078	0.0003824	3.473551	1.229964	1.068829	1.257369
reteratio	97,686	-0.1538316	1.374183	-10.6917	0.8362576	0.1629035	-0.0797781	-0.4988989
retaratio	97,686	-0.1942011	1.936304	-117.0538	3.185593	0.1615436	-0.0963028	-0.591824
lvrgratio	97,373	0.0205816	0.0739933	-0.1262101	0.5900591	0.0183442	0.0138055	0.0272686
capxratio	97,006	0.0559828	0.0491085	0.0003321	0.271612	0.0567416	0.0563519	0.0550293
roa	98,025	-0.0135602	0.2192432	-1.474333	0.2552592	0.0326349	0.0016685	-0.0666269
ebitdaratio	97,750	0.0802126	0.2028395	-1.218589	0.397767	0.1266225	0.0917925	0.0292786
size	98,030	4.954555	2.200123	0.4725005	10.5502	5.466657	5.217467	4.302368
fcfratio	52,819	-0.0081381	0.3616535	-9.236738	42.21759	0.0346974	0.0025942	-0.0542718
age	98,030	38.68793	13.67428	7	58	41.72837	38.24774	36.1756

Table 2 presents the correlation matrix. I report only the statistically significant pairwise correlation between the variables. The significance of the correlation between the respective variables is in alignment with the existing literature. For example, firms with profitability measured by ROA or EBITDA are showing a positive relationship with the dividend payout ratio. Likewise, the firm age has a positive relationship with the dividend payout. R&D and Amortization of Intangibles have a negative relation with the dividend. Similarly, the innovation index shows a negative relationship with the dividend payout.

Table 2-Correlation Matrix

This table presents the correlation matrix of the variables of interest. I exclude the data with missing values for total assets, sales, and retained earnings. I also exclude the data with total assets and sales revenue of less than one million. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017. I exclude the data with missing values for total assets, sales, and retained earnings. I also exclude the data with total assets and sales revenue of less than one million. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017. All the ratios are normalized with total assets except for retained earnings, which normalized with total equity.

	divratio	rdratio	amratio	lagRDint	k_innIndex	CitIndex	k_npatratio	growth	saleratio	reteratio	retaratio	lvrgratio	capxratio	roa	ebitdaratio	size	fcfratio	age
divratio	1																	
rdratio	-0.2434	1																
amratio	-0.0706	0.0281	1															
lagRDint	-0.1091	0.4928	-0.0257	1														
k_innIndex	-0.0505	0.2279	0.0389	0.0662	1													
CitWtedIndex	-0.0639	0.1681	0.0109	0.0437	0.9411	1												
k_npatratio	-0.1438	0.3584	-0.0052	0.1137	0.7012	0.6864	1											
growth	-0.0526	0.234	0.0775	0.3651	0.0844	0.0851	0.1502	1										
saleratio	0.1606	-0.2997	-0.1331	-0.2914	-0.0552	0.0022	0.0029	0.05	1									
reteratio	0.2592	-0.6517	-0.0733	-0.3277	-0.2329	-0.2032	-0.4415	-0.2272	0.2269	1								
retaratio	0.2013	-0.549	-0.0629	-0.291	-0.2006	-0.1652	-0.3963	-0.203	0.1647	0.8856	1							
lvrgratio	-0.0682	0.042	-0.0197	-0.002	0.1084	0.1313	0.2133	0.0418	0.0707	-0.1203	-0.09	1						
capxratio	0.0704	-0.0365	-0.169	-0.0438	0.0305	0.0125	-0.0014	0.0051	0.1342	0.1117	0.0729	0.0009	1					
roa	0.267	-0.6766	-0.1265	-0.3836	-0.223	-0.1996	-0.3906	-0.2227	0.2856	0.7205	0.6229	-0.0949	0.064	1				
ebitdaratio	0.3035	-0.717	-0.0312	-0.441	-0.2278	-0.2089	-0.4105	-0.1769	0.3918	0.7371	0.6267	-0.0891	0.1301	0.9022	1			
size	0.4023	-0.4098	0.0544	-0.169	-0.1422	-0.1906	-0.4215	-0.1355	-0.0843	0.4362	0.3541	-0.2041	0.0308	0.3987	0.4438	1		
fcfratio	0.1835	-0.5685	0.0185	-0.3712	-0.2086	-0.1848	-0.3674	-0.1823	0.2272	0.587	0.6105	-0.026	-0.1092	0.6763	0.7239	0.3329	1	
age	0.452	-0.3548	-0.151	-0.1881	-0.0649	-0.0563	-0.1338	-0.1015	0.2643	0.3316	0.2591	-0.0246	0.0962	0.2974	0.332	0.3987	0.2155	1

The preliminary investigation of the relationship between the key variables in the sample data is consistent with the correlation matrix, as shown in the bin diagram below. Figure 1 shows that when there is high R&D, firms either do not pay or pay a very little dividend. However, for a low R&D ratio, dividend payout is significant.

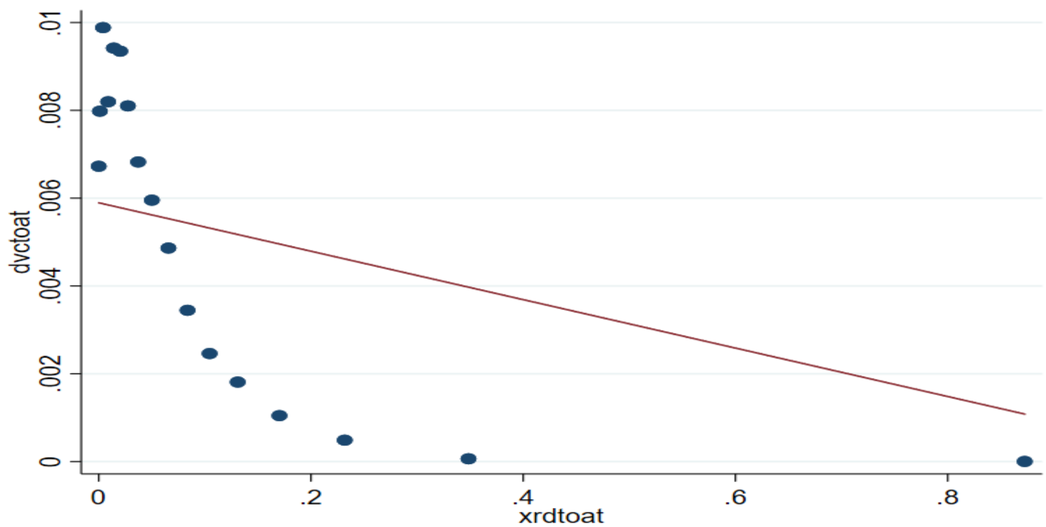


Figure 1 - Inverse Relation Between Dividend Payout and R&D Expenses

Likewise, in figure 2, the bin scatter plot diagram depicts a direct relationship between the age and the dividend payout. However, the dividend payout doesn't seem to be monotonous as the firm ages through.

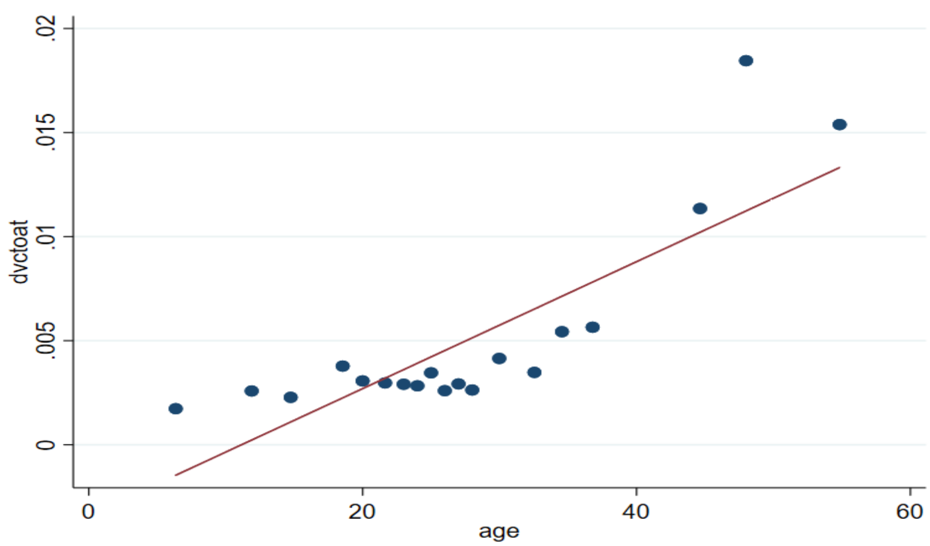


Figure 2 - Dividend Payout Behavior by Firm Age

In Figure 3, the sample data show a strong inverse relationship between the R&D and the firm age. The graph shows a clear pattern that as firms ages thru, R&D steadily going down.

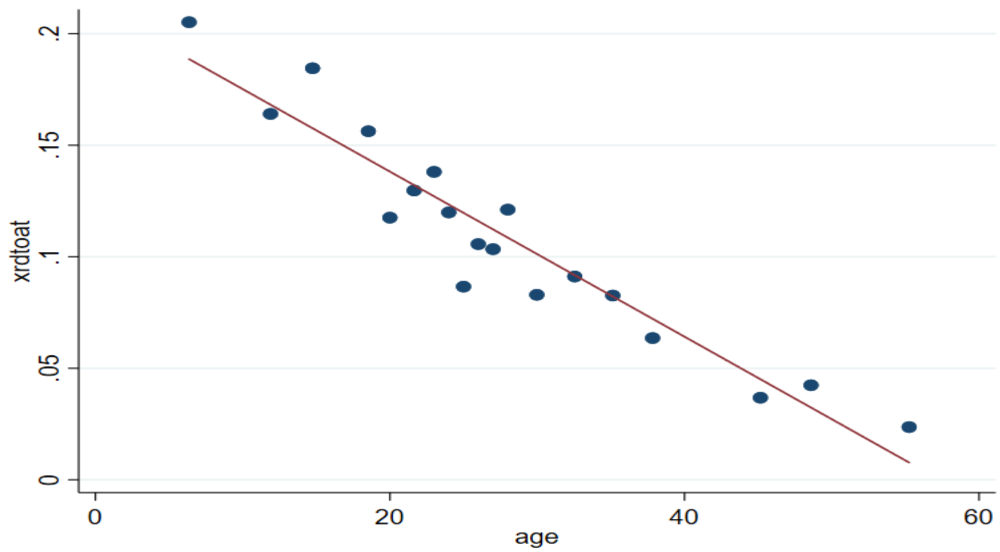


Figure 3 – Firm Age vs R&D Ratio in the Manufacturing Industry

5.2 Methodology and Multivariate Analysis

I summarize the empirical approach that is employed in sequential order as follows:

a. In the first step, I examine the impact of innovation intensity on firm growth, focusing on R&D-rich US manufacturing firms.

b. In the second step, I examine whether dividend payout is a function of firm maturity[14]. I investigate the existence of higher dividend payout during the 'mature phase' as defined by each of the popular life cycle proxies – cash flow patterns, re/te ratio, age, and the innovation intensity.

c. In the third step, I investigate the relationship between the 'degree of innovation' and the 'dividend payout.' I create two models each for a) the dollar-based dividend payout, and b) the probability-based dividend payout (likelihood of paying a dividend). First, I run the regression on the full sample. Then I perform a comprehensive analysis by dividing the

[14] Maturity as defined by firm age, retained earnings (DeAngelo et al,2006), and cash flow pattern Dickinson (2011)

samples into three sub-categories: a) less (or no) innovation, b) above-average innovation, and c) persistent innovation.

d. In the final step, I investigate the dividend payout behavior of the three groups of firms (less innovative, innovative, and persistent innovative). I select firms that belong to the 'same life cycle stage', such as 'maturity' or 'growth' or 'introduction' phase as defined by popular life cycle proxies but are different in innovation intensity. In this section, I prove the working hypothesis that between groups of firms with similar characteristics (industry affiliation, size, life span/age, re/te, cashflow[15]), the one with a higher degree of innovation output has a lower dividend payout.

I largely follow the existing literature such as Fama French(2001) and DeAngelo et al. (2006), among others, to design the empirical models and to determine the model specification for the above scenarios, and I discuss the details of the models and the empirical results in the following sections.

5.2.1 Growth and Innovation:

In section 5.2.1, I study the impact of innovation intensity on the firm's sales growth. The effect of innovation on sales is different for different types of firms (Coad and Rao, 2008; Mason et al., 2009) and firms with varying levels of R&D intensity (Del Monte and Papani, 2003). The existing literature document heterogeneity in a firm's innovativeness across and within the industry sector. Besides, I find no prior literature that explores the relationship between innovation and sales growth in the US manufacturing sector. Therefore, even if the main objective of the research is to examine the impact of innovation on the life cycle and dividend payout, I recognize that I first need to establish the role of innovation in sales growth focusing on the manufacturing industry.

[15] I do not find existing literature that test the dividend behavior based on the Dickinson(2011) cashflow pattern. This is the additional contribution to the literature.

To examine the impact of innovation on firm growth, I designed the panel regression model as in equation one below. In this model, I regress the (lagged) firm sales, age of the firms, and the (lagged) R&D intensity against the growth rate of a firm 'i' at time t. I follow a similar approach as in growth vs innovation literature such as Spescha and Woerter(2018)[16], Demirel and Mazzucato (2012) and Colombelli et al.(2013)[17]:

$$growth_{i,t} = \beta_0 + \beta_1 \ ln\ (sale_{i,t-1}) + \beta_1 \ ln\ (innovint_{i,t-1}) + \beta_1 \ ln\ (age_{i,t-1}) + \varepsilon_{i,t} \quad \text{---- } \textit{Equation 1}$$

where,

$growth_{i,t} = ln\ (sale_{i,t}) - ln\ (sale_{i,t-1})$,

$innovint_{i,t-1}$ *refers to citation weighted patents as defined by Kogan et al.* (2016) *or*

R&D intensity proxied by $\frac{RD_{i,t}}{S_{i,t-1}}$ *as in Demirel and Mazzucato (2012)*

The dependent variable is the firm's growth rate, which is the log-difference of the annual percentage change in sales. As a robustness check, I also use five-year rolling asset growth as an independent variable and confirm the consistency in the result.[18] I define R&D intensity as the R&D for the firm (i) in year t, scaled by its sale in year t-1. I divide R&D intensity by lagged value of sales to avoid potential problems that arise due to the correlation between the right-hand side 'sales' and 'R&D' variables (see *Demirel and Mazzucato, 2012)*. In the model, I control for the size of a firm's sales and its age. I follow existing literature[19] to cross-reference and to come up with the model specification including the control variable. Besides R&D intensity, I also use Kogan et al. (2017)'s citation weighted patent and stock market-weighted patent output measures as an innovation intensity variable.

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[16] See page 12 and 13 on Andrin Spescha & Martin Woerter, 2019. "Innovation and firm growth over the business cycle," Industry and Innovation, Taylor & Francis Journals, vol. 26(3), pages 321-347, March.
[17] See page 13 on Alessandra Colombelli, Naciba Haned, Christian Le Bas. On firm growth and innovation: Some new empirical perspectives using French CIS (1992–2004). Structural Change and Economic Dynamics, Elsevier, 2013, 26, pp.14-26. ff10.1016/j.strueco.2013.03.002ff. ffhal-01079383f
[18] See Appendix A - Table C
[19] A similar approach is taken in Dunne and Hughes (1994), Yasuda (2005), Colombelli et al.(2013), Demirel and Mazzucato (2012)

I perform the Hausman specification tests to check whether the fixed or random effects is a better fit. The examination reveals that the fixed effect is a better choice. Further, the fixed effect specification allows for the correlation of the unobserved firm-specific effects with the independent variables. I use both the firm fixed effects and the time fixed effects (to control for the years).

According to Grossman and Helpman (1994A), a firm's R&D investment is an endogenous strategy that is implemented based on the costs and potential outcomes of R&D as well as the institutional, legal, and economic settings that determine the success and profitability of these outcomes. Therefore, to address the endogenous nature of R&D investments, I use the System GMM. The data sample has large N (firms) and small T(year), so, I think, that the GMM is an appropriate method to address the possible endogeneity in this particular panel settings (see the similar line of literature Demirel and Mazzucato (2012), and Colombelli et al.(2013) among other that use GMM in a similar setting).

The regression results based on equation one is in Table 3. Specifications 1, 2, and 3 in Table 3 represent the FE regression with robust standard errors each for Kogan's innovation output-based index, citation weighted patent output, and R&D intensity. I also check with clustered standard errors on the firm, and I got the same results as with the robust option. So, I report only the 'robust' FE regression result in Table 3. The last specifications are from the system GMM for the corresponding regression on Kogan's innovation output-based index; citation weighted patent output, and R&D intensity.

Table 3-Impact of Innovation Intensity on Firm Growth

In this table, I regress the (lagged) firm sales, age of the firms, and the innovation intensity against the growth rate of firm i at time t. $growth_{i,t} = \beta_0 + \beta_1\ ln\ (sale_{i,t-1}) + \beta_1\ ln\ (RDin_{i,t-1}) + \beta_1\ ln\ (age_{i,t-1}) + \varepsilon_{i,t}$ *where,* $growth_{i,t} = ln\ (sale_{i,t}) - ln\ (sale_{i,t-1})$. The dependent variable is the firm's growth rate, which is the log-difference of the annual percentage change in sales. I follow the existing literature to design the model and to select the model specification[20]. I define R&D intensity as the R&D for the firm (i) in year t, scaled by its sale in year t-1[21]. I divide R&D intensity by lagged value of sales to avoid potential problems that arise due to the correlation between the right-hand side 'sales' and 'R&D' variables. In addition, to R&D, I also check innovation impact on growth using Kogan et al. (2017) innovation index as well as citation weighted patents. Specification 1 reports the result from the FE regression with Robust standard error with Kogan's innovation index as the main independent variable.; specification 2 reports the result from the FE regression with Kogan's citation weighted patents output as an independent variable. Specification 3 reports the result for the laggedRDIntensity as an independent variable. Specification 4, 5, and 6 are from the Sys-GMM regression for the endogeneity checks. I perform the Hausman test that reveals that FE is better-fit compare to the RE. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

	(1) Growth-FE	(2) Growth-FE	(3) Growth-FE	(4) Growth Sys-GMM	(5) Growth Sys-GMM	(6) Growth Sys-GMM
lnlagsaleratio	-0.349***	-0.349***	-0.276***	-1.014***	-1.014***	-0.860***
	(-97.69)	(-97.70)	(-92.23)	(-126.87)	(-125.95)	(-125.93)
lnage	0.117***	0.114***	0.105***	0.459***	0.452***	0.151***
	(5.22)	(5.08)	(9.85)	(5.63)	(5.52)	(9.55)
Kogan_index	0.0248***			0.0585***		
	(10.72)			(17.55)		
CitWtedIndex		0.0348***			0.0635***	
		(12.88)			(13.52)	
lnlagRDint			0.0903***			0.153***
			(46.78)			(47.05)
L.growth				0.0394***	0.0371***	0.0446***
				(9.19)	(8.54)	(13.09)
_cons	-0.444***	-0.430***	-0.0931*	-1.685***	-1.653***	-0.0506
	(-5.36)	(-5.19)	(-2.39)	(-5.57)	(-5.45)	(-0.88)
N	33902	33902	63555	24494	24494	51991
adj. R-sq	0.141	0.142	0.219			
No of Firms	5,786	5,786	5,786	2,911	2,911	4,697
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 shows that the impact of innovation (in all three measures as in spec1, 2, and 3) on firm growth is positive and statistically significant. The results of the three specifications are showing that innovation intensity induces positive growth for the firm. However, as shown in the table, the lagged sales variable has a significantly negative impact on growth. And the 'firm

[20] I cross reference and extended the models following Hall and Mairesse (1995) and Demirel et al. (2012). I chose control variable based on Yasuda (2005)

[21] SEE Demirel et al. (2012).

age' variable is a firm's public age. It has a positive and statistically significant impact on the fixed-effect as well as in the SYS-GMM model. The positive sign of age is unexpected because the effect of age on growth is often adverse, suggesting that growth slows down as firms ages (Dunne and Hughes, 1994). The positive sign for public age (listing age in the stock exchanges) maybe because of its association of "publicly-held" for a longer time[22]. The firms that trade in the stock market have a lower financial constraint in compare to the private firms. So, lower financial constraints may play a positive role in publicly traded aging firms. I do not report statistically insignificant control variables.

5.2.2 Maturity Stage and Dividends

In section 5.2.2, I examine whether the dividend payout is a function of the firm maturity based on different life cycle proxies. The mainstream literature that defines the life cycle based on the firm age document that dividend payouts increase along the lifecycle until peaking in the mature stage[23]. Dividend initiators exhibit mature tendencies (Fama French,2001; Grullon et al., 2005). Moreover, the dividend-paying growth firms pay small dividends in comparison to dividend-paying mature firms (Brockman and Unlu 2009). Theoretically, firms paying higher dividends are already in the maturity phase that implies that the firms paying low or no dividends are in the growth phase. So, in this section, I check the impact of the innovation intensity on the dividend payout. I examine whether firms with low innovation intensity signals the maturity phase of the firm life cycle. Similarly, firms with high growth but no or low dividend payout suggests that these firms are currently in the growth phase. Therefore, I primarily study the dividend life cycle and how they differ based on innovativeness, but similar in firm characteristics, including age, retained earnings, and cash-flow patterns.

I follow Owen and Yawson (2010) and use RE/TE to group firms into quantiles representing the lifecycle in young or mature or old/decline stages. The higher the RE/TE ratio,

[22] Carpenter and Peterson(2002) argue that when firms start to trade on the exchanges, they are subject to relaxed financial constraints which has positive effect on the firm growth.
[23] See Flavin and O'Connor (2017)

the mature the firm is. Likewise, based on Dickinson's (2011) cashflow patterns, I group firms into introduction, growth, mature, and shakeout/decline stages. Similarly, I use firm age to group firms into different 'age' quantiles to study if the older firms pay higher dividends.

Table 4 presents the median value for different life cycle stages measured by the most popular life cycle proxies. The data shows a clear pattern along the life cycle stages. The life cycle model of dividends follows maturity hypothesis implying that the mature firms pay significant dividends than growth firms regardless of the lifecycle measures employed. In alignment with the expectation, the median values of each of the proxies in Panel A, Panel B, and Panel C shows that the maturity stage has the highest dividend payout in comparison to other stages. The innovation, however, has an inverse relation with the dividend payout. Unlike the other three proxies, innovation intensity shows the lowest median value during the maturity phase.

Table 4-Median Values by Life Cycle Stages for the Most Popular Proxies

In this table, Panel A presents the median dividend payout by the life cycle stage proxied by each of the three popular life cycle measures, such as age, re/te, and cashflow pattern. In Panel A -exhibit 1, I first sort the firms by age and then group in to four quartiles. In Panel B, I group the firms based on Dickinson (2011) cashflow patterns(see appendix table 4 for reference). In Panel C, I group the firms based on re/te (ratio of retained to total equity). In Panel B, I present the new measure 'the innovation intensity'. Panel B-exhibit 1 shows how the dividend payout pattern evolves as the citation weighted patent output increases. The second exhibit shows how the dividend payout pattern evolves when the innovation output index (combined both the citation weighted and stock market dollar value-weighted output) increases. Dividend payout is either dividend to assets or dividend to annual sales as indicated. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

Panel A – Existing Life Cycle Measures:

1. Dividend payout and lifecycle using 'age' quartiles

	Age quartile 1 (young firms)	Age quartile 2	Age quartile 3	Age quartile 4 (old firms)
Div to Assets	0.0201628	0.0177098	0.0139483	**0.0181977**
Div to Sales	0.0157739	0.0129941	0.0133836	**0.0197956**

2. Dividend payout and lifecycle using Cashflow Patterns of 'Dickinson (2011)' life cycle stages

	Introduction	Growth	Mature	Shakeout/decline
Div to Assets	0.0098069	0.012661	**0.0212916**	0.018121
Div to Sales	0.0080905	0.0126352	**0.0189042**	0.013897

3. Dividend payout and lifecycle using 'RE/TE' DeAngelo et al. (2006) life cycle stages

	Introduction	Growth	Mature
Div to Assets	0.0217522	0.0163264	**0.0235058**
Div to Sales	0.0200189	0.0164639	**0.0247742**

Panel B - Innovation Output Based Measure:

1. Dividend payout and lifecycle using 'Citation Weighted Innovation Output based on Kogan et al.(2016)'

	innovation index quartile 1 (lowest innovators)	innovation index quartile 2	innovation index quartile 3	innovation index quartile 4 (highest innovators)
Div to Assets	.0162476	.0140002	.0113865	**.006076**
Div to Sales	.0169939	.0132373	.0100431	**.00924993**

2. Dividend payout and lifecycle using 'Citation and Stock Market Value Weighted Innovation Index based on Kogan et al.(2016)'

	innovation index quartile 1 (lowest innovators)	innovation index quartile 2	innovation index quartile 3	innovation index quartile 4 (highest innovators)
Div to Assets	.0141634	.012478	.0117392	**.0098505**
Div to Sales	.0136382	.0114052	.0105774	**.0104740**

Extant literature primarily tests the maturity hypothesis of the dividend life cycle using firm age and re/te ratio. As far as I am aware, the empirical studies are not available on how the dividend payout relates to the firm maturity based on the cash flow patterns. Therefore, in Table 5 and Table 6, I further confirm whether the 'maturity stage' (defined by cash flow patterns, age, re/te, and the innovation intensity) captures the higher dividend payout. The idea is that when a firm matures and if the higher dividend payout is the function of a firm maturity, then any appropriate life cycle proxies should be able to detect the higher dividend payout of the mature stage.

In Table 5 and Table 6, I regress the 'mature stage' from different life cycle measurements against the dividend payout to confirm that dividend payout is related to maturity, regardless of the life cycle proxies used. The model is below:

Div ~ F(life cycle stage + Control Variables) ---------- equation 2

Prob(Payer = 1) = F(life cycle stage + Control Variables) -------------- equation 3

Table 5 reports the results from the cross-sectional OLS regression in which the dependent variable is the dollar amount of the dividend paid to total asset ratio. In Table 6, I present the likelihood of paying dividends due to the firm life cycle stages. I run the logistic regression in which the dependent variable is the dummy takes on a value of 1 for dividend payers and 0 for the dividend non-payers.

Table 5 -Impact of Lifecycle Stages on Dividend Payout Based on Four Lifecycle Proxies

This Table reports the impact of life cycle stages on dividend payout regardless of the life cycle proxies used. The dependent variable is the dollar value of dividend to total asset ratio. Specification 1 thru specification 4 shows the impact of each life cycle stage on dividend payout based on Dickinson(2011) cashflow patterns. Specifications 5, 6, and 7 are based on DeAngelo et al. (2006). Specification 8 thru 11 are based on age category quantiles, and specification 12 is from the less innovative firms, Specification 13 is from average innovative firms and Specification 14 reports the impact of persistent innovations(highly innovative firms) on the dividend payout. All regressions are robust stand error. I reported statistically significant control variables. The objective of the table is to show that the dividend payout is a function of firm maturity regardless of the life cycle measures in the literature. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

	(1) DicIntro divratio	(2) DicGrwth divratio	(3) DicMature divratio	(4) DicDecline divratio	(5) RETE-Y divratio	(6) RETE-G divratio	(7) RETE-M divratio	(8) AgeCat1 divratio	(9) AgeCat2 divratio	(10) AgeCat3 divratio	(11) AgeCat4 divratio	(12) Less-Innov divratio	(13) Innov. divratio	(14) Pers-Innov divratio
lnage	0.0151***	0.0135***	0.0153***	0.0161***	0.0156***	0.0173***	0.0138***					0.00835***	0.00838***	0.00863***
	(44.49)	(39.24)	(44.96)	(47.50)	(45.22)	(55.45)	(44.45)					(45.24)	(45.09)	(46.70)
lnebitdaratio	0.00657***	0.00670***	0.00670***	0.00622***	0.00689***	0.00695***	0.00558***	0.00676***	0.00658***	0.00674***	0.00655***	0.00610***	0.00610***	0.00613***
	(33.26)	(34.56)	(33.79)	(32.54)	(34.95)	(37.49)	(31.60)	(33.66)	(32.21)	(32.99)	(32.82)	(54.84)	(54.91)	(55.21)
reteratio	0.00449***	0.00436***	0.00457***	0.00427***				0.00588***	0.00667***	0.00716***	0.00595***	0.00416***	0.00422***	0.00416***
	(11.93)	(12.01)	(12.06)	(11.63)				(13.22)	(14.63)	(14.60)	(14.06)	(22.06)	(22.31)	(22.09)
lvrgratio	-0.0446***	-0.0480***	-0.0444***	-0.0430***	-0.0453***	-0.0511***	-0.0358***	-0.0454***	-0.0355***	-0.0384***	-0.0277***	-0.0323***	-0.0324***	-0.0324***
	(-11.05)	(-11.55)	(-11.01)	(-11.33)	(-11.63)	(-13.69)	(-11.20)	(-10.72)	(-8.65)	(-9.23)	(-8.02)	(-35.25)	(-35.27)	(-35.45)
CitWtedIndex	-0.00145***	-0.00159***	-0.00145***	-0.00114**	-0.00175***	-0.00207***	-0.00184***	-0.00167***	-0.00131**	-0.00148***	-0.000703*			
	(-3.46)	(-3.55)	(-3.45)	(-3.09)	(-3.82)	(-4.14)	(-4.23)	(-3.57)	(-3.20)	(-3.30)	(-2.17)			
saleratio	-0.000604**	-0.00133***	-0.000644**	-0.000438*	-0.000833***	-0.000793***	-0.000944***	0.000801***	0.00126***	0.00195***	0.000816***	-0.00154***	-0.00159***	-0.00166***
	(-2.68)	(-5.81)	(-2.86)	(-1.97)	(-3.69)	(-3.58)	(-4.33)	(3.58)	(5.59)	(8.64)	(3.75)	(-12.63)	(-13.01)	(-13.72)

capxratio	**-0.0199*****	**-0.0163*****	**-0.0198*****	**-0.0135*****	**-0.0201*****	**-0.0134*****	**-0.0153*****	**-0.0163*****	**-0.0123*****	**-0.0123*****	**-0.0139*****	**-0.0196*****	**-0.0201*****	**-0.0193*****
	(-9.57)	**(-7.90)**	**(-9.53)**	**(-6.47)**	**(-9.60)**	**(-6.52)**	**(-7.61)**	**(-7.59)**	**(-5.78)**	**(-5.70)**	**(-6.89)**	**(-15.39)**	**(-15.84)**	**(-15.25)**
DIntrod	**-0.00160*****													
	(-4.24)													
DGrowth		**-0.00565*****												
		(-26.97)												
DMature			**0.04023*****											
			(18.28)											
Ddeclineshakeout				**0.00272****										
				(3.28)										
retecat1dum					**-0.00418*****									
					(-15.37)									
retecat2dum						**-0.00663*****								
						(-38.15)								
retecat3dum							**0.00963*****							
							(47.59)							
agecat1dum								**-0.00709*****						
								(-26.09)						

agecat2dum									**-0.00790*** **					
									(-36.63)					
agecat3dum										**-0.000648** **				
										(-3.01)				
agecat4dum											**0.0113*** **			
											(52.23)			
innovlevel1dum												**0.01046*** **		
												(11.62)		
innovlevel2dum													**-0.000430*** **	
													(-3.47)	
innovlevel3dum														**-0.02067*** **
														(-14.96)
_cons	**-0.0276*** **	**-0.0194*** **	**-0.0279*** **	**-0.0338*** **	**-0.0268*** **	**-0.0316*** **	**-0.0279*** **	**0.0284*** **	**0.0273*** **	**0.0253*** **	**0.0229*** **	**-0.00316*** **	**-0.00237*** **	**-0.00312*** **
	(-21.73)	**(-14.46)**	**(-21.97)**	**(-26.48)**	**(-19.96)**	**(-25.28)**	**(-23.07)**	**(41.59)**	**(40.27)**	**(37.61)**	**(35.70)**	**(-4.43)**	**(-3.30)**	**(-4.38)**
N	**28742**	**28742**	**28742**	**28742**	**28755**	**28755**	**28755**	**28742**	**28742**	**28742**	**28742**	**29126**	**29126**	**29126**
adj. R-sq	**0.235**	**0.248**	**0.235**	**0.245**	**0.224**	**0.250**	**0.278**	**0.184**	**0.196**	**0.165**	**0.245**	**0.155**	**0.154**	**0.157**

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5- Impact of Lifecycle Stages on the Propensity to Pay Dividend Based on Four Lifecycle Proxies

This Table reports the propensity to pay dividends due to the life cycle stages regardless of the life cycle proxies selected. The dependent variable is the binary 'dividend payer'(equals 1 if DVC > 0 , 0 otherwise). Specification 1 thru specification 4 are the propensity of paying dividends due to the life cycle stage based on Dickinson(2011) cashflow patterns, specifications 5, 6, and 7 are the propensity of paying dividend due to life cycle stage based on DeAngelo et al(2006). Specification 8 thru 11 are the propensity of paying dividend based on age category quantiles, and specification 12 is the propensity of paying dividend due for the less innovative firms(less than median R&D/TA), Specification 13 is the propensity of paying a dividend for the average innovative firms(above average R&D/TA) and Specification 14 reports the propensity of paying a dividend for the persistent innovations. I reported statistically significant control variables. I examine if the propensity of paying a dividend is a function of firm maturity based on all the popular life cycle proxies in the literature. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017. I extended the cross-sectional logit regression model of Fama-French(2001).

	(4) Dick. - I	(3) Dick. - G	(1) Dick. - M	(2) Dick. - D	(5) DAng.-Y	(6) DAng.-G	(7) DAng.-M	(8) AgeCat1-Y	(9) AgeCat2	(10) AgeCat3-M	(11) AgeCat4	(12) LessInnov	(13) Ave.Innov	(14) Pers.Inno
	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer	DivPayer
lnage	0.616***	0.590***	0.642***	0.623***	0.564***	0.625***	0.592***				0.480***	0.589***	0.613***	0.623***
	(70.21)	(65.45)	(73.87)	(70.93)	(65.51)	(71.06)	(69.78)				(42.93)	(67.63)	(68.73)	(72.47)
lnebitdaratio	0.0790***	0.0865***	0.0779***	0.0828***	0.0660***	0.0827***	0.0647***	0.0826***	0.0812***	0.0844***	0.0832***	0.0856***	0.0845***	0.0852***
	(19.66)	(21.73)	(19.56)	(20.40)	(17.51)	(20.70)	(17.29)	(20.66)	(20.45)	(21.02)	(20.87)	(21.49)	(20.98)	(21.48)
reteratio	0.150***	0.150***	0.148***	0.152***				0.158***	0.153***	0.154***	0.161***	0.148***	0.154***	0.145***
	(14.43)	(14.58)	(14.32)	(14.41)				(14.94)	(14.81)	(14.48)	(14.84)	(14.27)	(14.48)	(14.22)
lvrgratio	-1.837***	-1.899***	-1.801***	-1.838***	-1.576***	-1.830***	-1.658***	-1.686***	-1.707***	-1.811***	-1.615***	-1.645***	-1.877***	-1.535***
	(-14.13)	(-14.35)	(-14.41)	(-14.12)	(-12.96)	(-14.23)	(-14.11)	(-13.46)	(-13.40)	(-14.01)	(-13.48)	(-14.19)	(-13.96)	(-14.28)
CitWtedIndex	-0.0737***	-0.0766***	-0.0677***	-0.0743***	-0.0736***	-0.0750***	-0.0782***	-0.0677***	-0.0687***	-0.0729***	-0.0626***			
	(-3.85)	(-3.88)	(-3.72)	(-3.85)	(-3.91)	(-3.88)	(-4.06)	(-3.74)	(-3.83)	(-3.81)	(-3.58)			
saleratio	0.0304***	0.0143**	0.0318***	0.0283***	0.0223***	0.0279***	0.0236***	0.0290***	0.0234***	0.0295***	0.0366***	0.0314***	0.0262***	0.0363***
	(5.60)	(2.61)	(5.86)	(5.21)	(4.18)	(5.14)	(4.43)	(5.37)	(4.34)	(5.39)	(6.78)	(5.85)	(4.82)	(6.82)
capxratio	-0.338***	-0.273***	-0.221***	-0.347***	-0.420***	-0.322***	-0.276***	-0.318***	-0.306***	-0.340***	-0.295***	-0.238***	-0.343***	-0.249***
	(-5.82)	(-4.71)	(-3.80)	(-5.99)	(-7.32)	(-5.57)	(-4.86)	(-5.58)	(-5.40)	(-5.87)	(-5.20)	(-4.24)	(-5.92)	(-4.35)
DIntrod	-0.127***													
	(-9.63)													
DGrowth		-0.111***												
		(-16.56)												
DMature			0.0832***											
			(15.59)											

Ddeclineshakeout				**-0.0654**										
				(-2.92)										
retecat1dum					**-0.251*****									
					(-26.58)									
retecat2dum						**-0.0304*****								
						(-6.11)								
retecat3dum							**0.154*****							
							(25.06)							
agecat1dum								**0.260***						
								(22.29)						
agecat2dum									**-0.201*****					
									(-29.94)					
agecat3dum										**-0.0179*****				
										(-3.43)				
agecat4dum											**0.166*****			
											(27.32)			
Innovlevel1dum												**0.173*****		
												(34.71)		
Innovlevel2dum													**-0.0556*****	
													(-10.18)	
Innovlevel3dum														**-0.160*****
														(-26.33)
_cons	**-1.578*****	**-1.428*****	**-1.708*****	**-1.598*****	**-1.348*****	**-1.594*****	**-1.574*****	**-2.520*****	**-1.319*****	**-1.618*****	**-1.127*****	**-1.543*****	**-1.536*****	**-1.569*****
	(-47.09)	**(-40.25)**	**(-51.13)**	**(-47.68)**	**(-39.12)**	**(-47.54)**	**(-47.74)**	**(-48.65)**	**(-38.95)**	**(-49.00)**	**(-28.27)**	**(-47.11)**	**(-44.52)**	**(-47.56)**
N	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**	**29126**

The results in Table 5 and Table 6 confirm that the mature stage has a statistically significant positive impact on the dividend payout. Likewise, age and re/te ratio have a statistically significant positive relationship with the dividend payout. The older the firm, the higher the propensity to pay dividends. The same is the case for the retained earnings ratio; the higher the re/te ratio, the higher the likelihood of paying a dividend. The innovation index, however, shows that the higher the innovation intensity, the lower the propensity to pay dividends. Specification 1 and Specification 2 also show that the introduction and growth phase have a statistically negative relationship with the dividend payout. For all the regression in table 5 and table 6, I control for firm profitability, sales size, and leverage ratio as in Fama-French(2001). I provide the evidence that regardless of the firm life cycle used; dividend payout is higher in the mature stage.

Further, I perform robust testing for each life cycle proxies interacting with high innovation dummy and low innovation dummy. The result is in Table 13. I find a consistent result that the higher innovation interaction weakens the dividend payout impact of the mature stage. The results are highly significant.

5.2.3 Degree of Innovation and Dividends

In section 5.2.3, I design the model to study the relationship between the degree of innovativeness and the dividend payout. In the first stage (5.2.3.1), I estimate the dividend payout regressions for the dividend payout amount vs. the innovation intensity measured by the innovation index. In the second stage, I investigate the propensity (likelihood) of paying a dividend based on the innovation intensity. In both cases, I perform the analysis based on cross-sectional regression[24] .

[24] in the first stage, I use cross-sectional OLS and in the second stage, I use cross-sectional logit regression

5.2.3.1. Innovation intensity and dividends

Table 7 reports the cross-sectional OLS regression result on the impact of innovation intensity on the dollar value of dividend payout. The main independent variable is the innovation index. I control for firm age, retained earnings, profitability as proxies by ebitdaratio, capxratio, and sales ratio. Specification 1 is the result of the below-median R&D sample; specification 2 is from the above-median R&D sample; specification 3 is from the persistent innovators. The last column is the result of the full sample. The dependent variable is the dividend payout (a dollar amount).

Div ~ F(innovation intensity as measured by innovation index + Control Variables) ---- equation 4

div ~ InnovationIndex + control variable --- Spec. Full Sample (eq 4.1)

The full sample is sorted by the innovation index in lowest to highest order to find the median value. I then divide the sample into two groups: a) less innovative firms that have citation weighted patent output below median value, and b) innovative firms that have citation weighted patent output above the median value. I also create the third sample with persistent innovators that has a citation weighted patent for at least three consecutive years. The results in Table 7 show how the 'innovation intensity' affects the dividend payout based on the degree of innovativeness.

Table 6- Impact of Innovation Intensity on Dividend Payout

In Table 7, I report the cross-sectional regression result on the impact of innovation intensity on the dollar value of dividend payout. The dependent variable is the dividend ratio (cash dividend payout normalized by total asset). The main independent variable is the innovation index. I control for firm age, retained earnings, roa, capxratio, and sales ratio. Specification 1 is the result of the below-median innovation sample; specification 2 is from the above-median; specification 3 is from the persistent innovators. The last column is the result of the full sample. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

	(1) Less-Innovative	(2) Innovative	(3) High-Innovative	(4) Full Sample
	divratio	divratio	divratio	divratio
CitWtedIndex	-0.00213^{*}	-0.2040^{***}	-0.8014^{***}	-0.00888^{***}
	(-2.21)	(-5.85)	(-7.34)	(-9.12)
lnage	0.0118^{***}	0.0215^{***}	0.0177^{***}	0.0186^{***}
	(9.17)	(17.81)	(34.97)	(41.37)
ebitdaratio	0.0172^{***}	0.0674^{***}	0.101^{***}	0.0740^{***}
	(5.00)	(14.14)	(36.07)	(35.11)
lvrgratio	-0.0146^{*}	-0.0866^{*}	-0.0214^{*}	-0.00869
	(-2.46)	(-2.44)	(-2.03)	(-1.42)
lnfcfratio	0.000822^{*}	0.00201^{***}	0.000371	0.000965^{***}
	(2.22)	(4.80)	(1.85)	(5.66)
saleratio	0.00246^{**}	-0.00446^{***}	-0.00202^{***}	-0.00182^{***}
	(3.28)	(-5.21)	(-4.57)	(-5.00)
_cons	-0.0386^{***}	-0.0610^{***}	-0.0616^{***}	-0.0603^{***}
	(-8.62)	(-13.25)	(-30.83)	(-34.76)
N	12085	11083	7730	30898
adj. R-sq	0.232	0.259	0.277	0.252

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I find a statistically significant negative relationship between the div payout and the innovation index. However, if when examining the coefficients, the persistent innovators have a more substantial negative impact in comparison to the other specifications in the Table. Similarly, the above-median innovators also show a higher negative impact compare to their less innovative counterparts. I confirm the statistical significance of the differences in coefficients for three levels of innovation as indicated in the table 7.

5.2.3.2 Innovation intensity and propensity to pay dividends

I examine the propensity to pay a dividend based on the cross-sectional logit regression. In this case, I mostly follow the approach adopted by Fama & French (2001) that employs the logit regression using distinct characteristics of dividend payers and non-payers as explanatory variables. The formal model used by Fama-French (2001) is as follow:

$Y_t = \beta_0 + \beta_1\, E_{t/TA_t} + \beta_2\, dTA_{t/TA_t} + \beta_3\, TA_t + \varepsilon_{i,t}$ *-- Equation 6*

where

Y_t *: the decision to pay dividends. It equals 1 for payers at time t and 0 otherwise.*

E_t *: earnings at time t*

TA_t *: total assets at time t*

$dTA_t : A_t - TA_{t-1}$ *the growth rate of assets*

E_{t/TA_t}, dTA_{t/TA_t} & TA_t *are proxies for profitability, growth, and size respectively*

Profitability, growth, and size are the distinct characteristics of payers and non-payers. I use sales growth to total asset ratio as a growth proxy. I design the logit models as presented below:

Div Payer$_t$ ~ *F(innovation intensity + Control Variables) ------------------ equation 7*

Div Payer$_t$~ *InnovationIndex + control variable.................................... Spec. Full Sample (eq 7.1)*

Where,

'Div Payer$_t$*' is the likelihood of paying a dividend. It equals 1 for payers at time t and 0 otherwise.*

The results are in Table 8. I repeat the same process as in equation 5 with the same specification in the right-hand side, except, the dependent variable, in this case, is the dummy 1 or 0 (div payer = 1 for payers otherwise 0 for non-payers).

Table 7 – Impact of Innovation Intensity on the Propensity to Pay Dividend Payout

In Table 8, I report the propensity to pay a dividend based on the degree of innovation. I follow Fama-French(2001) to model the logit regression. The dependent variable is the binary variable 'dividend payer'(equals 1 if payer, 0 otherwise). The main independent variable is the innovation index. I control for firm age, retained earnings, roa, capxratio, and sales ratio. Specification 1 is the result from the below-median R&D sample; specification 2 is from the above-median R&D sample; specification 3 is from the persistent innovators. The last column is the result from the full sample. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

	(1) Less-Innovative	(2) Innovative	(3) High Innovative	(4) Full Sample
	divpayer	divpayer	divpayer	divpayer
CitWtedIndex	-0.431^{*}	-0.735^{***}	-0.773^{***}	-1.144^{***}
	(-2.52)	(-4.60)	(-6.97)	(-14.34)
lnage	5.202^{***}	3.644^{***}	2.942^{***}	3.227^{***}
	(12.43)	(20.87)	(35.80)	(44.90)
ebitdaratio	4.335^{***}	5.989^{***}	5.280^{***}	5.531^{***}
	(4.04)	(8.02)	(10.43)	(14.60)
lvrgratio	-27.81^{***}	-25.57^{***}	-32.09^{***}	-33.22^{***}
	(-4.86)	(-4.22)	(-7.98)	(-11.17)
saleratio	0.530^{**}	0.128	-0.0924	-0.0952
	(2.78)	(1.20)	(-1.34)	(-1.76)
lnfcfratio	0.0913	-0.173^{**}	-0.125^{***}	-0.122^{***}
	(1.00)	(-3.14)	(-3.71)	(-4.57)
capxratio	-1.870	-6.143^{***}	5.733^{***}	1.153
	(-0.76)	(-3.61)	(5.31)	(1.41)
_cons	-20.67^{***}	-14.35^{***}	-11.27^{***}	-12.30^{***}
	(-13.18)	(-21.08)	(-34.29)	(-43.53)
N	12085	11083	7755	30898
Pseudo R2	0.2863	0.2345	0.2073	0.2384

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 8, I examine the propensity to pay dividends based on the degree of innovativeness. I use cross-sectional logit regression with the dependent variable as dividend payer (1 for the payer, 0 for non-payer). In this table, I find a very similar pattern as in the cross-sectional OLS. Therefore, I present convincing evidence that dividend payout does depend on the degree of innovativeness, the more substantial the innovation, the stronger the negative relationship between the dividend payout and the innovation intensity.

5.2.4. Dividend Payout: Same Life Cycle Stage but Different Degree of Innovation

Finally, in section 5.2.4, I examine the propensity to pay a dividend by three groups of firms (less innovative, innovative, and persistent innovative) that belong to the 'same life cycle stage such as 'maturity' or 'growth' as defined by popular life cycle proxies but are significantly different in degree of innovation. The purpose is to test the primary hypothesis that among groups of firms in the same life cycle stage and with similar characteristics (industry affiliation, size, life span/age, re/te, cashflow[25]), the one with a higher degree of innovation output has a lower dividend payout.

5.2.4.1 Life Cycle Defined by Cash Flow Pattern: Same Stage but Different Degree of Innovation

In this section, I test whether groups of firms (based on the degree of innovations) in the same life cycle stage as defined by cash flow pattern (Dickinson,2011) have a similar propensity to pay dividends. I run the following cross-sectional logit regression similar to Fama-French (2001) in which the dependent variable is the div payer equal to 1 if the firm pays dividends and 0 otherwise.

Div Payer$_t$*~ life cycle stage defined by cashflow pattern*[26] *+ InnovationIndex + control variable -- equation 9*

Table 9 tests the main hypothesis for the firms in the same life cycle stage defined by the cashflow patterns. Table 9 Panel A reports the result for the firms in the life cycle stage '3-mature' (Dickinson,2011). Similarly, Panel B presents the result for the firms in the life cycle stage, '2-Growth' (Dickinson,2011). I run the logit model of equation 9 on the full sample as well on the other three sub-samples based on a different degree of innovation: 1. Below average innovators

[25] I do not find existing literature that test the dividend behavior based on the Dickinson(2011) cashflow pattern. This is the additional contribution to the literature.

[26] See appendix reference table 1 for the cashflow pattern as defined by Dickinson(2011)

2. Above-average innovators, and 3. Persistent Innovators. In both cases in Panel A and Panel B, the results undoubtedly show that innovation differentials cause disparities in dividend payout for the firms in the same life cycle stage defined by Dickinson(2011) cash flow patterns.

Table 8-Likelihood of Paying Dividend due to Different Degree of Innovation for the Same Cashflow Patterns Group (Based on the Life Cycle Stages of Dickinson,2011)

In Table 9, I present the of logit regression result performed on the firms of the same 'cashflow pattern' group (based on Dickinson,2011) but with different degrees of innovation. I follow Fama-French(2001) to model the logit regression. The dependent variable is the binary variable 'dividend payer'(equals one if payer, 0 otherwise). The main independent variable is the innovation index. I control for firm age, retained earnings, roa, capxratio, and sales ratio. Specification 1 is the result of the below-median R&D sample; specification 2 is from the above-median R&D sample; specification 3 is from the persistent innovators. The last column is the result of the full sample. Panel A reports the logit regression result for the mature stage as defined by cashflow patterns. Panel B reports the result for the Shakeout stage as defined by the cashflow patterns. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

Panel A (Dickinson,2011 - life cycle stage 3-Mature')

	(1) Less-Innovative divpayer	(2) Innovative divpayer	(3) High Innovative divpayer	(4) Dic-Mature Sample divpayer
CitWtedIndex	3.598	-6.31^{***}	-17.04^{**}	-9.202^{**}
	(0.28)	(-4.13)	(-3.12)	(-3.06)
lnage	7.371^{**}	2.044^{***}	1.893^{***}	2.017^{***}
	(2.62)	(3.94)	(10.07)	(11.70)
reteratio	4.669	2.850^{***}	1.483^{***}	1.596^{***}
	(1.73)	(4.30)	(7.32)	(8.26)
lnebitdaratio	0.946	0.293	-0.108	0.140
	(0.86)	(0.88)	(-0.61)	(1.03)
lnsaleratio	0.844	-0.641	0.832^{***}	0.487^{**}
	(0.40)	(-1.28)	(3.76)	(2.60)
lnlvrgratio	-0.325	-0.0806	-0.283^{***}	-0.211^{***}
	(-1.56)	(-0.98)	(-6.89)	(-6.27)
lncapxratio	-1.271	1.179^{***}	0.259^{*}	0.263^{**}
	(-1.65)	(3.74)	(2.29)	(2.65)
_cons	-34.40^{**}	-3.629	-8.473^{***}	-7.937^{***}
	(-2.88)	(-1.71)	(-10.05)	(-10.62)
N	4500	2640	1397	8537
Pseudo R2	0.5801	0.3641	0.2509	0.2509

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B (Dickinson,2011 - life cycle stage 2-Growth')

	(1) Less-Innovative divpayer	(2) Innovative divpayer	(3) High Innovative divpayer	(4) Dic-Growth Sample divpayer
CitWtedIndex	-5.655	-19.19	-2.594^{**}	-3.871^{***}
	(-1.89)	(-1.95)	(-3.07)	(-4.25)
lnage	1.849^{*}	-0.305	2.668^{***}	2.298^{***}
	(2.19)	(-0.14)	(7.24)	(7.45)
reteratio	3.772^{**}	4.339	1.700^{***}	2.276^{***}
	(3.28)	(1.42)	(4.10)	(6.02)
lnebitdaratio	0.118	-0.561	0.218	0.0284
	(0.21)	(-0.29)	(0.78)	(0.12)
lnsaleratio	0.594	-3.468	0.452	0.286
	(0.65)	(-1.33)	(1.30)	(0.94)
lnlvrgratio	-0.230	-0.300	-0.0344	-0.0724
	(-1.46)	(-1.11)	(-0.52)	(-1.32)
lncapxratio	-0.00974	-0.422	0.0638	0.0293
	(-0.03)	(-0.51)	(0.40)	(0.21)
_cons	-10.29^{**}	-5.529	-9.211^{***}	-9.279^{***}
	(-2.65)	(-0.49)	(-5.80)	(-6.58)
N	4050	3500	1415	8965
Pseudo R2	0.3580	0.2863	0.4532	0.3117

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All the variables in empirical models in sections 2, 3, and 4 are normalized by dividing with the total asset except for RETE in which case I normalize retained earnings with total equity. I follow the existing literature Fama-French(2001), Deangelo (2006), Dickinson(2011), and Faff et al. (2016) to identify the control variables. I do not report statistically insignificant control variables. The dividend amount equations 2, 4, and 5 are estimated using cross-sectional ordinary least squares with standard errors clustered by firms[27]. The payer specification in equation 3, 7, 8, 9, 10, and 11 are estimated using the logistic regression.

[27] See Peterson(2009)

5.2.4.2 Life Cycle Defined by RE/TE: Same Stage but Different Degree of Innovation

I test whether groups of firms (based on the degree of innovations) in the same life cycle stage as defined by earned contributed capital (DeAngelo,2006) have a similar propensity to pay dividends. I run the following cross-sectional logit regression similar to Fama-French(2001) in which the dependent variable is the div payer equal to 1 if the firm pays dividends and 0 otherwise.

Div Payer$_t$*~ life cycle stage defined by re/te + InnovationIndex + control variable -- equation 10*

I apply similar logic as in Table 9 for earned contributed capital mix re/te ratio in Table 10. I run the logit model as given in equation 10 on the full sample as well as on the other three sub-samples based on a different degree of innovation: 1. Below average innovators 2. Above-average innovators, and 3. Persistent Innovators.

Table 9-Likelihood of Paying Dividend due to Different Degree of Innovation for the Same RETE Group (Based on DeAngelo et al.,2006)

In Table 10, I present the of logit regression result performed on the firms of the same 'RE/TE' group (based on DeAngelo et al.,2006) but with different degrees of innovation. I follow Fama-French(2001) to model the logit regression. The dependent variable is the binary variable 'dividend payer'(equals one if payer, 0 otherwise). The main independent variable is the innovation index. I control for firm age, retained earnings, roa, capxratio, and sales ratio. Specification 1 is the result from the below-median R&D sample; specification 2 is from the above-median R&D sample; specification 3 is from the persistent innovators. The last column is the result from the full sample. Panel A reports the logit regression result for the re/te quartile two groups. Panel B reports the result for the re/te quartile four groups. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

Panel A: RE/TE Quartile 1

	(1) divpayer	(2) divpayer	(3) divpayer	(4) divpayer
CitWtedIndex	-0.868	-3.890***	-5.557**	-4.059***
	(-0.21)	(-4.64)	(-2.24)	(-6.22)
lnage	21.20*	1.835***	1.836***	1.949***
	(1.98)	(3.51)	(7.61)	(9.19)
reteratio	46.21*	3.490*	2.015**	2.490***
	(2.25)	(2.31)	(2.84)	(4.05)
lnebitdaratio	5.415*	0.787*	0.347	0.563***
	(2.02)	(2.39)	(1.80)	(3.64)
lnsaleratio	-6.492	-0.260	1.188***	0.737***
	(-1.72)	(-0.52)	(4.61)	(3.52)
lnlvrgratio	-1.447	-0.0260	-0.286***	-0.214***
	(-1.81)	(-0.32)	(-5.90)	(-5.55)
_cons	-99.36*	-5.862**	-8.406***	-7.974***
	(-1.99)	(-2.73)	(-8.34)	(-9.03)
N	5092	1790	1116	8048
Pseudo R2	0.5742	0.2327	0.2015	0.2216

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel A: RE/TE Quartile 3

	(1) Less-Innovative divpayer	(2) Innovative divpayer	(3) High Innovative divpayer	(4) RETE Q3 Sample divpayer
CitWtedIndex	-1.138	-2.167***	-2.350***	-2.015***
	(-1.78)	(-4.25)	(-6.63)	(-8.81)
lnage	3.406***	2.811***	2.442***	2.536***
	(4.09)	(8.27)	(16.86)	(19.56)
reteratio	4.626***	2.613***	1.592***	1.843***
	(4.19)	(5.98)	(9.73)	(12.07)
lnebitdaratio	1.147*	0.511**	0.289**	0.386***
	(2.42)	(2.73)	(2.73)	(4.43)
lnlvrgratio	-0.151	-0.178***	-0.274***	-0.235***
	(-1.74)	(-3.50)	(-9.76)	(-10.41)
lnsaleratio	-0.0316	0.155	0.660***	0.482***
	(-0.05)	(0.55)	(4.47)	(3.84)
_cons	-13.62***	-11.20***	-10.47***	-10.48***
	(-3.84)	(-7.97)	(-17.01)	(-19.17)
N	2521	585	162	3268
Pseudo R2	0.3987	0.3311	0.3772	0.3003

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results in Table 10 presents the dividend payout differentials among the firms in the same RE/TE group. Panel A shows RE/TE 'quartile one' firms (young firms, according to the re/te classification), and the data clearly shows that the persistent innovators have a stronger negative effect on the dividend payout even if all the three groups are in the same re/te quartile. The innovation impact distinction is even more apparent in Panel B that presents the RE/TE 'quartile three' firms (mature firms, according to the re/te classification). The results are consistent with the story that two groups of firms that are in the same life cycle phase, as defined by RETE have a different dividend policy.

5.2.4.3 Life Cycle Defined by 'Age': Same Stage but Different Degree of Innovation

I have extensively discussed that mainstream literature still uses firm age to proxy for the firm life cycle. Therefore, I also attempt to test whether groups of firms(based on the degree of innovations) in the same age category have a similar propensity to pay dividends. I run the following cross-sectional logit regression similar to Fama-French(2001) in which the dependent variable is the div payer equal to 1 if the firm pays dividends and 0 otherwise.

Div Payer$_t$ *~ age + InnovationIndex + control variable -- equation 11*

Table 11 Panel A reports the result for the firms in the age group 25 to 30. Similarly, Panel B presents the result for the firms in the age group 45 to 50. The results in Table 11 include three sub-samples based on a different degree of innovation: a). Below average innovators, b) Above-average innovators, and c) Persistent Innovators.

Table 10-Likelihood of Paying Dividend due to Different Degree of Innovation for the Same Age Group

In Table 11, I present the of logit regression result performed on the firms of the same 'age' group but with different degrees of innovation. I follow Fama-French(2001) to model the logit regression. The dependent variable is the binary variable 'dividend payer'(equals 1 if payer, 0 otherwise). The main independent variable is the innovation index. I control for firm age, retained earnings, roa, capxratio, and sales ratio. Specification 1 is the result of the below-median R&D sample; specification 2 is from the above-median R&D sample; specification 3 is from the persistent innovators. The last column is the result of the full sample. Panel A reports the logit regression result for the age group 50 to 55. Panel B reports the result for the age group 25-30. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

Panel A (Age Group 25 to 30)

	(1) Less-Innovative	(2) Innovative	(3) High Innovative	(4) Full Sample
	divpayer	divpayer	divpayer	divpayer
CitWtedIndex	-0.340	-2.474***	-3.072***	-2.628***
	(-1.19)	(-4.15)	(-8.74)	(-12.11)
lnage	4.455**	2.094**	2.253***	2.448***
	(3.10)	(2.99)	(5.27)	(7.08)
lnebitdaratio	0.484*	0.764***	0.463***	0.542***
	(2.18)	(5.79)	(5.81)	(8.65)
lnlvrgratio	-0.252***	-0.214***	-0.333***	-0.291***
	(-4.28)	(-5.92)	(-14.23)	(-16.41)
lnsaleratio	1.457***	0.113	0.414***	0.266**
	(3.59)	(0.63)	(3.56)	(2.89)
_cons	-18.16***	-7.928**	-9.308***	-9.745***
	(-3.58)	(-3.24)	(-6.24)	(-8.07)
N	607	1000	2439	4046
Pseudo R2	0.1310	0.1182	0.1202	0.1200

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B (Age Group 45 to 50)

	(1) Less-Innovative	(2) Innovative	(3) High Innovative	(4) Full Sample
	divpayer	divpayer	divpayer	divpayer
divpayer				
CitWtedIndex	-3.955	-2.715	-26.50***	-14.88***
	(-1.46)	(-0.17)	(-9.01)	(-9.71)
lnage	4.161***	27.04**	6.477***	5.475***
	(4.70)	(2.87)	(10.11)	(11.05)
lnebitdaratio	0.881***	-0.377	0.598***	0.567***
	(4.53)	(-0.71)	(5.80)	(6.54)
lnlvrgratio	-0.298***	-0.118	-0.361***	-0.313***
	(-7.08)	(-0.67)	(-11.43)	(-13.19)
lnsaleratio	0.177	-3.953*	0.000383	0.0282
	(0.73)	(-2.28)	(0.00)	(0.21)
reteratio	2.140***	10.74**	2.317***	2.273***
	(6.87)	(2.92)	(10.13)	(12.60)
_cons	-17.26***	-113.2**	-26.19***	-22.33***
	(-4.91)	(-2.96)	(-10.31)	(-11.36)
N	870	660	2275	3811
Pseudo R2	0.2895	0.6026	0.2775	0.2820

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As shown in Table 11, firms in the same age group (Panel A 25 to 30 years) but the one with persistent innovations have the propensity to pay less dividends in comparison to the other less innovative groups. Similarly, Panel B, I run the regression for the firms' age 45 to 50, and I see the consistent patterns that persistent innovators tend to pay less dividends even if the three groups of firms based on the degree of innovation are in the same age group.

6. ROBUST TESTING

In Table 3, I use sales growth as dependent variable to study the innovation impact on the firm growth. In Table 12, I use five year rolling asset growth[28] as a proxy for firm growth. The variables of interest are the life cycle proxies innovation index, RETE ratio, Cashflow ratio and Age. The results are consistent that innovation proxy (in this case Kogan index as innovation index) have statistically significant positive relationship with the asset growth. Whereas RETE and age has statistically significant negative relationship with the asset growth. On the other hand, cashflow pattern has positive relationship with the asset growth.

Table 12 - Impact of Life Cycle Proxies on Asset Growth

In this table, the dependent variable is the asset growth and variables of interest are the life cycle proxies such as RETE, CASHFLOW, AGE and INNOVATION. The control variables are the log of EBITDARATIO, SALES RATIO, and LEVERAGE RATIO. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

	(1)	(2)	(3)	(4)
	assetgrwth	assetgrwth	assetgrwth	assetgrwth
lnebitdaratio	-0.0312	0.0704**	0.0602*	0.0993***
	(-0.53)	(2.62)	(2.15)	(3.77)
lvrgratio	-1.320	-0.515	-0.514	-0.515
	(-0.88)	(-1.30)	(-1.24)	(-1.32)
saleratio	-1.045***	-0.734***	-0.739***	-0.654***
	(-12.43)	(-21.64)	(-20.17)	(-19.00)
koganindex	0.421***			
	(4.29)			
reteratio		-0.0118*		
		(-0.39)		
cashflowratio			0.308**	
			(1.56)	
age				-0.0194***
				(-13.05)
_cons	2.216***	2.121***	2.073***	2.912***
	(12.04)	(26.21)	(23.88)	(29.24)
N	24293	59351	55162	59483

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[28] See Fama French(2001) that uses asset growth as a proxy for firm growth

In Table 13, I check the impact of firm growth measured by five year rolling asset growth on the dividend payout. The first two specifications are from the cross-sectional OLS and the last two specifications are form the logit regression. The results are consistent that firm growth have negative relationship with the dividend payout.

Table 13 - Impact of Asset Growth on Dividend Payout

In this table, the variables of interest is the five year asset growth as a growth proxy and the dependent variable is the dividend payout. The control variables are the log of EBITDARATIO, SALES RATIO, CAPX Ratio and LEVERAGE RATIO. Specification 1 and specification 2 are from the OLS regression in which the dividend ratio is the dollar value of dividend payout normalized by total asset. Specification 3 and 4 are the results from the cross-sectional logit regression in which dependent variable is the binary 1 for dividend payer and 0 is for non-payer. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

	(1-robust OLS)	(2- robust OLS)	(3-logit)	(4-logit)
	divratio	divratio	divpayer	divpayer
main				
fiveyearassetgrwthrate	-0.000241***	-0.000208***	-0.125***	-0.273***
	(-15.42)	(-12.81)	(-26.72)	(-30.43)
lnebitdaratio		0.00777***		0.812***
		(61.73)		(39.64)
lvrgratio		-0.0430***		-30.62***
		(-21.89)		(-32.77)
rdratio		-0.0416***		-15.69***
		(-25.47)		(-55.28)
capxratio		0.000184		4.730***
		(0.09)		(16.14)
_cons	0.0122***	0.0327***	0.113***	2.804***
	(170.84)	(78.20)	(13.23)	(42.88)
N	70415	40695	70707	40780

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finally, in Table 14, I create an interaction term of high innovation vs low innovation against the mature phase defined by each of the life cycle proxies. Panel A is for the maturity stage defined by cashflow pattern. Panel B is for the maturity stage defined by RETE and Panel C is for the maturity stage defined by firm age. In all the panels, dividend payout ratio is the dependent variables. I create two dummy variable one each for low innovation (if the firms have citation weighted patent less than the industry median) and high innovation (if the firms have citation weighted patent above the industry median). Then I create corresponding variables interacting with the mature phase defined by each of the life cycle proxies.

Table 14 - Impact of 'Maturity' and High vs Low 'Innovation Interaction' on Dividend Ratio

In this table, the variable of interest is the maturity stage defined by each of the popular life cycle proxies RETE, CASHFLOW and AGE. The dependent variable is the dividend payout. The control variables are the log of ebitda ratio, sales ratio, capx ratio, free cashflow ratio and the leveraged ratio. Specification 3 has the interaction term of mature phase and low innovation index dummy. Specification 4 has the interaction term of mature phase and high innovation index dummy. Panel A is for Cashflow pattern maturity stage, Panel B is for RETE maturity phase and Panel C has firm age. The sample consists of Compustat US manufacturing firms, and the duration is from 1973 to 2017.

Panel A - Cashflow Pattern Maturity Stage

	-1	-2	-3	-4
	divratio	divratio	divratio	divratio
DMature	0.00699***	0.00700***	0.00631***	0.00730***
	(51.88)	(37.13)	(32.26)	(38.46)
lnebitdaratio		0.00540***	0.00536***	0.00539***
		(40.68)	(40.42)	(40.67)
lvrgratio		-0.0268***	-0.0259***	-0.0262***
		(-13.82)	(-13.38)	(-13.55)
saleratio		-0.00160***	-0.00146***	-0.00161***
		(-9.48)	(-8.65)	(-9.54)
fcfratio		0.000767**	0.000809**	0.000772**
		(2.84)	(3.00)	(2.86)
capxratio		0.000729	0.000457	0.00161
		(0.35)	(0.22)	(0.77)
DMXlowinovdum			0.00454***	
			(12.50)	
DMXhighinnovdum				-0.00802***
				(-11.71)
_cons	0.00884***	0.0210***	0.0207***	0.0209***
	(132.06)	(48.07)	(47.53)	(47.98)
N	92502	39016	39016	39016
adj. R-sq	0.082	0.101	0.105	0.104

Panel B – RETE (Maturity Phase)

	-1	-2	-3	-4
	divratio	divratio	divratio	divratio
retecat3dum	0.0142***	0.0120***	0.0117***	0.0120***
	(54.56)	(38.65)	(34.76)	(38.68)
lnebitdaratio		0.00583***	0.00583***	0.00583***
		(44.66)	(44.64)	(44.67)
lvrgratio		-0.0253***	-0.0253***	-0.0253***
		(-13.06)	(-13.07)	(-13.06)
saleratio		-0.000696***	-0.000693***	-0.000696***
		(-4.14)	(-4.12)	(-4.14)
fcfratio		0.00146***	0.00146***	0.00146***
		-5.43	-5.44	-5.44
capxratio		-0.00113	-0.00114	-0.00112
		(-0.54)	(-0.54)	(-0.53)
reteXlowinovdum			0.00172*	
			(2.21)	
reteXhighinnovdum				-0.00669*
				(-2.79)
_cons	0.00982***	0.0231***	0.0231***	0.0231***
	-164.76	-55.31	-55.28	-55.31
N	92502	39016	39016	39016
adj. R-sq	0.091	0.104	0.104	0.104

Panel C - AgeCat4 (Age Maturity)

	-1	-2	-3	-4
	divratio	divratio	divratio	divratio
agecat4dum	0.0132***	0.0135***	0.0126***	0.0134***
	(86.56)	(50.22)	(44.31)	(49.84)
lnebitdaratio		0.00605***	0.00601***	0.00604***
		(47.13)	(46.85)	(47.08)
lvrgratio		-0.0239***	-0.0231***	-0.0235***
		(-12.48)	(-12.07)	(-12.29)
saleratio		-0.000627***	-0.000551***	-0.000645***

		(-3.78)	(-3.31)	(-3.89)
fcfratio		0.00146***	0.00146***	0.00146***
		(5.51)	(5.52)	(5.50)
capxratio		-0.00686***	-0.00676**	-0.00578**
		(-3.33)	(-3.28)	(-2.80)
ageXlowinovdum			0.0000537***	
			(8.66)	
ageXhighinnovdum				-0.000113***
				(-9.66)
_cons	0.00838***	0.0232***	0.0228***	0.0234***
	-134.84	-56.76	-55.53	-57.11
N	92502	39016	39016	39016
adj. R-sq	0.075	0.126	0.127	0.128

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 14, Panel A shows that higher innovation interaction with the mature phase (defined by cashflow) have negative impact on the dividend payout ratio whereas less innovation interaction with the mature phase (defined by cashflow) have a positive impact on the dividend payout ratio. Similarly, Panel B shows that higher innovation interaction with the mature phase (defined by RETE) have negative impact on the dividend payout ratio whereas less innovation interaction with the mature phase (defined by RETE) have a positive impact on the dividend payout ratio. Likewise, Panel C shows that higher innovation interaction with the mature phase (defined by age) have negative impact on the dividend payout ratio whereas less innovation interaction with the mature phase (defined by age) have a positive impact on the dividend payout ratio. In all the Panels, both positive and negative relations of lower innovation vs higher innovation are statistically significant at 0.1% level. Thus, we have a strong evidence that there is a clear difference in dividend payout even if the firms are in the 'same life cycle stage' defined by RETE, Cashflow Patterns or the firm age.

7. CONCLUSIONS

I provide sufficient evidence that the existing firm life cycle proxies failed to capture the innovation impact differentials on the dividend life cycle stages. I prove that among the two groups of firms, one with the higher innovation pays lower dividends in comparison to its lower innovative counterparts controlling for the firm characteristics such as age, size, profitability, growth opportunity, re/te, and the cashflow patterns. The last proxy in the life cycle literature is Faff et al. (2016) MLDA measure, which is the function of age, RE/TE, profit(EBIT/asset), and sales). It is highly likely that this proxy also suffers from the weakness as it does not account for the innovation intensity impact in its measurement. However, I left this part for future research.

I believe that I present comprehensive research on the dividend life cycle and how it is impacted due to the degree of innovation. I establish a positive relationship between innovativeness and firm growth. Likewise, I examine whether the maturity hypothesis holds regardless of the firm life cycle proxies used. I then investigate the relationship between the dividend payout (as a firm's maturity characteristic), and the degree of innovativeness. I document that the more persistent the firm innovation, the stronger the negative relationship between the innovativeness and the dividend payout. Finally, I empirically highlight the shortcomings of the existing life cycle proxies that they are not fully capturing the firm characteristics, especially, the impact of innovation output while defining the life cycle stages.

Further, I study retained earnings ratio and the cash flow patterns to determine whether and, if so, how the life cycle of a firm affects its dividend policy. Based on the evidence presented, I argue that innovation intensity is the most effective measure to estimate the dividend life cycle. While I have provided sufficient empirical evidence (with multiple robustness checks) on the superiority of innovation intensity as a life cycle proxy to measure the maturity of a firm, there is a certain limitation that demands further exploration. For example, the approximate cut-off line between the life cycle stages will need to be determined based on the degree of innovation, firm growth rate, and the dividend payout of a firm. I conclude that while none of the life cycle proxies are perfect, the citation weighted innovation output effect is the key growth driver that determines the firm life cycle, and surprisingly, the innovation characteristics of the firm are not sufficiently examined in the life cycle literature. I claim that this study contributes to the literature by attempting to fill the void. Perhaps, based on this fact, I can also claim that innovation intensity stands better among all the life cycle proxies available on this line of literature. I provide convincing evidence that citation backed innovation output better captures the cross-sectional variability of the dividend payout during the firm maturity regardless of the life cycle proxies used.

The final sequence in the empirical study is to examine whether firm innovation is the result of good corporate governance. This notion has been sufficiently tested and has supporting evidence in the existing studies. I can still verify that the persistent innovators in the manufacturing sample have good corporate governance. I left this part also for future research because corporate governance is a separate topic and should be studied within its own merits.

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Appendix A (Chapter 1)

Chapter 1 Appendix Table A - Variable Selection

Name	Variable	Formula	Comments
Dividend Ratio	divratio	div/at	
R&D Ratio	rdratio	xrd/at	
Lag R&D Intensity	lagRDint	xrd/lagsale	
Amort. Intangible Ratio	amratioratio	am/at	Amortization of Intangible Assets includes trademark, patents, copyright, etc..
Citation Weighted Innovation Index	tcw	I use Kogan et al.(2017) model	
Kogan Index	tcw + tsm	Following Kogan, I use also the combination of citation weighted and stock market value weighted patents output.	
Growth	growth	lnsale - lnlagsale	
Return on Equity Ratio	roeratio	roe/at	
Return on Asset	Roaratio	ni/at	
EBITDA Ratio	ebitdaratio	ebitda/at	
SALE Ratio	saleratio	sale/at	
Retained earnings to total equity	reteratio	re/te	
Retained earnings to total asset	retaratio	re/at	
Leverage Ratio	lvrgratioratio	lvrg/at	
CAPX Ratio	capxratioratio	capx/at	
Size	size	log(at)	
Total Equity	totequity	te	
Free Cash Flow	fcf	oancf - xidoc + intpn - ((pi-ni)/pi)*xint - capx	
Firm Age	age	current year - linkeddt	
Four Factor Innovation Index		tcw + tsm + rdratio + amratio	

Chapter 1 Appendix Table B – Compustat Derived Variables References

Variable	Formula	Variable Name
eps	ni/csho	Earnings per share
epsratio	eps/at	Earnings per share to total asset
divratio	dvc/at	Dividends Common/Ordinary
rdratio	xrd/at	R&D to total asset
payoutratio	(dvp+dvc+prstkc)/ib	Payout ratio as defined by compustat
capxratio	capx/at	CAPEX to total asset
roa	ni/at	Net income to total asset / Return on Assets

roe	ni/(csho*prcc_f)	Return on Equity
be	prcc_c * csho	Book Equity Value
mv	csho*prcc_f	Market Value
markettobook	mkvalt/bkvlps	Market to Book Value
cashflowratio	(ibc + dp)/at	Cashflow
cashholdingratio	che/at	Cash holding
costofcapital	xint/dlc	Cost of Capital
lvrg	(dltt+dlc)/seq	Leverage
lvrgratio	lvrg/at	Leverage Ratio
tangibleassetratio	ppent/at	Tangible Assets
tobinsq	(at + (csho*prcc_f)-ceq)/at	Tobin's Q
totalequity	pstkc+csho	Total Equity
freecashflow	oancf - xidoc + intpn - ((pi-ni)/pi)*xint - capx	Free Cash Flow
totalequity	pstkc+csho	Total Equity
retainedearningstotatalequity	re/te	Retained earnings to total equity
retainedearningstotatalasset	re/ta	Retained earnings to total asset
totalequitytototalasset	te/ta	Total equity to total asset
cashflowtototalasset	cash/ta	Cash to total asset
am	Amortization of Intangible Assets	Amortization of Intangible Assets includes trademark, patents, copyright, etc..

Chapter 1 Appendix Table C - Dickinson (2011) Life Cycle Stages Based on Cashflow Patterns

Cash Flow	Introductory	Growth	Maturity	Shakeout	Shakeout	Shakeout	Decline	Decline
Operating	-	+	+	-	+	+	-	-
Investing	-	-	-	-	+	+	+	+
Financing	+	+	-	-	+	-	+	-

From the table, the maturity of the firm starts when the financing cash flow reaches to zero.

CHAPTER 2

SCALE EFFECTS ON ETFS PERFORMANCE

1 INTRODUCTION

According to Zhu (2018) "if the nature of the returns to scale is not constant, fund size is informative". The paper claims that the unobserved skill is reflected in two observable measures: return and size. It goes on saying that the traditional framework that studies managerial skill and ignores size fails to fully utilize the available information. So, the paper implies that if the returns to scale is constant, then size doesn't matter; otherwise, it does. Now, the question is - does index-tracking funds such as ETFs exhibit managerial portfolio selection skill? And according to Crane et al. (2018), the answer is 'surprisingly yes'. The paper applies methods designed to measure mutual fund skill to a cross-section of index funds that is unlikely to exhibit managerial portfolio selection skill and find that the index tracking fund does exhibit skill that is persistent and is in similar proportion as in active funds. Therefore, a critical question arises, does ETFs have constant returns to scale?[29] or do they have either increasing or decreasing returns to scale?[30] Zhu(2018) findings suggest that if ETFs follow increasing or diminishing returns to scale, then size does matter, so it demands investigation.

The motivation also comes from the conflicting findings in the extant literature for the size effect on fund performance. One side of the argument suggests that size does erode fund performance due to diseconomies of scale (see Chen et al. , 2004; Yan, 2008) whereas the other side implies that fund size has no relation to the fund performance (see Phillips et al., 2018; Pastor, Stambaugh, and Taylor, 2015; Reuter and Zitzewitz, 2015). Consistent with Chen et al.

[29] Evidence of constant returns to scale include Edelen, Evans, and Kadlec (2007), Elton, Gruber and Blake (2012), Ferreira, Keswani, Miguel, and Ramos (2013), Reuter and Zitzewitz (2015), Pástor, Stambaugh, and Taylor (2015) and Phillips, Pukthuanthong, and Rau (2016).

[30]Evidence supporting diseconomies of scale at the fund level include Yan (2008), Busse, Jiang, and Tang (2014), Golez and Shive (2015), Harvey and Liu (2017), and Zhu (2018).

and Yan(2008), Zhu (2018) and Pastor et al. (2019) also document stronger evidence of decreasing returns to scale. However, older papers such as Grinbalt and Titman (1989) find mixed evidence that fund returns decline with fund size. Further, Berk and Green (2004) conclude that there should be no significant relation between fund size and performance in the cross-section. Unlike all these papers, Indro et al. (1999) find a nonlinear relation between fund size and performance. They observe that performance initially increases and then decreases in fund size. These results from the conventional funds are simply perplexing.

Now, let's take a closure look on where the broader equity ETFs falls in the fund categories. SEC classifies ETFs as open-end funds[31]. However, by design ETFs are a hybrid asset fund between an open-end and a closed-end fund. They share a resemblance to an open-end fund because units can be created when investors buy the ETF. They share a similarity to closed-end funds in the sense that units can be freely traded regardless of whether units are created or not. The hybrid structure allows for a mechanism where funds can be traded continuously during the trading hours, and this intraday trading feature makes the ETFs as one of the most liquid instruments that attract high turnover clientele, such as hedge funds and high-frequency traders for speculation, arbitrage, and hedging (Ben-David et al., 2018).

Furthermore, market index-tracking ETFs is expected to capture the equity market return by replicating the performance of a broad capitalization-weighted market index at low fees compare to the traditional funds. Hence, many consider the terms passive and ETF to be synonyms[32]. However, I argue that there are multiple concerns in generalizing the 'broader universe of ETFs' as a passive investment. One concern is that continuous trading of ETFs in the exchanges should be of no relevance for the passive investors because investing in passive funds supposed to be based on buy and hold strategy for the long-term investors who need to avoid frequent trading. Ben-David et al. (2017) test the propositions that "the mutual funds may appeal to short-term investors due to the absence of commission fees, while ETFs may appeal to long-term investors due to lower management fees", however, they find exact opposite results and

[31] See https://www.sec.gov/reportspubs/investor-publications/investorpubsinwsmfhtm.html
[32] See similar discussion in Blitz, David and Vidojevic, Milan, The Performance of Exchange-Traded Funds (September 23, 2019). Available at SSRN: https://ssrn.com/abstract=3458275

document that investors in ETFs have significantly shorter horizons[33.] Another concern is that not every equity ETFs contain low costs. There are ETFs with expense ratios higher than many mutual funds, and there is no homogeneity in cost across the ETFs spectrum.

Crane et al. (2018) cite Elton et al. (2004) to make a point that net-of-fee performance is persistent within S&P 500 funds due primarily to fee differences to which investor flows respond. Crane et al. paper further show not only performance differences across a wider set of index funds but also performance differences in terms of tracking error among funds with the same benchmark (e.g., S&P 500), suggesting heterogeneity within the same benchmark itself. Likewise, I argue if the objective of ETFs is to promote passive investing, then, in theory, few ETFs on the broader market should be sufficient for the investors; in reality, there are thousands of ETFs now competing for different 'active investment strategies' via custom-designed exchange-traded funds.

In the sample for this study, the non-leveraged, non-inverse, non-active 'equity only ETFs' consists of one thousand fifty-one ETFs, and among those, only a few tracks the market index, and the majority of them track indices that are focusing on a particular sector or investment theme (value, growth, small-cap, large-cap, momentum, dividend, emerging markets, sector, etc.). According to Easley, Michayluk, O'Hara, and Putniņš (2018), ETFs have a median active share of 93.1% and median tracking error of 8.8%, relative to the passive market portfolio. Robertson (2018) further concludes that far from being passive, ETFs are a different form of delegated management, where the delegee is the index creator rather than the fund manager[34].

Therefore, with their hybrid structure under a different form of delegated management via index, I think that ETFs demand separate investigation of returns to scale behavior within its own merits. Moreover, due to the lack of empirical study on ETFs performance in the existing literature, the risk-return superiority over mutual funds or the broader market is anecdotal at best. The gap in the literature is surprising, given the significant rapid growth in the number of

[33] See page 9-10 on Ben-David, Itzhak and Franzoni, Francesco A. and Moussawi, Rabih, Exchange Traded Funds (ETFs) (August 2017). Annual Review of Financial Economics, Volume 9, 2017
[34] See similar discussion in Blitz, David and Vidojevic, Milan, The Performance of Exchange-Traded Funds (September 23, 2019). Available at SSRN: https://ssrn.com/abstract=3458275

ETFs debut and the asset base size growth in recent years. Thus, in light of massive fund inflow[35] into this relatively new financial innovation lately, it is vital to empirically find out the various aspects of the scale effect on the exchange-traded funds' performance, including the tracking error.

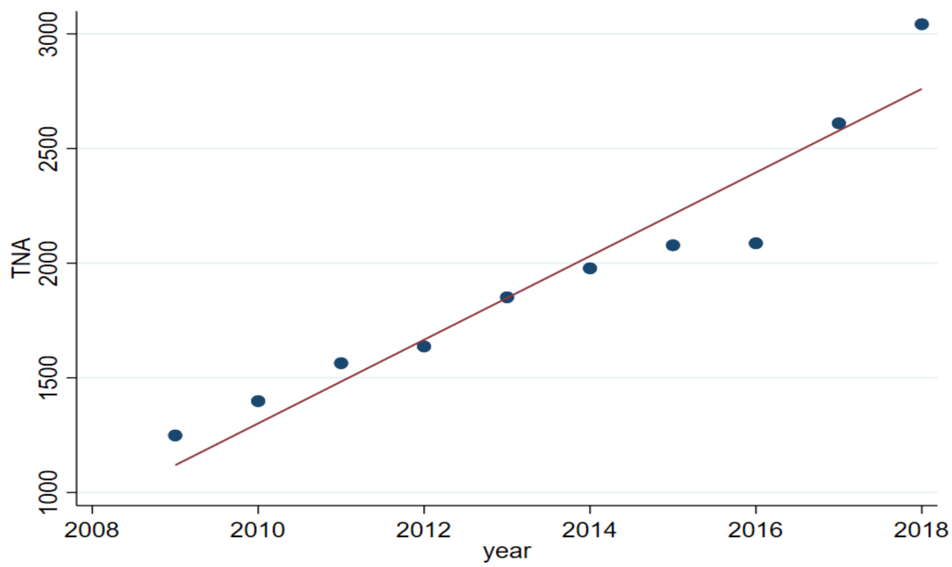

Figure 1-Increase in ETFs Size Over the Years

Potential Factors Behind the Rapid Growth in ETFs Size:

i. Diversification at a low cost

Risk mitigation via diversification at a low cost is one of the main incentives for ETF investors. Hakansson (1978) and Rubinstein (1989) first imagine the idea of trading a diversified basket of stocks such as exchange-traded funds. They suggest that investors should be able to trade a diversified asset to mitigate investment risk. They imply that traditional mutual funds are diversified but not tradable in the stock exchanges. Stocks are tradable but not diversified. Therefore, ETFs are developed as a diversified ‘stock baskets’ to trade in the exchanges. The first ETF (S&P500 ETF ticker ‘SPY’) debut in the US market in 1993. Since then, ETFs growth story has

[35] See figure 1, how quickly the ETFs asset base has grown over the years

been phenomenal[36.] They have revolutionized the asset management industry by taking market share from traditional investment vehicles such as mutual funds and index futures (Ben-David et al., 2018).

ii. Liquidity and Trading Flexibility

Hill (2015) suggests ETFs provide liquid access to virtually every financial market and allow large and small investors to build institutional-caliber portfolios. ETFs trade on the exchanges like the individual stocks but seeks to replicate the performance of a particular index like an index mutual fund. They track a defined benchmark such as specified index, a sector of the industry, the stock market of a foreign country, or a specific portfolio of fixed income securities. Thus, they are the innovative products that put together favorable characteristics of open-ended and closed-ended mutual funds and present a more flexible and liquid product for larger investors[37]. Besides, high levels of transparency and the quick availability of custom-designed ETFs for the specific investment objectives offer additional incentives to the investors. Likewise, ETFs have high tax efficiency with no material premiums or discounts to the funds' intraday net asset value and no fund load (entrance fees, or exit fees, like in many mutual funds).

No doubt, these key features make the investors to warmly embrace the phenomenal growth of the exchange-traded funds in recent decades. However, the big question that remains unclear is whether these great features of ETFs are helping to create higher risk-adjusted returns for the investors? In other words, do ETFs beat the broader market? Likewise, do they beat the traditional index funds? Similarly, another aspect of interest is whether and how these features are impacting the tracking ability of the ETFs to their underlying indexes.

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[36] see the book title "Exchange- Traded Funds and the New Dynamics of Investing." The author provides an extensive discussion on the history, extraordinary growth in recent years, and where it is heading as an alternative investment asset in the future. It mentions that the first ETF (ticker 'SPY') tracking the S&P 500 broader market index debut in 1993. Sector ETFs tracking the nine sectors of the S&P 500 come to the market in 1998. In the same year, ETFs providers introduce the first actively managed ETFs. Also, in the international market, Europe debut first ETF in 1998. The number of ETFs trading in the US exchanges surpassed 2000 by 2018.

[37] See broader discussion on Martin Lettau & Ananth Madhavan, 2018. "Exchange-Traded Funds 101 for Economists," Journal of Economic Perspectives, American Economic Association, vol. 32(1), pages 135-154, Winter.

The research focus and the summary of findings:

The fund economies of scale offer cost reductions obtained from increasing asset base size growth. And with an increase in scale, costs per unit of output decrease. The fixed costs spread over more units of output. As a result, operational efficiency is often higher, with increasing scale leading to lower variable costs (Haslem,2017). I argue that if ETFs are a passive investment, then theoretically, they should hold increasing returns to scale[38]. If they are hybrid instruments, then there should be an existence of inefficiencies that may promote diseconomies of scale. Furthermore, as discussed, ETFs trade in the exchanges very frequently violating passive buy and hold philosophy, and they have a wide range of expense ratios. There are ETFs with a higher expense ratio than many mutual funds[39.]

With all these analyses thus far, I attempt to investigate the 'returns to scale behavior' in connection to the broader 'equity ETFs universe' using the quantile regression approach. Primarily, I focus on three main research questions; first, do ETFs risk-adjusted-performance increases with the increase in size? (in other words, do ETFs hold economies of scale?). Second, does size matter for the tracking ability of the ETFs to their underlying index? And third, do other fund attributes (such as liquidity, expense ratio, number of holdings, fund age, lagged fund return, fund flows, and the investment styles (small-cap, large-cap, value, growth, core/blend, among others) promotes or worsens the size vs. performance relationship? In other words, do these factors play any role in returns to scale? A better understanding of these critical questions would naturally be useful for investors, and policymakers, especially in light of the enormous money inflows that have increased the mean size of ETFs in the recent past. I believe that the study will help address even more important question what matters most in ETFs selections from a performance perspective for both the retail and the institutional investors?

In terms of methodology, Zhu(2018) criticizes existing literature that quantifies scale effects based on the ordinary least squares (OLS) approach that directly regresses fund returns

[38] See discussion in Adams, John C. and Hayunga, Darren K. and Mansi, Sattar, Returns to Scale in Active and Passive Management (December 4, 2018). Available at SRN: https://ssrn.com/abstract=3295799

[39] See Blitz, David and Vidojevic, Milan, The Performance of Exchange-Traded Funds (September 23, 2019). Available at SSRN: https://ssrn.com/abstract=3458275

on lagged fund sizes. The paper raises the concern that the validity of the OLS model is based on the assumption that fund size is uninformative. To address the issue, I primarily use quantile regression to investigate the size impact on the risk-adjusted alpha and the tracking error. However, I perform robust testing using cross-sectional regression (using Fama McBeth(1973) and panel OLS with clustered standard error on ETFID) so that I can compare the results with the existing findings in the literature. I use a similar cross-sectional model specification as in Yan(2008) and Chen et al. (2004) to examine how the scale impact on ETFs performance differs from the conventional mutual fund's size impact on their returns. I also investigate the interaction effect of various fund attributes, investment styles, and fund types on the ETF size to find out whether the fund attributes, investment styles, and the fund types play any role in the returns to scale behavior.

The empirical findings show that ETFs, in general, do not have increasing returns to scale[40]. I find some evidence of positive returns while increasing the asset base initially; however, the positive returns have a distinct decreasing pattern as the size grows, and ultimately the positive alpha turns in to negative at the high end of the size cluster (largest quantiles). I find an inverse size effect i.e., size has a more substantial negative impact on the highest performing quantiles of the ETFs (high performing cluster). I observe that the decay in performance is steady as the asset base size increases. However, I find that the size impact on the tracking ability of ETFs to their underlying index is marginal. I observe that illiquidity and expense ratio aggravate the inverse relation of size and return performance, including the tracking error performance as well. I also notice that growth and value investment styles positively impact the size vs. performance relationship. Likewise, I observe that ETFs with capitalization-weighted index composition have a positive role, but the equal-weighted index composition has a negative influence on the size performance relationship.

The rest of the paper follows as below: a brief discussion on the related literature review is in section two. Section three presents the data and univariate analysis, and section four

[40] The results are similar to the extant literature that find evidences supporting diseconomies of scale at the fund level include Yan (2008), Busse, Jiang, and Tang (2014), Golez and Shive (2015), Harvey and Liu (2017), and Zhu (2018).

presents the empirical details, including the findings of the study. Finally, section five concludes the paper.

2 LITERATURE SURVEY AND HYPOTHESIS DEVELOPMENT

In the index-based fund literature, Frino and Gallagher (2001,2002) imply that the index represents a paper portfolio that enables the instantaneous and costless implementation of a passive benchmark strategy. However, other papers argue that liquidity of the stock and the size of the fund have an essential impact on the replication technique implemented by the index-tracking funds such as ETFs (see Keim,1999; and Frino et al.,2004). Likewise, Dellva (2001) perform a comparative study between the index mutual funds and the ETFs, and document that ETFs are relatively unattractive to retail investors dealing in small asset due to the transaction costs associated with trading. The paper implies that there are little or no benefits associated with tax-deferred, long term retirement class investors utilizing such products.

Likewise, some studies cite demand shocks due to market volatility as one of the potential factors that may cause absolute price inefficiency in ETFs (Coval and Stafford 2007). As ETFs trades in the exchanges, the trading cost is another concern that may contribute to the diseconomies of scale.[41] Perold and Salomon (1991) also argue that a large asset base erodes performance as a result of increased trading costs due to liquidity constraints and price movement. They imply that returns decline while wealth created increases up to a point where the cost of additional trading exceeds the opportunity cost of not trading. Thus, I argue that ETFs are not free of inefficiencies, especially, the higher tracking error is the evidence that ETFs have inefficiencies that may introduce diseconomies of scale. In the next section, I attempt to relate the findings from the conventional funds' literature in the context of the research focus 'returns to scale'.

[41] Edelen, Evans, and Kadlec (2007) find that trading costs are a major source of diseconomies of scale.

2.1 Examining Returns to Scale

According to Gao and Livingston(2008), scale economies enable the cost per unit of output to decrease when the asset base increases. Likewise, Latzko (2002) document that cost economies of scale from asset growth go to fund investors as lower expense ratios. Tufano and Sevick (1997) also agree with the notion that the fund expense ratio declines with the fund size. So, there is a general consensus that a lower expense ratio generally helps increase the funds' asset base.

Fund size represents the total amount of capital committed by the investors of the Fund. Chen et al. (2004) investigate the effect of size on the performance of actively managed funds for the years 1962–1999. They use cross-sectional variation to see whether performance depends on the scalability of the fund. They find that fund returns both before and after fees, and expenses decline with the lagged fund size. The paper explains that the association of size vs. fund alpha is most notable among funds that have small and illiquid stocks implying that scale effects are related to liquidity. Chen's paper further argues that the lack of liquidity requires large funds to invest in less-than-best ideas with larger positions that decrease performance. The paper also mentions that the fund size may be correlated with other factors such as fund age, the number of holdings, investment styles, etc. that these factors can also drive the return performance.

Consistent with Chen's observation, few other papers also find that size erodes fund performance because of diseconomies of scale due to trading costs[42] related to liquidity or price impact (Lowenstein, 1997). Likewise, Pollet and Wilson (2008) find evidence that when funds become larger, they failed to diversify into new assets. They argue that instead of adequately diversifying, those funds just scale up their current asset allocation. They conclude that illiquidity makes a large fund to have to invest in non-optimal assets, thereby eroding performance. Becker and Vaughan (2001) also argue that as a fund grows larger, it becomes difficult to execute desired reallocation resulting reduction in the speed and nature of portfolio adjustment that ultimately

[42] Edelen, Evans, and Kadlec (2007) find that trading costs are a major source of diseconomies of scale.

impairs fund performance. Similarly, Chu (2009) study the impact of size on tracking error in the Hong Kong market and document that the magnitude of the tracking errors has a negative relation to the size of ETFs. Chu’s study also documents a positive relation to the expense ratios of the funds.

In recent research, Zhu (2018) finds weaknesses in Pastor et al. (2015), which document that there is no relation between size and performance. Zhu argues that the method of Pástor et al. suffers misspecification bias resulting from a model restriction, which may be problematic for the fund size process. Unlike Pástor et al., Zhu finds evidence of diseconomies of scale at the fund level after correcting for the misspecification. One caveat, though, Zhu’s research includes only funds that fall into one of the nine size categories (small, mid, and large-capitalization stocks) and style (value, blend, and growth) and excluded bond, international, sector, money market, and other non-equity funds. However, the implications of the data restriction are unclear. Reducing the number of investment categories may yield a reduction in potential misclassifications, but it may also compromise the robustness of the results. Nevertheless, Pastor et al. (2019) discover additional evidence of decreasing returns to scale and support Zhu’s findings.

To sum up, first, there is no broad consensus on the size impact on fund performance based on the conventional funds’ researches, and second, when it comes to ETFs, there is not even an economically meaningful empirical research available yet in the literature. Therefore, I argue that the research has a unique contribution to the literature that I provide a broader perspective on ‘the returns to scale behavior’ based on the evidence from the ‘large universe of equity exchange-traded funds’.

2.2 The role of ‘other’ investment factors on the size vs. performance relationship

Yan (2008) reconfirmed previous findings from Chen et al.'s (2004) that performance declines with fund size, and fund liquidity plays a mediating role in size vs. return relationship. The study also observes that it is both the fund size and the liquidity that is combinedly responsible for causing performance to decrease. His research also finds trading costs as one of the factors contributing to the diseconomies of scale. Pastor et al. (2018) find that funds with a larger size, lower expense ratio, and higher turnover hold more-liquid portfolios. Their findings also show that better-diversified funds hold less-liquid stocks. They study tradeoffs among active mutual funds' characteristics and confirm model-predicted tradeoffs that larger funds are relatively cheaper. Nevertheless, based on their new measure of activeness, larger and less expensive funds are not active compare to the small funds.

Elton, Gruber, and Blake (2012) propose that the decrease in expense ratio can offset the diseconomies of scale of the large funds. They state that fund size has no impact on future fund performance. Rompotis (2012) study the impact of expense ratio on the ETFs tracking error and finds no statistically significant relationship between tracking error and the expense ratio. The paper argues that since the expense ratios for the ETFs do not change that often (and sometimes not at all) during the data period investigated, there may not be a statistically significant relationship between tracking error and the expense ratio. The expense ratio can be omitted for several ETFs because of collinearity.

Similarly, other researches such as Pastor et al. (2018); Carhart (1997); Elton, Gruber & Blake (2012) have shown that expense ratio declines with size and decline with success, with the top-performing funds decreasing fees and the poor performing funds increasing fees. Yan (2008) cites Chan and Lakonishok (1995) and Keim and Madhavan (1997) to make an argument that investment style can provide additional insight into the nature of economies of scale in fund management. The paper document that the adverse effect of scale on performance is more pronounced among low book to market, i.e., growth funds. Further, Chen et al. (2004) use cross-sectional variation to see whether performance depends on lagged fund size. They find an inverse relationship between the lagged asset base and the risk-adjusted returns. Thus, many 'other' funds attribute, as highlighted in this paragraph, may also play a mediating role in the scale vs. performance relationship that needs empirical investigation.

2.3 Hypothesis Development

Theoretically, when a fund performs well every year, the money inflows grows, the size increases, and the cost decreases. The scale economies offer further insights into the role of other investment factors that include the importance of the liquidity, number of holdings, age, and various investment styles on size vs. performance relation. The scale is also often associated with the lagged fund flow, lagged fund return, and the lagged fund size. Lower expense ratios and higher liquidity drive the inflows and which in turn help determine the persistence of performance that is expected to increase the asset base. Similarly, as ETFs holdings are transparent, the lower information asymmetry helps mitigate the investment risks and contributes to the decrease in cost that helps increase in fund inflows. However, what is unknown is how the increase in scale affects ETFs risk-adjusted return performance. Besides, scale impact on the tracking ability of the ETFs with their benchmark while increasing their asset base growth is also another critical aspect of empirical investigation.

As discussed earlier, we cannot rule out the diseconomies of scale in ETFs because of its hybrid nature and varying degree of activeness among the broader equity ETFs universe. The fund companies custom design ETFs to achieve specific investment objectives, including active strategies. Besides, ETFs trade heavily in the exchanges violating the passive strategy of buy and hold. The heavy intraday trading may also introduce other inefficiencies due to demand shocks and market volatilities. Furthermore, some industry practitioners often cite low expense ratios as the reason to invest in ETFs; however, if that is true, I argue that it is not in alignment with the economic theory that often said, 'you get what you pay for.'

Therefore, based on all these analyses thus far and based on the literature survey, I examine the increasing returns to scale hypothesis focusing on non-active, non-inverse, and non-leveraged equity ETFs. I test whether the scale has a positive impact on ETFs performance in terms of risk-adjusted return as well as in terms of tracking error. I subdivide the full sample into four size quantiles and then examine the performance differential in those quantiles. Further, I use quantile regression to see the size impact on the lowest-performing funds vs. the highest performing funds. In addition, I analyze the pattern by examining the size effect on the 10^{th}, 25^{th}, 50^{th}, $75^{th,}$ and 90^{th} percentile of the performance metrics. Finally, to investigate the reasons why ETFs failed to hold the increasing returns to scale, I perform an exploratory investigation on various investment factors that potentially play a mediating role[43] and drives the relationship between the scale economies and ETFs performance.

3 DATA AND THE UNIVARIATE ANALYSIS

I examine the US-listed ETFs because the US ETF industry is relatively matured in comparison to the financial markets in other countries. The primary source of time-series data is the Thomson Reuters DataStream database, and some of the cross-sectional variables are from the Morningstar and ETFDB.COM[44]. The data sample period is from 2009 through 2018 (10 years). The total number of ETFs in the sample is 1051. I use the monthly time series data for the ETFs that have inception dates from 1993 through 2015. I exclude ETFs created after 2015 to ensure that I have three years of minimum data. I exclude bonds, currency, commodities, inverse, leveraged, and volatility ETFs. I include only non-leveraged equities ETFs that trade in the US stock exchanges. Further, I exclude ETFs that are marked as 'active.' The variables list is shown in the variable selection table (see in the appendix). Edwin J. Elton et al. (2001) suggests that it is not a good idea to make inferences based on the performance of small funds due to a potential upward bias in the reported returns among the observations consisting of small funds. This bias is problematic for the analysis in this study as well because the focus of the research is the relationship between scale economy and performance. Therefore, I exclude ETFs with less than $15 million in total net assets.

Table 1 shows the summary statistics for the ETF sample. TNA is the total net assets (in millions). The expense ratio is the total annual management fees and expenses divided by year-end TNA. Liquidity is proxied from normalized bid-ask price spread[45]. Flow is the percentage of new fund flow into the Exchange Traded Fund over the period under investigation. Age is the

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[43] See earlier discussion in literature review, Chen et al(2004) and Yan(2008) among others highlights how other factors such as fund attributes like liquidity, and investment styles can worsen or promotes size performance relationship.

[44] Please, see the variable selection table in the appendix.

[45] I follow Hameed et al(2010) to create normalized bid-ask spread.
Hameed, A., Kang, W., Viswanathan, S., 2010. Stock market declines and liquidity. Journal of Finance 65, 257–293.

number of years since the inception of the ETF. The number of holdings is the number of stocks in an ETF. NAV is the net asset value. Volume Turn Over is the total trade transactions that occurred in a month. Historical volatility is the five-year standard deviation of the asset return. Premium/Discount is the difference between the NAV and the current market value of the ETFs. Lagged variables indicated are the previous time period value for the respective variables. Net Asset Return is the monthly ETF return after the expense ratio.

Table 1 - Descriptive Statistics

Table 1 shows the descriptive statistics for the ETF sample, excluding 'active ETFs'. TNA is the total net assets under management in millions of dollars. Expense Ratio is the total annual management fees and expenses divided by year-end TNA. Liquidity is proxied from normalized bid-ask price spread. Flow is the percentage of new fund flow into the Exchange Traded Fund over period under investigation. Age is the number of years since the establishment of the ETF. The number of Holdings is the number of stocks in an ETF. NAV is the net asset value. Volume Turn Over is the total trade transactions that occurred in a month. Historical Volatility is the five-year standard deviation of the asset return. Premium/Discount is the difference between the NAV and the current market value of the ETFs. Lagged variables indicated are the previous time period value for the respective variables. Net Asset Return is the monthly ETF return after the expense ratio. The ETF sample is from January 2009 to December 2018. I include non-leveraged equity ETFs with TNA more than $15 million. I sort the total net assets and create the size quintiles. In the table, the left side provides the summary statistics of the full sample, and the right side provides the descriptive statistics of the size quantiles.

	Summary Statistics						Descriptive Statistics by Size (lnTNA) Quantiles			
Variables	N	Mean	SD	Median	Min	Max	Size1 Mean	Size2 Mean	Size3 Mean	Size4 Mean
TNA	87135	2085.474	8759.851	264.5	15	306670.6	43.57181	157.7836	536.0237	7604.821
LogTNA	87135	5.776646	1.786539	5.57784	2.70805	12.63353	3.664858	5.008457	6.212919	8.220756
AGE	87004	12	4	13	3	27	10	11	12	15
No.Holdings	86346	334	651	101	0	8572	199	246	323	562
TradVol	87135	26134.48	179131.8	1290	0	8979386	429.9184	1478.634	6700.485	95932.71
Expratio	86346	0.442309	0.374474	0.42	0.03	9.62	0.5311368	0.4931522	0.4389424	0.3083885
Norm.BASpread	76325	0.006443	0.075306	0.00098	-0.0022	1.980101	0.0098389	0.0077896	0.0056212	0.0026229
HistVol	87135	0.19385	0.10435	0.1762	0	1.1737	0.2000133	0.1999479	0.1949981	0.1804412
NAV	54478	51.01998	36.39026	39.8174	1.1867	372.53	34.84094	44.09509	52.3524	69.83654
NOSH	87135	35220	104541	6550	50	1696702	1645	4870	14267	120102
PremDisc	54478	0.513868	3.913892	0.0065	-44.78	65.8259	0.1353033	0.4146493	0.8679351	0.6009388
VIX	87135	17.39478	6.41507	15.73	9.51	46.35	17.73408	17.61208	17.27957	16.95334
Alpha_CAPM	82133	-0.005552	0.020155	-0.00272	-0.326	0.2549092	-0.0109822	-0.0053383	-0.0039831	-0.0026382
NetExcRet	85095	-0.032358	0.07698	-0.02018	-0.4901	0.5610936	-0.031527	-0.0295469	-0.0316673	-0.0365979
LagFlow	84666	0.398181	48.15397	0	-0.9996	12805	0.330296	0.5577195	0.6709446	0.0307266

The mean size for the overall sample is $2085 million. The smallest ETF has a value of $15 million, and the largest ETF has a value of $306670 million. The average age of all sample funds is 12 years. The average number of stocks in an ETF is 334. The average monthly trading volume is 26134 transactions. The mean expense ratio of the sample ETFs is 0.44%. I calculate the normalized bid-ask spread using the formula: spread = (ask price/bid price - 1)/midpoint of ask price plus bid price[46]. The average normalized spread is 0.6%. Likewise, the historical volatility is 19%. The average number of shares outstanding in the sample ETFs is 35220. The average CAPM alpha is negative 0.5%, and the average net excess return is negative 0.3%. The average lagged fund flow is 39%.

I sort the total net assets and create the size quantiles. In Table 1, the left side provides the summary statistics of the full sample, and the right side provides the descriptive statistics of the size quantiles. The summary statistics report the number of observations, the monthly time-series cross-sectional mean, the standard deviations, median, minimum, and maximum value for the full ETFs sample. The descriptive statistics on the right side provide mean values comparison by size quantiles. I create size quantiles (smallest to largest) sorted by the total net asset. As observed from Table 1 under descriptive statistics, size represented by total net asset is in increasing order. The mean size for quantile 1 is $43 million, for quantile 2 is $157million, for quantile 3 is $536 million, and quantile 4 is $7604 million. Under the descriptive statistics, as the size increases, the bid-ask spread shows decreasing. This pattern is consistent with Chordia et al. (2001) and Jones(2002) that documents that bid-ask spreads of US equities decline substantially over the past decade. The same is the case for expense ratio, historical volatility, and the CAPM alpha. On the other hand, while size increases, the trading volume, net asset value (NAV), age, the number of holdings, the number of shares outstanding, and the premium or discount are increasing. I do not see a consistent pattern for historical volatility. The variables of interest are reported in the appendix table 'Variable Selection.'

The subsequent univariate analysis is to examine the correlation matrix. Table 2 reports the correlation matrix among the fund attributes and the lagged asset returns. I take cross-sectional correlations on monthly data and report the time-series averages of the cross-sectional correlations.

[46] See Hameed et al. (2010)

Table 2 - Correlation Matrix

Table 2 present the correlation matrix of the variables of interests TNA is the total net assets under management in millions of dollars. Expense Ratio is the total annual management fees and expenses divided by year-end TNA. Liquidity is proxied from normalized bid-ask price spread. Flow is the percentage of new fund flow into the Exchange Traded Fund over period under investigation. Age is the number of years since the establishment of the ETF. The number of Holdings is the number of stocks in an ETF. NAV is the net asset value. Volume Turn Over is the total trade transactions that occurred in a month. Historical Volatility is the five-year standard deviation of the asset return. Premium/Discount is the difference of the NAV and the current market value of the ETFs. Lagged variables indicated are the previous time period value for the respective variables. Gross excess return is the asset return minus risk free rate before expense ratio, and the Net Asset Return is the monthly ETF return after expense ratio. The ETF sample is from January 2009 to December 2018. I include non-leveraged equity only ETFs with TNA more than $15 million.

	TNA	LogTNA	Expratio	AGE	TradVol	NHoldings	HistVol	NBASpread	NAV	NetExcRet	alpha_capmp	lagRet	LagFlow
TNA	1												
LogTNA	0.5097	1											
Expratio	-0.1372	-0.2502	1										
AGE	0.2746	0.4713	-0.1247	1									
TradVol	0.5749	0.3437	-0.037	0.2406	1								
NHoldings	0.1569	0.2643	-0.2101	0.012	0.0495	1							
HistVol	-0.0473	-0.1036	0.1423	0.1761	0.1006	-0.1777	1						
NBASpread	-0.0239	-0.0802	0.0329	-0.0401	-0.0181	-0.0165	0.0331	1					
NAV	0.3534	0.4178	-0.2506	0.367	0.084	0.1288	-0.1524	-0.0502	1				
NetExcRet	-0.0153	-0.0016	-0.0755	0.1015	-0.0043	0.0248	0.1147	-0.0142	-0.0096	1			
Alpha_capmp	0.0826	0.2459	-0.2983	0.3923	0.032	0.0793	0.0385	-0.0428	0.2363	0.5211	1		
LagRet	0.009	0.0129	-0.0092	0.0108	-0.0062	0.0014	-0.0039	-0.0076	0.0211	0.3155	0.0294	1	
LagFlow	-0.0022	-0.0051	0.0029	-0.0026	-0.0021	-0.0035	-0.0058	-0.0005	-0.0066	-0.0011	-0.0042	0.0016	1.0000

As observed in the table, TNA and log(TNA) have similar relationships with other variables. The expense ratio, historical volatility, normalized bid-ask spread, net excess return, and the lagged fund flow have a negative relation with the size. On the other hand, age, trading volume, number of holdings, NAV, CAPM alpha, and lagged gross return have a positive relationship with the size. Similarly, the normalized bid-ask spread has an inverse relation with turnover, the number of holdings, and it has a direct relation with expense ratio, nav, age, historical volatility, and asset return. Likewise, expense ratio has a positive relation with fund flow and historical volatility, and it has a negative relation with turnover ratio, nav, age, number of holdings, and asset return.

4 EMPIRICAL

Zhu (2018) suggests that the natural log of FUNDSIZE is a better measure to study the scale effect because of severe (positive) skewness in dollar FUNDSIZE. As such, I use the log of the total net asset (logTNA) as a proxy for the ETF size. Following a similar line of literature, including Zhu's paper, the base model is as shown below :

$$riskadjusted\ alpha = \alpha + \beta(LogTNA_{i,t}) + \mathrm{u}_{i,t}$$

As the paper explains, this model allows for $\beta = 0$, which is constant returns to scale, and $\beta > 0$, which is economies of scale. The paper argues that these two situations are theoretically unrealistic because a non-negative β implies that a fund's investment strategy is infinitely scalable. According to the paper, a large fund would become the market and hence a zero-gross alpha. Likewise, $\beta < 0$ is considered a diminishing return to scale. In the model, the dependent variable is the risk-adjusted return, and the independent variable is the ETF size proxied by the log of the total net asset. The term $\mathrm{u}_{i,t}$ represents the unobserved variable and the error term together. I extend this base model, as shown in equation 3.

Chen et al. (2004) explain that the fixed-effect approach is subject to a regression to the 'mean bias.' The paper caution that a fund with a year or two of lucky performance will experience an increase in fund size, but performance regress to the mean, will lead to a spurious conclusion that an increase in fund size is related to a decrease in fund returns. The paper claims that measuring the effect of fund size on performance using cross-sectional regressions is less subject to such bias. Therefore, I chose quantile and the cross-sectional regression for empirical research. I adopt two main approaches based on the extant literature: first, as a preliminary analysis, I use a cross-sectional regression approach, and then I use a quantile regression approach to investigate the scale effect in a more detailed setting. I use quantile regression to study the scale impact on the tracking error as well.

Study 1: Scale Effect on ETFs Performance - Cross-Sectional Regression Approach

In this approach, the purpose is to analyze the performance of ETF securities through the lens of the expected return theory, such as the Capital Asset Pricing Model (CAPM) and Factor-Based Asset Pricing model. The factor values and the risk-free rate are from the Fama French website. Asset Return is the monthly ETF return. I calculate the excess return as asset return minus the risk-free rate.

There are two steps involved in the process. First, I run the factor regressions, as shown in equations one and two below:

CAPM: $R_i - R_f = \alpha_i + b_i\,(R_m - R_f) + \varepsilon_i$ --- (1)

4-Factor Carhart: $R_i - R_f = \alpha_i + b_i\,(R_m - R_f) + s_i$ SMB + h_i HML + w_i WML + ε_i --- (2)

Where: $R_i - Net\ asset\ return,\quad R_f - Risk\ free\ rate\ proxied\ by\ 30\ day\ treasury\ note$

Then I save the estimated constant of the above regression generating the rolling estimated monthly alpha distributions for each ETF in the dataset. Once I have the alpha distribution for each fund, I then perform the cross-sectional regression using risk-adjusted factor-alpha that I get from equation 1 and equation 2 above as dependent variables, and the log of the total net asset as the leading independent variables. I add control variables in accordance with the related existing literature.

$riskadjusted\ alpha$ = α + $\beta(LogTNA_{i,t})$ + $\beta_{i,t}(X_{i,t})$+ $\varepsilon_{i,t}$, where, $X_{i,t}\ denotes\ the\ control\ variables$ + ε_i --- (3)

I run the regression on each of the ETFs size quantiles and present the results of equation 3 in Table 3. The Table provides information on how the performance benchmarks compare when the ETFs asset growth increases. If the alpha coefficient is positive, the expected excess return on the fund is automatically higher than the risk-adjusted market return.

Table 3 - Scale Effect on ETFs Performance (A Cross-sectional Approach)

Table 3 shows the cross-sectional regression estimates of the risk-adjusted alpha regressed on ETF size measured by total net asset size (logTNA). I use OLS regression (with clustered standard errors on ETFID) and Fama-MacBeth (1973) cross-sectional regression. TNA is the total net assets under management in millions of dollars. Expense Ratio is the total annual management fees and expenses divided by year-end TNA. Liquidity is proxied from normalized bid-ask price spread. Flow is the percentage of new fund flow into the Exchange Traded Fund over the period under investigation. Age is the number of years since the establishment of the ETF. The number of Holdings is the number of stocks in an ETF. NAV is the net asset value. Volume Turn Over is the total trade transactions that occurred in a month. Historical Volatility is the five-year standard deviation of the asset return. Premium/Discount is the difference of the NAV and the current market value of the ETFs. Lagged variables indicated are the previous time period value for the respective variables. Net Excess Return is the monthly ETF return after the expense ratio. The ETF sample is from January 2009 to December 2018. I include non-leveraged equity, only ETFs with TNA more than \$15 million. The dependent variables are risk-adjusted alpha (CAPM and Carhart four-factor). The main independent variable is the size of the asset under management measured by log(TNA), and control variables are Expense Ratio, Fund Age, Liquidity, Trading Volume Turnover, Number of Holdings, Historical Volatility, Lagged Excess Return, and the Lagged Fund Flow. Each regression in Panel A and Panel B is run on four size quantiles. Panel A is from the Fama-McBeth regression. Panel B is the result of the OLS regression. The first four columns are for CAPM Alpha, and the second four columns are for Carhart Four Factor Alpha. In both cases, the log of total net asset is the proxy for fund size and is the main independent variable. I control for different investment styles and fund types dummies, as shown in the table.

Table 3 Panel A : Fama McBeth(1973) Cross-Sectional Regression by Size Quantiles

	(1) CAPM_Alpha	(2) CAPM_Alpha	(3) CAPM_Alpha	(4) CAPM_Alpha	(5) Carhart Alpha	(6) Carhart Alpha	(7) Carhart Alpha	(8) Carhart Alpha
LogTNA	0.656***	0.274***	0.211***	-0.0333	0.570***	0.293***	0.192***	0.00843
	(5.56)	(4.73)	(6.28)	(-1.11)	(4.89)	(5.02)	(6.63)	(0.37)
Expratio	-0.871***	-1.049***	-1.085***	-0.536***	-0.972***	-1.202***	-1.194***	-0.552***
	(-6.91)	(-29.42)	(-21.06)	(-7.11)	(-9.61)	(-20.66)	(-23.37)	(-7.20)
AGE	0.200***	0.0897**	0.0537*	0.0530***	0.171***	0.0787**	0.0567*	0.0516***
	(4.54)	(3.08)	(2.30)	(6.70)	(3.85)	(2.95)	(2.65)	(8.64)
LogTVOL	-0.178***	-0.147***	-0.112***	-0.0804***	-0.183***	-0.151***	-0.112***	-0.0830***
	(-5.39)	(-5.83)	(-6.75)	(-6.23)	(-4.75)	(-5.80)	(-7.69)	(-6.22)
NHoldings	-0.000118	-0.000228***	-0.0000577*	0.000224	-0.000309*	-0.000284***	-0.000107***	-0.000268**
	(-1.11)	(-12.56)	(-2.17)	(1.42)	(-2.52)	(-13.43)	(-4.26)	(-2.69)
NBASpread	-26.69***	-69.84***	-101.6***	-135.0***	-38.51***	-81.33***	-95.99***	-188.3***
	(-3.62)	(-11.02)	(-7.52)	(-5.50)	(-5.98)	(-9.66)	(-6.77)	(-6.24)
PremDisc	-0.0870	0.0159***	-0.0272	0.00435	-0.0727	0.0224***	-0.0487	0.00510
	(-1.16)	(7.00)	(-1.08)	(1.44)	(-0.71)	(8.87)	(-1.50)	(1.85)
LNetExRetPctg	0.0456***	0.0309***	0.0240***	0.0190	0.0368***	0.0260***	0.0181**	0.0123*
	(6.40)	(4.30)	(3.80)	(1.79)	(5.22)	(4.01)	(3.19)	(2.24)
HistVol	-2.725***	-1.011	-1.533***	-0.273*	-2.958***	-0.612	-1.743***	-0.0160
	(-7.10)	(-1.86)	(-4.38)	(-2.60)	(-6.78)	(-1.15)	(-4.98)	(-0.15)
GrowthDum	0.204	0.867***	1.042***	0.328***	0.156	0.796***	0.977***	0.338***
	(1.02)	(12.51)	(16.77)	(6.98)	(1.38)	(12.38)	(16.53)	(7.12)
ValueDum	0.717***	0.613***	0.764***	0.198***	0.790***	0.583***	0.747***	0.225***
	(4.78)	(6.95)	(12.15)	(6.00)	(5.14)	(6.61)	(11.36)	(6.35)
CoreDum	0.395***	0.488***	0.740***	0.225***	0.362***	0.536***	0.771***	0.242***
	(7.61)	(5.33)	(8.53)	(6.64)	(9.89)	(5.66)	(8.69)	(6.86)
IndCapWtD	0.129	-0.0585*	-0.0438*	-0.0418**	0.0676	-0.149***	-0.0501**	-0.0373**
	(1.64)	(-2.22)	(-2.53)	(-3.34)	(0.68)	(-3.75)	(-2.96)	(-3.24)
IndEqWtD	0.130**	-0.0314	0.218***	0.162***	0.0676	-0.125***	0.198***	0.162***

	(2.93)	**(-1.52)**	**(8.57)**	**(6.35)**	**(0.94)**	**(-4.70)**	**(7.29)**	**(6.41)**
_cons	**-4.189*****	**-1.697***	**-1.474***	**-0.0993**	**-3.172*****	**-1.497***	**-1.312***	**-0.108**
	(-4.17)	**(-2.60)**	**(-2.66)**	**(-0.74)**	**(-3.55)**	**(-2.40)**	**(-2.62)**	**(-0.81)**
N	**8948**	**10460**	**11539**	**12828**	**7624**	**9614**	**11024**	**11806**
adj. R-sq	**0.4926**	**0.5671**	**0.5100**	**0.7668**	**0.4919**	**0.5575**	**0.5139**	**0.7668**

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B: OLS by Size Quantiles

	(1) AlphaCAPM	(2) AlphaCAPM	(3) AlphaCAPM	(4) AlphaCAPM	(5) AlphaCarhart	(6) AlphaCarhart	(7) Alpha_Carhart	(8) Alpha_Carhart
LogTNA	**0.488*****	**0.184*****	**0.205*****	**0.117*****	**0.375*****	**0.218*****	**0.166*****	**0.106*****
	(8.77)	**(4.55)**	**(6.80)**	**(12.24)**	**(6.17)**	**(5.23)**	**(5.54)**	**(10.48)**
Expratio	**-0.740*****	**-0.969*****	**-1.050*****	**-1.092*****	**-0.728*****	**-1.001*****	**-1.141*****	**-1.118*****
	(-16.63)	**(-42.26)**	**(-24.72)**	**(-27.77)**	**(-16.09)**	**(-43.65)**	**(-26.99)**	**(-27.11)**
AGE	**0.297*****	**0.141*****	**0.0979*****	**0.0620*****	**0.276*****	**0.130*****	**0.0979*****	**0.0670*****
	(44.38)	**(38.17)**	**(33.64)**	**(38.01)**	**(37.70)**	**(33.96)**	**(34.01)**	**(39.71)**
LogTVOL	**-0.0820*****	**-0.0892*****	**-0.0821*****	**-0.149*****	**-0.108*****	**-0.0895*****	**-0.0768*****	**-0.134*****
	(-3.74)	**(-7.04)**	**(-8.23)**	**(-24.57)**	**(-4.50)**	**(-6.91)**	**(-7.72)**	**(-21.12)**
NHoldings	**0.000314*****	**-0.0000958***	**0.0000105**	**-0.0000158***	**0.000105**	**-0.000179*****	**-0.0000126**	**-0.0000228****
	(3.68)	**(-2.54)**	**(0.47)**	**(-2.17)**	**(1.09)**	**(-4.63)**	**(-0.49)**	**(-2.67)**
NBASpread	**-5.010***	**-1.586***	**-1.524**	**-1.494**	**-10.13*****	**-1.550**	**-1.439**	**-1.913***
	(-2.54)	**(-2.40)**	**(-1.82)**	**(-1.93)**	**(-3.31)**	**(-1.61)**	**(-1.77)**	**(-2.39)**
lnVIX	**-0.661*****	**-0.200*****	**-0.220*****	**-0.140*****	**-0.675*****	**-0.146****	**-0.165*****	**-0.0461**
	(-7.22)	**(-3.78)**	**(-4.76)**	**(-5.20)**	**(-6.78)**	**(-2.66)**	**(-3.60)**	**(-1.63)**
PremDisc	**0.0461*****	**-0.0000826**	**0.00476***	**0.00582*****	**0.0473*****	**0.00711**	**0.00630****	**0.00702*****
	(3.91)	**(-0.02)**	**(2.01)**	**(3.99)**	**(3.39)**	**(1.57)**	**(2.60)**	**(4.28)**
LNetExRetPctg	**0.178*****	**0.129*****	**0.121*****	**0.0955*****	**0.175*****	**0.125*****	**0.118*****	**0.0967*****
	(62.19)	**(74.42)**	**(79.88)**	**(106.11)**	**(55.92)**	**(69.77)**	**(78.24)**	**(102.59)**
LagFlow	**-0.00162**	**-0.000318**	**0.000109**	**-0.000273**	**0.000477**	**-0.000308**	**0.000170**	**-0.000279**
	(-1.10)	**(-0.42)**	**(0.22)**	**(-0.71)**	**(0.18)**	**(-0.41)**	**(0.36)**	**(-0.72)**
GrowthDum	**0.784*****	**0.782*****	**0.974*****	**0.598*****	**0.838*****	**0.737*****	**0.948*****	**0.665*****
	(4.51)	**(10.41)**	**(15.86)**	**(18.79)**	**(4.66)**	**(9.72)**	**(15.47)**	**(19.28)**
ValueDum	**0.646*****	**0.425*****	**0.668*****	**0.363*****	**0.876*****	**0.450*****	**0.683*****	**0.456*****
	(4.53)	**(6.31)**	**(10.62)**	**(11.15)**	**(5.85)**	**(6.58)**	**(10.86)**	**(12.98)**
CoreDum	**0.0558**	**0.336*****	**0.522*****	**0.371*****	**0.0931**	**0.397*****	**0.569*****	**0.439*****
	(0.94)	**(10.49)**	**(17.97)**	**(20.28)**	**(1.38)**	**(11.35)**	**(18.52)**	**(19.94)**
IndCapWtD	**0.228*****	**-0.0860****	**-0.129*****	**-0.0759*****	**0.246*****	**-0.171*****	**-0.125*****	**-0.0687*****
	(4.57)	**(-2.92)**	**(-5.04)**	**(-4.13)**	**(4.52)**	**(-5.63)**	**(-4.95)**	**(-3.66)**
IndEqWtD	**0.123**	**-0.109****	**0.128****	**0.370*****	**0.143***	**-0.191*****	**0.103****	**0.396*****
	(1.80)	**(-2.85)**	**(3.19)**	**(12.05)**	**(1.98)**	**(-4.88)**	**(2.59)**	**(12.07)**
_cons	**-3.181*****	**-1.458*****	**-1.432*****	**-0.0746**	**-2.297*****	**-1.549*****	**-1.299*****	**-0.396*****
	(-10.28)	**(-6.05)**	**(-6.41)**	**(-0.79)**	**(-6.79)**	**(-6.22)**	**(-5.82)**	**(-3.99)**
N	**8506**	**9966**	**11074**	**12310**	**7259**	**9180**	**10563**	**11379**
adj. R-sq	**0.486**	**0.531**	**0.500**	**0.602**	**0.474**	**0.528**	**0.510**	**0.607**

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I mainly use the regression framework proposed by Fama McBeth (1973), to study the impact of size on risk-adjusted fund alpha. Table 3 Panel A reports the results. I estimate a cross-sectional regression of risk-adjusted alpha and report the average regression coefficients. I adjust the t-statistics for the serial correlation using the Newey-West Method. I provide evidence that both CAPM alpha and four-factor Carhart alpha are positively related to ETF size; however, the size impact shows a distinct decreasing pattern as the size quantile grows. The findings support the existing literature such as Yan (2008), Harvey and Liu (2017), and Zhu (2018), among others, that provide evidence for the diminishing returns to scale.

As shown in Table 3, Panel A, on the largest size quantile, CAPM alpha has a negative relationship with the ETFs size. That means the largest ETFs have inferior performance compare to the risk-adjusted market return. Panel A also reports that expense ratio, the log of trading volume, illiquidity (as measured by normalized bid-ask spread), and historical volatility have a negative relation with the risk-adjusted returns. On the other hand, age, lagged asset return, investment styles such as value and blend, and equal-weighted index composition have a statistically significant positive relationship with the size. The literature also mentions that the Fama McBeth approach addresses the possible issue of other fund attributes correlating with the fund size[47].

As robust testing, I also use the pooled panel OLS regression (both robust and clustered standard error on the ETF ID). I find the same results from both the regressions - robust as well as the clustered standard error on ETFs. I report the results of panel OLS in Panel B. The coefficient of interest is the 'loading' on fund size (log of TNA), which captures the relationship between fund size and the fund performance, controlling for other fund attributes. The results in Panel B are comparable with the results in Panel A. In this case also, expense ratio, log of trading volume, illiquidity (as measured by normalized bid-ask spread), and historical volatility have a negative relation with the risk-adjusted returns. Likewise, age, lagged asset return, investment styles such as value, and blend have a statistically significant positive relationship with the size. The positive relation between the lagged fund return and fund risk-adjusted-

[47] See Chen et al(2004), Yan(2008)

performance indicates that there is some persistence in fund performance. The results are statistically significant at 0.1% level. The decreasing effect of size on fund performance is consistent in both Fama McBeth as well as in OLS results.

Chen et al. (2004) caution that there could be a problem when using a cross-sectional variation. The paper mentions that funds of different sizes may be in different styles. It explains that small funds might be more likely than large funds to pursue small stock, value stock, and price momentum strategies, which have been documented to generate abnormal returns. To address these issues, they suggest adjusting the fund performance by various benchmarks that can mitigate the heterogeneity in fund styles. As such, in the study, I cross-compare the benchmark adjusted returns using CAPM and the Carhart four-factor models. In addition, I control for investment style and fund style dummies in the regression. I find that the decreasing trend in size effect is consistent in both CAPM alpha as well as in Carhart four factor-alpha.

Study 2: Scale Effect on ETFs Performance - Quantile Regression Approach

Koenker and Basset (1978) introduce quantile regression, and it has been widely used in the finance literature, for example, Wang et al.(2015)[48] uses QR to study the risk analysis in mutual funds, likewise, Chen & Huang (2011)[49] investigates the relationship between fund governance and performance using quantile regression approach. The quantile regression is useful in situations where the relationship between the independent variable(s) and the dependent variable changes at different levels of the dependent variable or where the association between the dependent and independent variables is heterogeneous. Likewise, quantile regression does not impose the assumptions of homogeneity and normality in the dependent variable, and it is effective when the dependent variable is heteroscedastic and/or highly skewed.

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[48] See Wang, N-Y., Chen, S-S., Huang, C-J., & Yen, C-H., (2015). “Using Quantile Regression to Analyze Mutual Fund Risk and Investor Behavior of Variable Life Insurance”. International Journal of Economics and Finance, 7(1), pp.97-106.

[49] See Chen, C. R., & Huang, Y., (2011). “Mutual Fund Governance and Performance: A Quantile Regression Analysis of Morningstar's Stewardship Grade”. Corporate Governance: An International Review, 19(4), pp.311-333

Highlighting the importance of quantile regression approach, Koenker, R. and Hallock, K. (2001) cites Mosteller and Tukey (1977)50 to suggest that "one can do better by computing several regression curves corresponding to the various percentage points of the distributions and get a complete picture of the data set." Accordingly, I use the quantiles to describe the distribution of the dependent variable (in this case, factor risk-adjusted alphas) against the explanatory variables. It is an appropriate method to study the different effects of the independent variable(s) on the dependent variable[51]. Therefore, I think that quantile regression is a better fit for empirical research as well because it gives a more comprehensive picture of the effect of the scale effect on the ETF performances. I reference the actual quantile regression model from Koenker and Basset (1978) as follows[52]:

The θth regression quantile, 0 < θ < 1 is defined as any solution to the minimization problem:

$$Min\ b\epsilon R^K \left[\sum_{t\epsilon\{t:y_t > x_t b\}} \theta\left|y_t - x_t b\right| + \sum_{t\epsilon\{t:y_t > x_t b\}}(1-\theta)\left|y_t - x_t b\right| \right]$$

Where $\theta\epsilon\ (0,1)$, $\{x_t : t = 1, \dots\dots, T\}$ denote sequence of (row) K-vectors of a known design matrix, and $\{y_t : t = 1, \dots\dots, T\}$ is a random sample on the regression process $u_t = y_t - x_t\,\beta$.

The classical OLS minimizes the sum of squared residuals, whereas, in the quantile regressions, I minimize the weighted sum of absolute deviations[53]. According to Tchamyou et al. (2017) the conditional quantile of the dependent variable or y_t given x_t is $Q_y\ (\theta/x_t)$ = $x'_t\beta_0$ where unique slope parameters are modeled for each θ^{th} specific quantiles. Tchamyou et al. implies that this formulation is analogous to E(y/x) = $x'_t\beta$ in the OLS slope where parameters are examined only at the mean of the conditional distribution of the dependent variable.

Further, I conduct a heteroscedasticity test to justify the use of quantile regression. I find that the Breusch-Pagan test statistic is significantly different from zero. Therefore, I have

[50] See page 12 in Koenker, R. and Hallock, K. (2001) Quantile Regression. Journal of Economic Perspectives, 15, 143-156.
[51] Note that, if the dependent variable is normally distributed, quantile regression will generate the same coefficient estimates at different estimates at different conditional percentiles of the dependent variable in which case it provides no additional information compare to classical OLS.
[52] See page 38 in Koenker and Basset (1978)
[53] See page 10 in S. Tchamyou, Vanessa and Asongu, Simplice, Conditional Market Timing in the Mutual Fund Industry (January 2017). Research in International Business and Finance, 42 (December), pp.1355-1366 (2007).

heteroscedasticity in the dataset that justifies the use of quantile regression. In section A below, I perform the quantile regression for the risk-adjusted alpha, and in section B, I perform the quantile regression for the tracking error.

Section A: Scale Effect on ETFs Risk-Adjusted Performance

I estimate the quantile regressions at the 10th, 25th, 50th, 75th, and 90th percentile to find the scale impact on ETFs with varying degrees of performances. The dependent variables are the risk-adjusted alpha that I generated using equation 1 (for CAPM alpha) and in equation 2 (for Carhart alpha). I use the same model as in equation 3 for the quantile regression as well. The results of the OLS and the quantile regressions are in Table 4.

Table 4 Scale Effect on the Risk Adjusted ETFs Performance - A Quantile Regression Approach

Table 4 reports quantile regression results for the risk-adjusted ETFs performance as measured by CAPM alpha as in Panel A, and the four-factor Carhart alpha as in Panel B. The first column?(spec1) in each panel is from the OLS regression, and the next five columns each are the results of the quantile regression performed on 10th, 25th, 50th, 75th, and 90th percentiles. The dependent variables are the CAPM alpha in Panel A, and the four-factor Carhart alpha in Panel B. The main independent variable is the ETF size. TNA is the total net assets under management in millions of dollars. LogTNA is the logarithm of TNA and is a proxy for ETF size. Expense Ratio is the total annual management fees and expenses divided by year-end TNA. Liquidity is proxied from normalized bid-ask price spread. Flow is the percentage of new fund flow into the Exchange Traded Fund over the period under investigation. Age is the number of years since the establishment of the ETF. Number of Holdings is the number of stocks in a ETF. NAV is the net asset value. Volume Turn Over is the total trade transactions that occurred in a month. Historical Volatility is the five-year standard deviation of the asset return. Lagged variables indicated are the previous time period value for the respective variables. This table provides information on how ETFs risk-adjusted performances (measured by CAPM alpha as in Panel A, four-factor Carhart alpha as in Panel B) are impacted by the ETF size under different quantiles.

Table 4 – Panel A {Dependent Variable - **CAPM alpha**)

	(1-OLS) CAPM Alpha	(1-QReg 10th) CAPM Alpha	(2-QReg 25th) CAPM Alpha	(3-QReg 50th) CAPM Alpha	(4-QReg 75th) CAPM Alpha	(5-QReg 90th) CAPM Alpha
LogTNA	0.202***	0.426***	0.281***	0.138***	0.0288***	-0.0608***
	(26.14)	(27.99)	(35.23)	(22.96)	(4.87)	(-6.70)
Expratio	-0.886***	-0.762***	-0.914***	-1.014***	-1.015***	-1.027***
	(-50.32)	(-21.89)	(-50.22)	(-73.96)	(-75.09)	(-49.56)
AGE	0.120***	0.149***	0.114***	0.0751***	0.0426***	0.00917***
	(66.11)	(41.55)	(60.97)	(53.24)	(30.63)	(4.30)
LogTVOL	-0.133***	-0.331***	-0.229***	-0.123***	-0.0394***	0.0290***
	(-21.34)	(-26.88)	(-35.54)	(-25.40)	(-8.25)	(3.96)
NBASpread	-2.669***	-19.16***	-6.054***	-2.531***	-1.216**	-0.837
	(-5.22)	(-18.98)	(-11.46)	(-6.36)	(-3.10)	(-1.39)
lnVIX	-0.245***	-0.768***	-0.269***	-0.0104	0.147***	0.161***
	(-8.59)	(-13.65)	(-9.14)	(-0.47)	(6.71)	(4.81)
PremDisc	0.00755***	0.0125***	0.00870***	0.00580***	0.00441**	0.00132
	(4.32)	(3.63)	(4.81)	(4.26)	(3.28)	(0.64)
LNetExRetPctg	0.130***	0.129***	0.113***	0.104***	0.0983***	0.0972***
	(140.45)	(70.43)	(117.79)	(144.43)	(137.94)	(89.01)
LagFlow	-0.000525	-0.00267***	-0.0000888	-0.000317	-0.0000665	-0.000283
	(-1.40)	(-3.60)	(-0.23)	(-1.09)	(-0.23)	(-0.64)
NHoldings	-0.0000120	0.00000393	-0.0000222	-0.0000328***	-0.0000308***	-0.0000572***
	(-1.05)	(0.17)	(-1.87)	(-3.67)	(-3.50)	(-4.24)
GrowthDum	0.642***	0.00243	0.275***	0.664***	0.900***	1.027***
	(16.88)	(0.03)	(6.98)	(22.42)	(30.83)	(22.94)
ValueDum	0.331***	-0.280***	-0.0672	0.369***	0.669***	0.872***
	(9.03)	(-3.87)	(-1.77)	(12.92)	(23.76)	(20.20)
CoreDum	0.268***	-0.270***	-0.0535**	0.279***	0.640***	0.838***

	(14.81)	(-7.56)	(-2.86)	(19.80)	(46.10)	(39.37)
IndCapWtD	-0.0940***	-0.121***	-0.120***	-0.104***	-0.0885***	-0.0524**
	(-5.83)	(-3.81)	(-7.18)	(-8.32)	(-7.15)	(-2.76)
IndEqWtD	0.101***	-0.151**	-0.00203	0.121***	0.143***	0.195***
	(4.30)	(-3.23)	(-0.08)	(6.57)	(7.87)	(7.02)
_cons	-1.172***	-0.901***	-1.100***	-0.863***	-0.630***	0.115
	(-14.32)	(-5.57)	(-12.99)	(-13.54)	(-10.02)	(1.19)
N	41856	41856	41856	41856	41856	41856
adj. R-sq	0.478					
Pseudo R2		0.3983	0.3720	0.3623	0.2797	0.2970

Table 4 Panel B: *Dependent Variable* ***<u>Carhart Four Factor Alpha</u>****:*

	(1-OLS) Carhart Alpha	(1-QReg 10th) Carhart Alpha	(2-QReg 25th) Carhart Alpha	(3-QReg 50th) Carhart Alpha	(4-QReg 75th) Carhart Alpha	(5-QReg 90th) Carhart Alpha
LogTNA	0.195***	0.412***	0.275***	0.153***	0.0400***	-0.0628***
	(24.80)	(27.08)	(34.12)	(24.86)	(6.38)	(-5.91)
Expratio	-0.916***	-0.803***	-0.966***	-1.057***	-1.026***	-1.048***
	(-52.77)	(-23.89)	(-54.35)	(-77.69)	(-74.11)	(-44.67)
AGE	0.113***	0.143***	0.114***	0.0800***	0.0494***	0.0129***
	(61.94)	(40.45)	(60.94)	(55.85)	(33.86)	(5.24)
LogTVOL	-0.125***	-0.326***	-0.226***	-0.133***	-0.0415***	0.0425***
	(-19.74)	(-26.65)	(-35.00)	(-26.79)	(-8.23)	(4.98)
NBASpread	-3.141***	-22.57***	-9.797***	-4.656***	-1.232*	-1.015
	(-5.10)	(-18.94)	(-15.55)	(-9.65)	(-2.51)	(-1.22)
lnVIX	-0.187***	-0.664***	-0.223***	0.0521*	0.227***	0.275***
	(-6.46)	(-11.87)	(-7.52)	(2.30)	(9.82)	(7.03)
PremDisc	0.00930***	0.0112**	0.0101***	0.0101***	0.00771***	0.00329
	(5.05)	(3.14)	(5.34)	(6.99)	(5.25)	(1.32)
LNetExRetPctg	0.128***	0.129***	0.111***	0.103***	0.0969***	0.0957***
	(135.41)	(70.78)	(115.20)	(139.82)	(128.94)	(75.22)
LagFlow	-0.000132	0.000115	-0.000106	-0.000231	0.0000115	-0.000212
	(-0.34)	(0.16)	(-0.27)	(-0.77)	(0.04)	(-0.41)
NHoldings	-0.0000318*	-0.000000443	-0.0000251	-0.0000416***	-0.0000543***	-0.0000814***
	(-2.49)	(-0.02)	(-1.92)	(-4.16)	(-5.34)	(-4.73)
GrowthDum	0.683***	0.137	0.323***	0.629***	0.839***	0.940***
	(17.86)	(1.85)	(8.25)	(20.95)	(27.48)	(18.19)
ValueDum	0.435***	-0.0823	0.0548	0.400***	0.658***	0.839***
	(11.75)	(-1.15)	(1.45)	(13.79)	(22.30)	(16.79)
CoreDum	0.344***	-0.146***	0.0276	0.337***	0.641***	0.804***
	(17.43)	(-3.81)	(1.37)	(21.77)	(40.67)	(30.14)
IndCapWtD	-0.107***	-0.111***	-0.134***	-0.128***	-0.108***	-0.0262

	(-6.58)	(-3.54)	(-8.08)	(-10.05)	(-8.33)	(-1.20)
IndEqWtD	0.100***	-0.154***	-0.0213	0.0857***	0.0841***	0.173***
	(4.21)	(-3.34)	(-0.87)	(4.59)	(4.43)	(5.39)
_cons	-1.217***	-0.987***	-1.127***	-1.053***	-0.890***	-0.207
	(-14.58)	(-6.11)	(-13.18)	(-16.09)	(-13.36)	(-1.84)
N	38381	38381	38381	38381	38381	38381
Adj. R2	0.4871					
Pseudo R2		0.3993	0.3721	0.3323	0.2758	0.2075

In the table, there are two types of significant coefficients: those that are significantly different from zero, and those that are significantly different from the OLS coefficients (outside of the confidence interval). The graphical visual is more intuitive than in the table to see the differences. For example, the coefficient on the log(TNA) at the 10th, 25th, 50th, and 75th quantiles are significantly different from zero. The coefficient on the log(TNA) on the 10th and 90th percentiles are also significantly different from the OLS coefficient. The quantile regression results in Table 4-Panel A for CAPM and Panel B for the Carhart four-factor model clearly show that the size effect is different for low performing vs. high performing ETFs clusters. The results in both the panels have a monotonously decreasing coefficients representing the size impact differentials on the increasing order of risk-adjusted performance percentiles. The tables also show that ETFs size negatively impacts the high performing ETFs in sharp contrast to the lower performing ETF quantiles.

Size has a strong positive impact on the individual ETFs belonging to the lowest end of the quantiles. The observations are consistent in both the panels CAPM and Carhart four-factor risk-adjusted-performance. In Panel A, the first specification is from the panel OLS; the second, third, fourth, fifth, and sixth specifications are from the quantile regression corresponding to the 10th, 25th, 50th, 75th, and 90th percentile of CAPM alpha. As shown from the table, at the 10th percentile, it has a positive coefficient of 0.429 whereas at the 90th percentile, it is negative 0.0634. Clearly, high performing ETFs have an inverse relation with the size, whereas the low performing ETFs have a positive relationship with the size. When it comes to expense ratio, it has a negative relationship with the alpha in all the quantiles; however, the high performing ETFs alpha has a stronger negative relationship with the expense ratio. When it comes to illiquidity, the highest performing percentile ETFs have the least negative impact of illiquidity, where is the lowest-performing percentile has the strongest negative impact of illiquidity. The results are very similar in Panel B for the Carhart four factor-alpha.

I present the coefficients from the quantile regressions in the graphs. As shown in the figures for Table 4 Panels A(figure 2) and B(figure 3), the quantiles of the dependent variable are on the horizontal axis and the coefficient magnitudes on the vertical axis. The OLS coefficient is plotted as a horizontal line with the confidence interval (see two horizontal lines around the coefficient line). The OLS coefficient does not vary by quantiles. The quantile regression coefficients are plotted as lines varying across the quantiles with confidence intervals around them. If the quantile coefficient is outside the OLS confidence interval, then I have significant differences between the quantile and OLS coefficients. The graph shows that the quantile coefficients for the independent variable (log of TNA) on risk-adjusted alpha (dependent variable) are significantly different from the OLS coefficients. Moreover, the effect of the log of TNA gradually decreases along the quantiles for individual ETFs with lower performance to individual ETFs with higher performance.

Figure 2 - Quantile Graphs from CAPM Regression

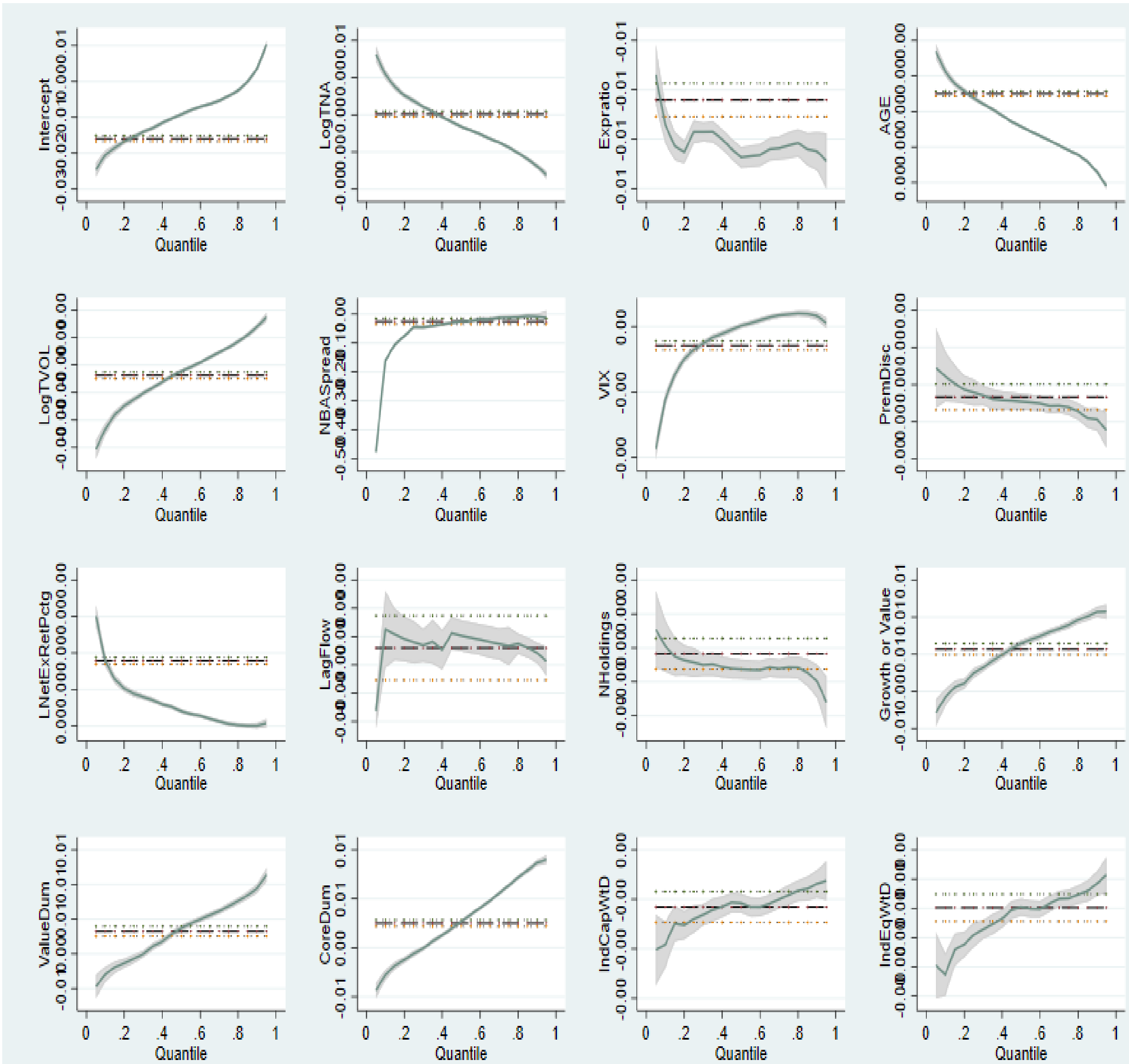
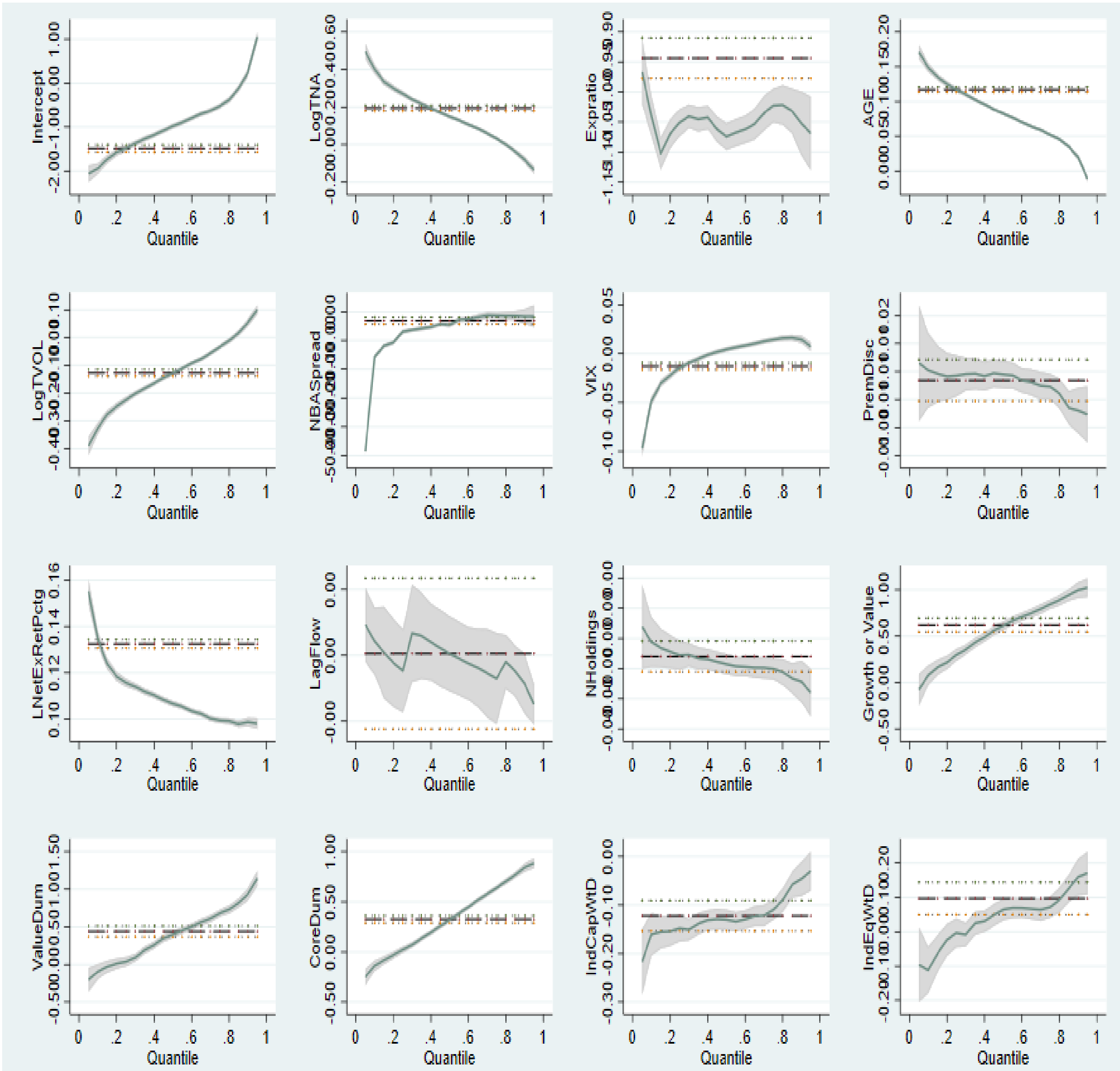


Figure 3 - Quantile Graphs from four factor Carhart Model



The results from the quantile regression is consistent with the results from the cross-sectional regression. I support Petajisto (2013) findings that larger funds are more likely to be closet indexers who earn inferior returns, implying that the indexation strategies employed by larger funds drive the poor returns earned by these funds.

Section B: Scale Effect on Tracking Error Performance

Wermers (2003) uses tracking error to measure fund performance and claims that it is positively related to the contemporaneous fund alpha. Cremers & Petajisto (2009), on the other hand, argue that tracking error represents the active share fraction of portfolio holdings that differ from the passive benchmark index, thus emphasizing stock selection. These papers study the index mutual funds, and the focus is on ETFs. I argue that tracking error is the volatility of fund return in excess of the benchmark, so it emphasizes beta risk. Therefore, it is important to see the scale effect on tracking errors as well.

I extend the following Rompotis (2012) model to estimate the tracking error :

$\boldsymbol{TE} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_2}\ \boldsymbol{lnTNA} + \boldsymbol{\alpha_3 Risk} + \boldsymbol{\alpha_4}\ \boldsymbol{discount\ or\ premium} + \boldsymbol{\alpha_5}\ \boldsymbol{spread} + \boldsymbol{\alpha_6}\ \boldsymbol{expense\ ratio} + \varepsilon$

where,

The tracking error is the dependent variable: σ_ε = Stdev $[\mathrm{R_{ETF}} - \mathrm{R_{BenchMarkIndex}}]$

*The discount or premium is the difference between the NAV – (price*shares outstanding).*

Risk is proxied using the historical volatility of the asset.

The main independent variable is the lagged asset size

Control variables are Expense Ratio, Liquidity, Flow, Age, Number of Holdings, NAV, Historical Volatility, and Lagged Fund Flow.

The results in Table 5 show that size has a marginal effect on the tracking ability of ETFs against their benchmark index. The 10th percentile of the TE has a stronger negative relationship with the size; however, other quantiles appears to be within the margin of a confidence interval. The coefficient of 'logTNA' is negative in all the quantiles that mean size has a marginal negative impact on the tracking error. The quantile graph(figure 4) underneath the table also clearly shows that the size effect is within the margin of the confidence interval. The illiquidity spread and the expense ratio both have statistically significant positive relation in all the quantiles that suggest higher the illiquidity spread higher the tracking error. The same is the case for the expense ratio that higher the expense ratio higher the tracking error.

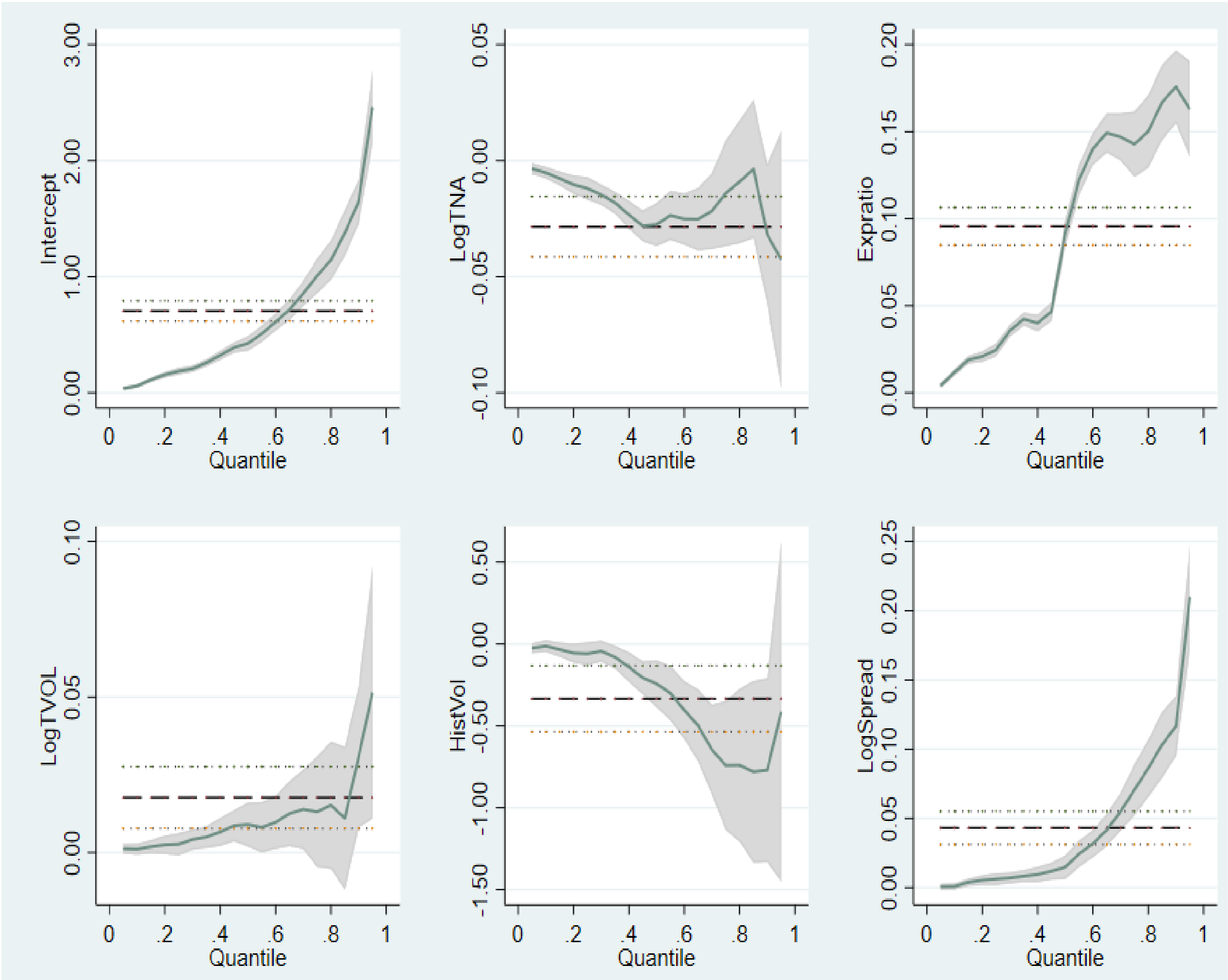
Table 5 -Impact of Size on Tracking Error

In this table, I investigate the impact of ETF size on the tracking error of ETFs. Tracking error is the std of differences between the ETF return percentage minus the underlying benchmark return percentage. The main independent variable is the ETF size measured by log of the total net asset(TNA) in millions of dollars. Expense Ratio is the total annual management fees and expenses divided by year-end TNA. Liquidity is proxied from normalized bid-ask price spread. Flow is the percentage of new fund flow into the Exchange Traded Fund over the period under investigation. Age is the number of years since the establishment of the ETF. The number of Holdings is the number of stocks in an ETF. NAV is the net asset value. Volume Turn Over is the total trade transactions that occurred in a month. Historical Volatility is the five-year standard deviation of the asset return. Premium/Discount is the difference of the NAV and the current market value of the ETFs. Lagged variables indicated are the previous time period value for the respective variables. The Net Asset Return is the monthly ETF return after the expense ratio. The ETF sample is from January 2009 to December 2018. I include non-leveraged equity, only ETFs with TNA more than \$15 million. I exclude the control variables that are statistically insignificant. I extend the following Rompotis (2012) model to estimate the tracking error: $\boldsymbol{TE} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_2}\ \boldsymbol{lnTNA} + \boldsymbol{\alpha_3 Risk} + \boldsymbol{\alpha_5}\ \boldsymbol{spread} + \boldsymbol{\alpha_6}\ \boldsymbol{expense\ ratio} + \varepsilon$ where the tracking error is σ_ε = Stdev $[R_{\text{ETF}} - R_{\text{BenchMarkIndex}}]$. Risk is proxied using the standard deviation of the five-year historical volatility of the asset returns. The first specification in the below is from the OLS regression, and the next five columns are from the quantile regression for the 10th, 25th, 50th, 75th, and the 90th percentiles.

	OLS	10th	25th	50th	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
	absTE	absTE	absTE	absTE	absTE	absTE
LogTNA	-0.0289***	-0.00516**	-0.0124***	-0.0290***	-0.0143	-0.0307
	(-4.34)	(-3.04)	(-4.83)	(-5.05)	(-1.34)	(-1.57)
Expratio	0.0954***	0.0117***	0.0246***	0.0907***	0.143***	0.177***
	(17.37)	(8.38)	(11.60)	(19.12)	(16.19)	(11.00)
HistVol	-0.357***	-0.0123	-0.0677	-0.261**	-0.781***	-0.786**
	(-3.44)	(-0.47)	(-1.69)	(-2.91)	(-4.70)	(-2.59)
LogTVOL	0.0187***	0.00110	0.00297	0.00971*	0.0143	0.0304*
	(3.68)	(0.85)	(1.51)	(2.22)	(1.76)	(2.04)
LogSpread	0.0442***	0.000810	0.00554*	0.0137**	0.0728***	0.118***
	(7.18)	(0.52)	(2.33)	(2.58)	(7.38)	(6.56)
_cons	0.711***	0.0595***	0.183***	0.426***	1.022***	1.656***
	(15.83)	(5.20)	(10.57)	(10.99)	(14.20)	(12.58)
N	3581	3581	3581	3581	3581	3581
adj. R-sq	0.4770	0.6400	0.6302	0.5040	0.6103	0.6345

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4 – Quantile Graphs from Tracking Error Regression



I reconfirm the results from the quantile regression in Table 5 with the regression using bootstrapped observations, and I find a consistent result. The results are similar to Chu (2009) study that documents that the magnitude of the tracking errors has a negative relation to the size of ETFs. Likewise, as I reported, Chu's paper also documents a positive relation to the expense ratios of the funds, and the results also support this finding.

Study 3: Interaction of investment factors on ETF size and their impact on the excess return performance

In Table 6, I study the interaction effects of the ETF size (log of TNA) with the various fund attributes, investment styles, and the fund types. I generalize the cross-sectional model with the interaction term as in equation 4.2 below in which excess return is the dependent variable, and the log of total net asset is the independent variable. Equation 4.1 reflects the base model with no interaction term.

R_i - R_f = α + β ($LogTNA_{i,t}$) + δ_i X_i + ε_i --- Equation (4.1)

R_i - R_f = α + β ($LogTNA_{i,t}$) + β_i * δ ($LogTNA_{i,t}$) * (Z_i) + δ_i X_i + ε_i --- Equation (4.2)

Where

$LogTNA_{i,t}$ *is the ETF size proxy*

Z_i *is the ineraction term for various fund attributes and dummies for investment styles and fund types*

X_i *represent the control variables*

I examine the interaction effect of 'Z_i' and log(TNA) on ETFs excess return performance where, 'Z_i' represent fund attributes such as liquidity, expense ratio, volume turnover, age, number of holdings, and historical volatility, and dummies for investment styles (such as growth, value, and core) and the fund types (such as small, medium and large-cap). Panel A of Table 6 reports the results for liquidity interaction, expense ratio interaction, trading volume interaction, age interaction, historical volatility interaction, and the number of holdings interaction. In the Table, specification 2, 3, 4, 5, 6 and 7 have the corresponding interaction term. Specification 1 is the base model without interactions. Likewise, Panel B of Table 6 reports the results for investment styles dummies – growth, value and core/blend, and the index composition dummies – capitalization weighted and the equal weighted composition. In the Table, specification 2, 3, 4, 5, and 6 has the corresponding interaction term. Specification 1 is the base models without interactions.

Table 6 Factors Affecting Size vs Performance Relationship

(Examining the interaction effect of various investment factors on the relationship between the ETF size and the net excess returns)

In table 6, I examine effect of interaction between the 'X_i' and the ETF size on its net excess return performance, where X_i are liquidity, expense ratio, trading volume, number of holdings, age and the historical volatility. I also included dummies for investment styles(value, growth, core blend), cap types(small, medium, large), and the index composition weight (equal weight, capitalization weight). I use cross-sectional OLS regression methodology as outlined in the following equations to study the interaction effects. TNA is the total net assets under management in millions of dollars. Expense Ratio is the total annual management fees and expenses divided by year-end TNA. Liquidity is proxied from normalized bid-ask price spread. Flow is the percentage of new fund flow into the Exchange Traded Fund over the period under investigation. Age is the number of years since the establishment of the ETF. The number of Holdings is the number of stocks in an ETF. NAV is the net asset value. Volume Turn Over is the total trade transactions that occurred in a month. Historical Volatility is the five-year standard deviation of the asset return. Premium/Discount is the difference between the NAV and the current market value of the ETFs. Lagged variables indicated are previous time period value for the respective variables. The Net Asset Return is the monthly ETF return after the expense ratio. The ETF sample is from January 2009 to December 2018. I include non-leveraged equity only ETFs with TNA more than $15 million. The dependent variable is the net excess return. The main independent variable is the size (Log of TNA). I exclude statistically non-significant effects.

	(1) BaseModel Net Excess Return	(2) Spread_Inter. Net Excess Return	(3) ExpRatio_Inter. Net Excess Return	(4) Trad.Vol_Inter. Net Excess Return	(5) Age Interaction Net Excess Return	(6) Vix Interaction Net Excess Return	(7) No. Of Hold Int. Net Excess Return
lntna	0.438***	-0.0620	0.485***	0.300***	-0.181***	0.387***	0.439***
	(32.75)	(-1.66)	(33.45)	(13.01)	(-5.11)	(6.10)	(32.61)
lnnbaspread	-0.219***	0.180***	-0.215***	-0.222***	-0.210***	-0.219***	-0.219***
	(-16.08)	(5.82)	(-15.81)	(-16.30)	(-15.56)	(-16.05)	(-16.08)
expratio	-0.193***	-0.186***	0.629***	-0.186***	-0.181***	-0.193***	-0.193***
	(-6.42)	(-6.21)	(6.08)	(-6.18)	(-6.07)	(-6.42)	(-6.42)
lnage	0.456***	0.458***	0.467***	0.458***	-1.043***	0.457***	0.456***
	(14.68)	(14.82)	(15.02)	(14.74)	(-12.25)	(14.69)	(14.67)
lntradingvol	-0.384***	-0.386***	-0.374***	-0.492***	-0.402***	-0.384***	-0.384***
	(-38.85)	(-39.21)	(-37.65)	(-27.85)	(-40.82)	(-38.86)	(-38.83)
lnnumberofholdings	-0.0322***	-0.0388***	-0.0373***	-0.0348***	-0.0414***	-0.0322***	-0.0301**
	(-4.11)	(-4.97)	(-4.76)	(-4.45)	(-5.32)	(-4.12)	(-3.22)
lnvix	0.186***	0.176***	0.182***	0.186***	0.196***	0.0711	0.186***
	(4.31)	(4.09)	(4.22)	(4.31)	(4.57)	(0.49)	(4.31)
lagnetexcessreturn	0.0639***	0.0637***	0.0624***	0.0658***	0.0622***	0.0638***	0.0639***
	(9.51)	(9.53)	(9.30)	(9.81)	(9.35)	(9.51)	(9.51)
growthdum	0.549***	0.543***	0.526***	0.564***	0.475***	0.549***	0.546***
	(9.45)	(9.39)	(9.06)	(9.70)	(8.22)	(9.44)	(9.27)

valuedum	0.171**	0.167**	0.154**	0.178**	0.0816	0.172**	0.168**
	(3.02)	(2.96)	(2.72)	(3.14)	(1.45)	(3.02)	(2.94)
coredum	0.112***	0.0987***	0.115***	0.104***	0.0778**	0.112***	0.110***
	(4.15)	(3.66)	(4.25)	(3.85)	(2.89)	(4.14)	(4.00)
indxcompcapwtdum	0.197***	0.181***	0.167***	0.194***	0.176***	0.197***	0.198***
	(7.99)	(7.36)	(6.69)	(7.85)	(7.19)	(7.98)	(8.00)
indxcompeqwtdum	0.195***	0.198***	0.178***	0.186***	0.197***	0.194***	0.196***
	(5.12)	(5.25)	(4.69)	(4.91)	(5.23)	(5.11)	(5.13)
lntnaspread_int		-0.0686***					
		(-14.37)					
lntnaexpratio_int			-0.165***				
			(-8.30)				
lntnatradingvol_int				0.0175***			
				(7.38)			
lntnaage_int					0.263***		
					(18.89)		
lntnavix_int						0.0192	
						(0.83)	
lntnanumberofholdings_int							-0.00000102
							(-0.40)
_cons	-3.329***	-0.433	-3.583***	-2.534***	0.356	-3.020***	-3.339***
	(-21.77)	(-1.72)	(-23.01)	(-13.56)	(1.44)	(-7.47)	(-21.53)
N	19780	19780	19780	19780	19780	19780	19780
adj. R-sq	0.193	0.201	0.196	0.195	0.207	0.193	0.193

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B (Interaction effect with investment styles dummies)

	(1) Base-Model	(2) Growth Interaction	(3) Value Interaction	(4) Core Interaction	(5) CapWted Interaction	(6) Equal Wted Interaction
	Net Excess Return	Net Excess Return	Net Excess Return	Net Excess Return	Net Excess Return	Net Excess Return
lntna	0.438***	0.434***	0.436***	0.394***	0.408***	0.438***
	(32.75)	(32.20)	(32.34)	(24.84)	(26.73)	(32.51)
lnnbaspread	-0.219***	-0.219***	-0.219***	-0.217***	-0.217***	-0.219***
	(-16.08)	(-16.11)	(-16.10)	(-15.96)	(-15.89)	(-16.07)
expratio	-0.193***	-0.193***	-0.193***	-0.195***	-0.187***	-0.193***
	(-6.42)	(-6.40)	(-6.41)	(-6.49)	(-6.20)	(-6.42)
lnage	0.456***	0.457***	0.454***	0.449***	0.452***	0.456***
	(14.68)	(14.71)	(14.60)	(14.44)	(14.52)	(14.68)
lntradingvol	-0.384***	-0.383***	-0.384***	-0.386***	-0.385***	-0.384***
	(-38.85)	(-38.71)	(-38.78)	(-39.06)	(-38.94)	(-38.77)
lnnumberofholdings	-0.0322***	-0.0315***	-0.0320***	-0.0338***	-0.0362***	-0.0321***
	(-4.11)	(-4.02)	(-4.08)	(-4.32)	(-4.59)	(-4.09)
lnvix	0.186***	0.186***	0.187***	0.184***	0.186***	0.186***
	(4.31)	(4.30)	(4.32)	(4.26)	(4.31)	(4.31)
lagnetexcessreturn	0.0639***	0.0629***	0.0637***	0.0649***	0.0635***	0.0638***
	(9.51)	(9.35)	(9.49)	(9.67)	(9.45)	(9.50)
growthdum	0.549***	0.107	0.552***	0.595***	0.554***	0.549***
	(9.45)	(0.52)	(9.49)	(10.12)	(9.52)	(9.45)
valuedum	0.171**	0.173**	-0.0795	0.204***	0.181**	0.172**
	(3.02)	(3.05)	(-0.43)	(3.58)	(3.19)	(3.02)
coredum	0.112***	0.111***	0.112***	-0.280***	0.118***	0.112***
	(4.15)	(4.12)	(4.16)	(-3.50)	(4.35)	(4.15)
indxcompcapwtdum	0.197***	0.195***	0.198***	0.204***	-0.109	0.198***
	(7.99)	(7.88)	(8.00)	(8.25)	(-1.41)	(7.97)
indxcompeqwtdum	0.195***	0.192***	0.197***	0.197***	0.185***	0.185
	(5.12)	(5.05)	(5.18)	(5.18)	(4.85)	(1.53)

lntnagrowthdum_int		0.0657*				
		(2.24)				
lntnavaluedum_int			0.0389			
			(1.42)			
lntnacoredum_int				0.0673***		
				(5.21)		
lntnaindxcompcapwtdum_int					0.0529***	
					(4.19)	
lntnaindxcompeqwtdum_int						0.00172
						(0.08)
_cons	-3.329***	-3.320***	-3.320***	-3.016***	-3.116***	-3.329***
	(-21.77)	(-21.70)	(-21.70)	(-18.37)	(-19.34)	(-21.76)
N	19780	19780	19780	19780	19780	19780
adj. R-sq	0.193	0.193	0.193	0.194	0.193	0.193

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results in Table 6 shows that the spread and expense ratio have the highest negative impact on size vs. performance relationship. In panel A, spec 2 shows the spread interaction, spec 3 shows the expense ratio interaction, spec 4 shows the trading volume interaction, spec 5 shows the age interaction, spec 6 shows the vix interaction, and spec 7 shows the number of holdings interaction. The result reports that the spread, and expense ratio negatively affects the size vs. performance relationship. While trading volume, and age positively affect the size vs. performance relationship. VIX and the number of holdings, however, have an insignificant effect.

In panel B, I test the interaction effect of investment style – growth, value and core, and fund types – equal-weighted and capitalization-weighted. Spec 2 has the growth dummy interaction, spec 3 has value dummy interaction, spec 4 has the core dummy interaction, spec 5 has the capitalization-weighted index composition interaction, and spec 6 has the equal-weighted index composition interaction. Core-blend style interaction positively affects the size vs. performance relationship; however, the 'growth' and the 'value' interaction show insignificant. Likewise, capitalization-weighted index interaction shows a statistically positive effect, while equal-weighted index interaction shows insignificant effect.

Yan(2008) finds that illiquidity worsens the size vs. performance relationship. The paper argues that if fund size erodes fund performance because of illiquidity, then the coefficient on the interaction term should be significantly negative. And it indicates that the fund size erodes performance more among funds that are less liquid. I find a statistically significant negative coefficient on the spread interaction with a size, and I confirm that the price spread worsens the size performance relationship in ETFs as well. I find a very similar result for the expense ratio as well, indicating that the higher expense ratio augments the inverse relationship of size vs. performance.

In Table 7, I perform robust testing for the scale effect on ETF performance. In this Table, I use the full ETF sample, excluding the active ETFs. I sort the full sample and create four size categories. Then I create an interaction term of size categories with log(TNA). I use risk-adjusted alpha (CAPM and Carhart Four Factor) as the dependent variable. I examine the interaction effect of size categories and the log(TNA) on the risk adjusted alpha.

Table 7 Impact of Size Category Interaction on Risk-Adjusted Alpha

Table 7 shows the cross-sectional regression estimates of the risk-adjusted alpha on the full sample regressed on ETF size measured by total net asset size (logTNA). Unlike in table 3, here I examine the interaction effect of four size categories using OLS (with clustered standard errors on ETFID) and Fama McBeth regression. TNA is the total net assets under management in millions of dollars. Expense Ratio is the total annual management fees and expenses divided by year-end TNA. Liquidity is proxied from normalized bid-ask price spread. Flow is the percentage of new fund flow into the Exchange Traded Fund over period under investigation. Age is the number of years since the establishment of the ETF. Number of Holdings is the number of stocks in an ETF. NAV is the net asset value. Volume Turn Over is the total trade transactions that occurred in a month. Historical Volatility is the five-year standard deviation of the asset return. Premium/Discount is the difference of the NAV and the current market value of the ETFs. Lagged variables indicated are the previous time period value for the respective variables. Gross excess return is the asset return minus risk-free rate before the expense ratio, and the Net Asset Return is the monthly ETF return after expense ratio. The ETF sample is from January 2009 to December 2018. I include non-leveraged equity, only ETFs with TNA more than $15 million. I sort the total net assets to create four different size categories. The dependent variables are the CAPM Alpha and the four-factor Carhart Alpha. The main independent variable is the size of the asset under management measured by log(TNA), and control variables are Expense Ratio, Fund Age, Liquidity, Trading Volume Turnover, Number of Holdings, Historical Volatility, Lagged Excess Return, and the Lagged Fund Flow. I control for investment styles and fund type dummies. Spec 1 thru spec 4 are from the CALPM alpha. Spec 5 thru spec 8 are from the Carhart Four Factor Alpha. Columns 2, 4, 6 and 8 have the interaction term added.

	(1) OLS alpha_capm	(2) OLS alpha_capm	(3) Fama-Beth alpha_capm	(4) Fama-Beth alpha_capm	(5) OLS alpha_4f	(6) OLS alpha_4f	(7) Fama-Beth alpha_4f	(8) Fama-Beth alpha_4f
LogTNA	0.147***	0.428***	0.0663	0.235***	0.205***	0.474***	0.107**	0.282***
	(4.34)	(6.51)	(1.82)	(4.29)	(5.89)	(6.78)	(3.09)	(5.89)
Expratio	-0.874***	-0.879***	-0.757***	-0.757***	-0.909***	-0.912***	-1.041***	-1.037***
	(-14.93)	(-15.00)	(-7.97)	(-7.99)	(-15.49)	(-15.78)	(-11.99)	(-12.03)
AGE	0.0756***	0.0752***	0.00857	0.00861	0.0740***	0.0736***	0.0353*	0.0356*
	(8.50)	(8.45)	(0.52)	(0.52)	(8.51)	(8.45)	(2.36)	(2.38)
LogTVOL	-0.134***	-0.132***	-0.0575*	-0.0573*	-0.149***	-0.148***	-0.0958***	-0.0966***
	(-4.95)	(-4.87)	(-2.60)	(-2.62)	(-5.50)	(-5.41)	(-4.57)	(-4.62)
LogNHold	-0.0219	-0.0227	-0.0433***	-0.0437***	-0.0516*	-0.0529*	-0.0445***	-0.0449***
	(-1.04)	(-1.08)	(-5.82)	(-6.08)	(-2.27)	(-2.33)	(-5.31)	(-5.36)
HistVol	0.905	0.888	-0.733*	-0.739*	-0.502	-0.517	-0.253	-0.255
	(1.71)	(1.67)	(-2.05)	(-2.07)	(-0.86)	(-0.88)	(-0.58)	(-0.59)
LogSpread	-0.115***	-0.117***	-0.132***	-0.136***	-0.0829***	-0.0839***	-0.151***	-0.154***
	(-6.78)	(-6.88)	(-11.08)	(-11.29)	(-4.89)	(-4.95)	(-12.34)	(-12.71)
LNetExRet	9.397***	9.377***	6.481***	6.465***	10.81***	10.80***	5.238***	5.230***
	(30.36)	(30.44)	(7.40)	(7.41)	(39.31)	(39.37)	(5.35)	(5.35)
GrowthDum	0.630***	0.639***	0.825***	0.830***	0.697***	0.703***	0.672***	0.674***
	(5.09)	(5.22)	(12.65)	(12.77)	(5.67)	(5.77)	(9.75)	(9.73)
ValueDum	0.150	0.154	0.344***	0.345***	0.374*	0.376*	0.326**	0.327**
	(0.98)	(1.01)	(4.14)	(4.15)	(2.49)	(2.52)	(3.32)	(3.34)
CoreDum	0.183	0.187*	0.393***	0.397***	0.345***	0.348***	0.355***	0.355***
	(1.92)	(1.98)	(7.77)	(7.83)	(3.48)	(3.53)	(5.51)	(5.46)
IndCapWtD	-0.111	-0.111	-0.00151	-0.00190	-0.199**	-0.198**	-0.196***	-0.195***
	(-1.61)	(-1.62)	(-0.03)	(-0.04)	(-2.98)	(-2.98)	(-3.80)	(-3.77)
IndEqWtD	0.0673	0.0556	0.0654**	0.0594**	0.0399	0.0316	-0.0478	-0.0494
	(0.54)	(0.45)	(3.06)	(2.80)	(0.34)	(0.27)	(-1.25)	(-1.29)
lntnasizecat_int		-0.0456***		-0.0273***		-0.0433***		-0.0279***
		(-5.08)		(-6.06)		(-4.73)		(-6.94)
_cons	-1.868***	-2.768***	-1.237***	-1.798***	-1.463***	-2.322***	-1.519***	-2.099***

	(-10.24)	(-10.58)	(-4.21)	(-5.59)	(-8.27)	(-8.80)	(-5.44)	(-6.81)
N	69026	69026	69026	69026	61923	61923	61923	61923
adj. R-sq	0.261	0.263			0.255	0.257		

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The result of Table 7 indicates a statistically significant negative interaction term for both the CAPM as well as the Carhart four factor alpha. Further, the result from the cross-sectional OLS regression and from the Fama-McBeth regression are consistent. This is an additional empirical evidence that there is a negative effect of size on the ETFs risk-adjusted-performance.

Thus, the findings from this study are largely in align with the existing results in the ETFs literature. Svetina (2015) document that, on average, ETFs underperform their benchmark indices and are not immune to tracking error. The paper mentions that only 17% of all ETFs directly compete with index funds; those that do, provide returns that are, for the most part, statistically indistinguishable from those provided by matched index funds54. Likewise, Bhattacharya et al. (2017)55 report that retail traders who invest in ETFs perform worse than retail traders who stick with traditional funds. They argue that the ease of ETF trading leads retail investors to attempt to time the market that results in poor performance. Similarly, Glushkov (2016) examines the performance of a smaller sample of smart beta ETFs and document a poor performance for factor ETFs compared to their mutual fund counterparts. With all these evidences, I conclude that the investment appeal of ETFs has weak empirical support in the data even though they have some competitive advantage in terms of trading, tax efficiency, and flexibility. In terms of risk-adjusted performance, there is no convincing empirical evidence that the ETFs can beat the conventional actively managed funds or the broader market index.

[54] Svetina, Marko, Exchange Traded Funds: Performance and Competition (November 19, 2015). Journal of Applied Finance (Formerly Financial Practice and Education), Vol. 20, No. 2, 2010.
[55] Bhattacharya, Utpal, Benjamin Loos, Steffen Meyer, and Andreas Hackethal, 2017, Abusing ETFs, Review of Finance 21 (3), 1217–1250.

5 CONCLUSIONS

In this paper, I make a comprehensive evaluation of a scale to returns hypothesis focusing on exchange-traded funds. Unlike most extant literature, I use quantile regression to examine the differentials in size impact on fund performances. I provide a robust result that ETFs do not provide increasing returns to scale; instead, I observe steady diminishing returns to scale. I observe slightly positive risk-adjusted returns initially when the asset base is growing; however, the positive effect disappears as the fund size grows. Zhu(2018) states that in a decreasing return to scale world, a positive alpha indicates that investors have not given enough money to a particular fund, while a negative net alpha suggests that investors have given the fund too much money. Consistent with this view, the result shows that at the lower end of the size quantiles, the risk-adjusted alpha is positive, and at the higher end of size quantiles, the alpha is turning in to negative.

Furthermore, the quantile regression results show that ETFs size has a stronger negative impact on the high performing quantiles. In contrast, it shows a positive impact on the individual ETFs belonging to the lowest end of the quantiles. The results are consistent in both the quantile as well as in the cross-sectional regression. Moreover, patterns are steady for CAPM and for Carhart four-factor risk-adjusted-performance. The robust testing result with size category interaction also shows a statistically significant negative impact on ETFs performance. The study support Zhu (2018) findings that documents a decreasing return to scale at the fund level, implying that the fund alpha and the fund size are not two independent entities. When it comes to the tracking error ability of the ETFs, the result shows that the tracking error has a negative relationship with the size[56;] however, the size impact is within the margin of the confidence interval.

Further, I provide evidence that spread (illiquidity) and expense ratios are the two main factors that worsen the size vs. performance relationship. This finding is consistent with the conventional fund research of Yan (2008). I observe that the higher the illiquidity, the stronger

[56] It is consistent with Chu (2009) findings that concluded a negative relation of size and tracking error

the negative effect of size on performance. However, I find that trading volume, age, and historical volatility positively affect the scale performance relationship. Likewise, ETFs with core blend investment styles positively affect the size performance relationship. The growth and value investment style have insignificant or weak effect. Finally, the capitalization-weighted index has statistically significant positive effect on the size performance relationship.

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Appendix B (Chapter 2)

Appendix B: Table A - Variable Selection:

Variable Name	Proxy for	Brief information	Data Source
pricesp500	S&P500 Monthly Time Series Price	S&P500 is generally considered broader US stock market	Thomson Reuters Datasreams
marketreturn	S&P500 monthly return	Calculated as change in monthly market price divided by previous month market price expressed in percentage	Derived Variable
price	ETF monthly time series price		Thomson Reuters Datasreams
grossreturn	ETF gross return	Calculated as change in monthly asset price divided by previous month asset price expressed in percentage	Derived Variable
expenseratio	Expense Ratio	ETF operating Cost	Morning Star
netreturn	Gross Return minus Expense Ratio	Monthly net asset return is after all costs	Derived Variable
tna	Total Net Asset	Total asset under management	Morning Star
logtna	ETF Size	Size as measured by total net asset	Derived Variable
nav	Net asset value	Total asset dividend by shares outstanding	Thomson Reuters Datasreams
premDiscount	Premium or Discount	Difference in net asset value minus market value	Derived Variable
bidprice	Bid Price	Monthly time series of ETF bid price	Thomson Reuters Datasreams
askprice	Ask Price	Monthly time series of ETF ask price	Thomson Reuters Datasreams
baspread	Bid-Ask Spread (Normalized) (Hameed, JF 2010)	(Ask Price-Bid price)/midpoint of bid price plus ask price	Derived Variable
Nosh	Number of shares outstanding		Thomson Reuters Datasreams
logfundflow	Log of Monthly Total Fund Flow into ETF	$flow_t = (nosh_t - nosh_{t-1}) / nosh_{t-1}$	Derived Variable
logage	Log of ETF age in Years	Current year minus year of inception	Morning Star
lgnumofholdings	Stock Holdings in a ETF		Morning Star
histvol	Asset risk	Five-year standard deviation of return	Thomson Reuters Datasreams
volturnover	Volume Turnover	total monthly buying and selling transactions	Thomson Reuters Datasreams
Vix	Market Risk or Volatility	market risk as measured by VIX	Thomson Reuters Datasreams
riskfreerate	Risk free rate	US treasury 30-day note. I use the data from Fama French Website	Fama French Website
mrktrf	Market factor risk	Fama French Factor – market factor	Fama French Website
shb	Value factor risk	Fama French Factor – small minus big	Fama French Website
hml	Size factor risk	Fama French Factor – high minus low	Fama French Website
mom	Momentum factor risk	Carhart – Momentum Factor	Fama French Website
valuegrowth	Investment Style	Growth, value	Morning Star
largesmall	Fund size category	Large Cap, Small Cap	Morning Star
passiveactive	Management Style	Active, Passive, Enhanced	Morning Star
lagassetreturn	Lagged ETF Return	Previous month return	Derived Variable

lagfundflow	Lagged ETF Flow	Previous month fund flow	Derived Variable
lagsize	Lagged ETF Size	Log of previous month total net asset	Derived Variable
te	Tracking Error	Standard deviation of the difference between the asset and the underlying benchmark returns, σ_{ε} = Stdev $[R_{\mathrm{ETF}} - R_{\mathrm{BenchMarkIndex}}]$	Derived Variable
indexprice	Price of underlying Index	Time series price of index	

Appendix B: Table B - Size and Performance Trend Over the Sample Duration

Panel A - TNA Quantiles Over the Years

year	mean	p25	p50	p75	p90	p99
2009	1248.811	66.8	181.4	643.5	2334.4	20055.2
2010	1398.509	67.85	201.9	705.3	2821.8	23121.1
2011	1563.955	79.65	229.25	762.8999	3131.5	27172.7
2012	1636.85	72.05	230.7	778.2	3158.1	31021.9
2013	1851.148	79.6	251	925.7	3849.2	33645.1
2014	1977.541	89.4	276.1	982.2	3960.1	30096.9
2015	2078.171	88.6	275.65	1020	4273.797	29114.2
2016	2086.856	79.2	249.1	915.2	4142.199	31589.6
2017	2609.898	90.5	306	1171.6	4810.398	37746.8
2018	3042.126	100.1	368.5	1453.45	5602.349	46685.5
Total	2085.474	82.7	264.5	996.3999	3968	33976.1

Panel B - Net Excess Return Quantiles Over the Years

year	mean	p25	p50	p75	p90	p99
2009	0.0114398	-0.0349601	0.0188323	0.0736269	0.1305012	0.232123
2010	-0.0034176	-0.037269	0.0014172	0.0371665	0.0708502	0.1218805
2011	-0.0110778	-0.0443068	-0.0031335	0.0244069	0.0610661	0.1625025
2012	-0.0032679	-0.0243842	-0.0026477	0.0266561	0.0601558	0.1246376
2013	0.0074021	-0.0159498	0.0076303	0.035831	0.061945	0.1030466
2014	-0.0013768	-0.0253829	0.0035291	0.0267232	0.0502888	0.0975321
2015	-0.0102625	-0.0328296	-0.0080646	0.0134781	0.0533422	0.1170547
2016	-0.0201768	-0.0432178	-0.0198448	0.0052093	0.033932	0.1156501
2017	-0.0584052	-0.0844144	-0.0613	-0.0348824	-0.0087778	0.0336824
2018	-0.1565181	-0.1878579	-0.1561113	-0.1209486	-0.0931186	-0.0352769
Total	-0.0337944	-0.0748996	-0.0203234	0.0141527	0.0490078	0.1347734

Panel C- Four-Factors Carhart Alpha Quantiles Over the Years

year	mean	p25	p50	p75	p90	p99
2009	-0.037666	-0.0407636	-0.020269	-0.0075654	0.0064792	0.0614347
2010	-0.0035605	-0.011646	-0.0030459	0.005683	0.0157814	0.0534621
2011	-0.0001848	-0.0067722	0.0002029	0.008132	0.0155141	0.0334173
2012	-0.0025598	-0.0069308	-0.0001677	0.0055759	0.0100219	0.0208943

2013	-0.0012837	-0.0061213	-0.0002483	0.0049606	0.0093819	0.031976
2014	0.0032384	-0.0032599	0.0032911	0.0091246	0.0147392	0.0376023
2015	0.0006232	-0.0048671	0.0017683	0.0076949	0.0118722	0.020963
2016	-0.005147	-0.0104997	-0.0038675	0.0029204	0.0061869	0.0113456
2017	-0.0108163	-0.0168471	-0.0090006	-0.0019668	0.0019976	0.0063716
2018	-0.0291395	-0.0367425	-0.0220299	-0.0133426	-0.0074679	-0.000857
Total	-0.0075597	-0.0136465	-0.0039806	0.0036634	0.0095016	0.0277087

Appendix B: Table C - Key differences between the Mutual Fund and the ETF

	Mutual Fund	**ETF**
Expense Ratio, Fees and loads	Vary but are typically higher than ETFs, may charge frontend fees	Common active exposures such as growth and value are available at low cost
Subscription & redemption costs	Typically paid from fund assets	Paid by broker creating or redeeming the ETF
Liquidity	All transactions occur at the close and at the fund's NAV	**Liquidity available intraday**. **Two levels of liquidity** – in the primary market due to creation/redemption process and in the secondary market due to intraday buy/sell activity in the exchanges
Taxes	Redemption gains are borne by remaining shareholders in the fund	In-kind transaction do not incur capital gains taxes. Bernstein (2001) demonstrates the tax advantages of ETFs in comparison to traditional mutual funds.
Transparency	Required quarterly but may be available at higher frequencies	Required daily
Trading/Access	Required set up with the mutual fund manager	Bought or sold from any brokerage account like individual stocks

Source: See book page 159 - Anantha N. Madhavan , "**Exchange- Traded Funds and the New Dynamics of Investing**"

VITA

The author, Kiran Paudel, was born in Nepal. He obtained a bachelor's degree in Computer Science from the University of Texas at Dallas in 2003 and a Master of Business Administration from the Amberton University in 2006. He also received an MS in Finance from the University of North Texas in 2015. He received his Ph.D. in Financial Economics from the University of New Orleans in 2020.