Innovation and Stock Returns

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Abstract

The main aim of this thesis is to determine the relevance of innovation for the average stock returns, thereby investigating if innovation is one the factors explaining the stock returns. Innovation has been identified as an important determinant of economic growth and has been incorporated in economic growth models. With respect to equity returns, one part of literature identifies innovation as source of increased risk given the uncertainty associated with its outcome while another part of literature finds high innovation to reduce technological risk of a firm. In this thesis, we find that there is a premium to high innovation particularly for small size stocks. The highest innovation stocks earn higher average returns than lowest innovation stocks and this effect is significant and prominent for small size stocks. This persists when innovation is accounted for along with other variables like book to market value, operating profitability and investment. Regressing innovation sorted portfolios against Fama-French 5 factors model generates positive significant alphas for high innovation portfolios, even when controlled for size. Based on this, an innovation factor is constructed that captures the difference between the average return on high and low innovation portfolios. This innovation factor is incorporated in the Fama-French 5 factors model as the sixth factor evaluating if the model better explains the average stock returns. The six factors model incorporating innovation factor is rejected based on the test statistic testing if the alphas produced by the model are jointly equal to zero. However, the six factors model produces lower values of test statistics and alpha based measures used for model comparison, implying an improvement over the existing model.

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Chapter 1 Introduction

Joseph Schumpeter is one the earliest economists who provided the interpretation of the word 'innovation'. In 1934, Schumpeter defined innovation as combining the existing and new knowledge and resources in a novel way. Schumpeter emphasized on the commercial purpose associated with innovation thus differentiating it from invention that may not have commercialization as one of the goals. According to Schumpeter, generating new ideas and putting them into commercial use are the main components of innovation along with the accompanying economic change. All other discussions on innovation following Schumpeter, define innovation as a systematic and structured process that creates new business opportunities (Shah et al., 2014).

As innovation results in creation of new market and business opportunities, therefore it is considered one of the important drivers of economic growth. An extensive literature exists that emphasizes the role of innovation in economic growth. Model by Solow (1957), defining technology as one of the essential components driving production function is the fundamental growth model that highlights the importance of technological progress for growth. Jinnai (2015), Schmid & Kung (2015) and Garleanu et al. (2012) are some of the many studies associating innovation to waves of economic activities. By linking innovation to economic activities, these studies have highlighted how innovation is a source of long-term uncertainty in an economy thus justifying the presence of equity risk premium in asset pricing. These studies analyze innovation and asset pricing at a macroeconomic level. There are number of papers that have studied the role of innovation on a micro level, identifying its role in determining stock market returns.

According to Bena & Garlappi (2019), over the period 1950-2010 only 15% of total US listed firms were active in technological innovation while they accounted for 57% of total market capitalization. Moreover, the top tercile of the innovating firms represented 5% of all firms but represented 41% of total market capitalization. Thus, innovation can be considered as one of the factors to understand the characteristics of entire cross section of stock returns. Hsu & Huang (2008), Pastor & Veronesi (2009), Li (2011), Dicks & Fulghieri (2020) and Garlappi & Song (2020) study the role of innovation in determining expected stock returns. Some of these studies identify innovation as the source of increased systematic risk demanding risk premium, while some establish that higher innovation output decreases a firm's exposure to technological risk.

Drawing from the literature that emphasizes the importance of innovation for overall economic growth and its effect on firms' expected stock returns, the main objective of this study is:

- to identify if innovation is priced and can be used as one of the factors to explain the expected stock returns
- to explore if innovation is a source of risk thereby requiring risk premium and compensation in stock returns

To answer these research questions, the study makes use of data on patents as the main measure of innovation. Using the data on patents granted to US listed firms, Kogan et al. (2016) have developed a measure that gauges the quality and economic value of a patent in dollar terms. This data has been employed in this study to measure innovation and evaluate its role in explaining stock returns. The period of study used for analysis is from 1960-2020.

We first evaluate how the average stock returns vary over different levels of innovation. In this respect, the stocks available in the Kogan et al. (2016) innovation data are sorted into deciles and average returns are calculated for each decile over 1961-2020. The results show higher average returns for highest innovation portfolios as compared to the lowest innovation portfolios, although the relationship between innovation level and average returns is not monotonically increasing. In addition to forming portfolios based on innovation alone, we also use bi-variate sorting where portfolios are formed based on innovation along with a second variable like size, book to market value ratio, operating profitability and investment. In almost all cases, the highest innovation portfolio generates higher return than lowest innovation portfolio showing that there is a premium to innovation. The difference between the average monthly return of the highest and lowest innovation portfolios is about 22 basis points that translates into yearly return of 2.7% both statistically and economically significant. However, when bivariate portfolios are formed based on size and innovation, it is observed that the innovation premium is much higher for small size firms as compared to big size firms. The innovation premium is both statistically and economically significant for small size establishing the presence of innovation premium mainly for small size firms.

Once we analyze how average returns vary across different levels of innovation, we use the Fama-French 5 factors model as the reference asset pricing model to evaluate if the model explains the returns on the innovation sorted portfolios. For the ten innovation sorted portfolios, the two highest innovation portfolios produce significant positive alphas. We also regress 6 portfolios formed based on size and innovation against Fama-French 5 factors. The high innovation portfolios within both small and big size produce positive significant alphas reflecting an innovation premium. Moreover, the average returns on the innovation based portfolios are not completely explained by the Fama-French 5 factors model. Based on this, an innovation factor is constructed and incorporated in the reference asset pricing model thereby analyzing if innovation can be one of the factors contributing to the explanation of average stock returns. Following the approach followed in Fama & French (2015) for factor construction, innovation factor is constructed as the difference between average return on highest innovation portfolio (average of small and big size high innovation portfolio) and average return on lowest innovation portfolio (average of small and big size low innovation portfolio). Further, using a set of test assets like Fama-French 25 size-BM portfolios, 25 size-operating profitability portfolios and 25 size-investment portfolios; we compare the Fama-French 5 factors model with the 6 factors model (Fama-French 5 factors plus innovation factor) to evaluate if 6 factors model brings about an improvement with respect to explaining the expected stock returns.

Different methods have been used in the literature to compare asset pricing models. In this study we use the Gibbons, Ross, Shanken (GRS) test to compare the Fama-French 5 factors model with Fama-French 5 factors plus innovation model. In addition to this, we also use equal weight measures like average absolute alphas and average absolute *t* value for model comparison. Based on GRS statistics, the 6 factors model like the 5 factors model does not completely explain the average stock returns as the alphas produced by the model are significantly difference from zero. However, for different sets of test assets, the value of GRS statistic for 6 factors model is lower than that for the 5 factors model showing an improvement by the 6 factors model. For the 25 size-BM and 25 size-operating profitability portfolios, the six factors model results in the reduction of the average absolute value of alpha but for 25 size-investment portfolios, average absolute alpha does not reduce. Moreover, when using Fama-French industrial portfolios to check the robustness of the results, both the GRS statistic and equal weight metrics reduce for the 6 factors model. Overall, we find that there is a premium for high innovation specifically for small size firms as reflected in the higher stock returns for high innovation portfolios. However, adding innovation factor to the existing asset pricing models still does not completely explain the expected stock returns.

The study contributes towards the literature studying the effect of innovation on the average stock returns. Literature holds different views regarding innovation as a source of risk; some studies find innovation to increase a firm's risk exposure given the uncertainty associated with it while others identify innovation to mitigate a firm's risk exposure. Through this study, we find high innovation results in high average returns reflecting that higher risk is associated with innovative firms whereby the investors may require higher return to hold such stocks. Moreover, the study finds the premium associated with innovation is higher and significant for small size firms as compared to big size firms making innovation more relevant for average returns on small size stocks. Thus, the study contributes by identifying a premium associated with innovation specifically for small size stocks and this coincides with the body of literature that underscores the uncertainty and risk associated with innovation thus requiring risk premium. It also contributes to the literature on asset pricing by evaluating if innovation is one of the factors that can explain the expected stock returns. Since the first asset pricing model was proposed, a number of factors have been identified and models have been developed to explain the average stock returns. While some models capture the average returns better than the other, we still lack a model that can completely explain the average stock returns. While this study shows that addition of innovation factor to the existing asset pricing models does not complete the model with respect to explaining the expected stock returns, however, the innovation factor shows an improvement in the reference asset pricing model.

The rest of the thesis proceeds as follow: Chapter 2 provides the literature review discussing innovation as source of risk premium at macroeconomic level along with reviewing studies on innovation and stock returns at micro level. Chapter 3 provides details of the data used in the research while Chapter 4 discusses the methodology adopted in this thesis. Chapter 5 summarizes the sample statistics and empirical analysis is provided in Chapter 6. Finally, we conclude the findings of this research in Chapter 7.

Chapter 2 Literature Review

One important characteristic emphasized in the earliest literature found on innovation is the goal of commercialization associated with it. Innovation is not only about generating new ideas, rather using those ideas to create and exploit market opportunities. It is based on this, that innovation and technological change has been proposed as an important component in the widely acknowledged models of economic growth. In addition to studying innovation at macroeconomic level, there are studies that focus on innovation at a micro level, identifying its impact on the cross-sectional variation of stock returns. While macroeconomic theories on innovation identify uncertainty and risk associated with it leading to risk premium for equity market as whole, the literature studying its relation to cross section stock returns has mixed outcomes. Some identify innovation to increase the risk of the firms involved in innovation while some find innovation to reduce firm's systematic risk. In either case, innovation can be a source of risk, either for high innovation firms or for firms that lack innovation, and thereby this study aims to investigate the relevance of innovation for asset pricing.

2.1 Innovation at a Macroeconomic Level

Romer (1990) presented the endogenous growth theory in which technological change is defined as central for economic growth. Romer (1990) considers technological change as an improvement with respect to the instructions on combining the raw materials. Moreover, the technological change is driven through the actions of the people responding to the market incentives leading to its endogeneity. Further, technological changes lead to increased capital accumulation resulting in increased output per hour worked. Romer (1990) characterizes technological change as nonrival input whereby its use by one firm does not exclude another firm from using it thereby leading to increasing returns and economic growth. However, as technological change occurs as result of motivated individuals responding to market incentives, the gains from improvements in technology must be partially excludable. Combining all these elements together, Romer (1990) proposes that economic growth is a result of technological change that is nonrival but partially excludable. Thus, Romer's growth theory by emphasizing on technological change highlights the importance of research and innovation for growth. Technological change not only leads to growth, but its excludable nature provides gains to the agents bringing about this change thus leading to the premises of this study to investigate relevance of innovation for explaining average stock returns

Following Romer's endogenous growth theory that identifies technological change as an important determinant of economic growth, there are many studies that link technological change and innovation to long run economic uncertainty and risk leading to equity risk premia. Garleanu et al. (2012) present a model explaining the behavior of asset prices during the technology adoption cycle at a macroeconomic level. The paper categorizes innovation into two phases; major technological shocks like internet and technology neutral shocks that put the technological shocks into play and thereby increase productivity. Based on this, there is a lag between the arrival of a major technological shock and its impact on productivity and consumption. The model is developed on the idea that firms' growth options follow a life cycle as technology evolves. With emergence of major technological shocks, growth options appear in the prices of all securities. These growth options being riskier than assets in place increase the volatility of equity prices resulting in an increase in risk premia in the economy. With time, as firms convert the growth options into assets in place, the risk premium on their equity is reduced. On a macroeconomic level, the paper links expected excess returns with future consumption growth owing to technological changes.

Kung & Schmid (2015) analyze the asset pricing implication for an economy where innovation and R&D are important determinants of long-term growth. They develop a model that identifies measures of innovation like R&D intensity and R&D growth as predictors of aggregate growth rates in an economy. In the model, favorable economic conditions encourage innovation. These innovations stimulate persistent growth in productivity that effects long term aggregate growth rates. Thus, any economic shocks effect the incentive to innovate thereby impacting long term growth rates. An event of an economic slowdown thereby not only lowers current productivity and consumption but also negatively impacts long term growth rates. The model with its assumption about recursive preferences of agents rationalizes the risk premia is asset markets as agents fear that prolonged economic slow-down corresponds with low asset valuations. Thus, the paper identifies innovation as a source of long run risk in an economy leading to the demand of risk premia is asset markets.

Jinnai (2015) also presents a model establishing innovation and R&D as sources of long run uncertainties in an economy thus justifying the presence of equity premium. The paper develops a model incorporating product life cycle i.e. transformation from monopoly to perfect competition and studies its effect on asset market. Innovation leads to monopolistic production of a product initially which is later competitively produced to benefit from productivity gains from competition. At high frequencies, ratio of monopolistic products to competitive products is pro cyclical and at medium frequencies it is countercyclical. These two effects combined make the profits pro cyclical and increase the persistence of economic fluctuations resulting in increased equity premium.

Hsu (2009) studies the effect of technological innovation on aggregate market returns and risk premium. The study finds that patents and R&D shocks increase expected market returns and premiums of G7 countries and thus have strong predictive power. Increased expected productivity, improved efficiency and greater volatility of returns against innovation as compared to physical investments are the main reasons identified for positive relation between technological innovations and expected market returns.

In addition to identifying innovation as a source of risk premium through its impact on economic growth, there exits significant literature on innovation as a source of destruction of old capital and its resulting impact on stock market capitalization and returns. Jovanovic & MacDonald (1994) develop a model explaining innovation as the factor leading to nonmonotonicity in firm numbers over a life cycle of an industry. As an industry evolves, the number of firms first increases and then declines. The paper proposes that it is a rise in innovation that causes a shakeout in an industry. Their model is developed on the theory that differentiates invention from innovation. Invention relates to the discovery of something new while innovation involves putting the invention into commercial use. Invention is thus an exogenous event that provides raw material for innovation and is accessible to all. With the arrival of an invention, firms enter an industry but only those survive which can refine the invention into innovation. The refinement may again attract more entrants into the industry but in the end only those will remain that are able to refine and innovate. Using the data from US automobile tire industry, the paper establishes technology-based innovation as an explanatory factor for shakeout in the tire industry.

Following a similar idea as that presented in Jovanovic & MacDonald (1994), Hobijn & Jovanovic (2001) show how IT revolution first lead to stock market decline which then recovered only after the entrance of new firms that had adopted the new technology. Their paper emphasizes that a major technological/innovation shock destroys the old capital leading to decline in stock prices of incumbents. Development of new capital that incorporates the new technology takes time. In the meantime, the stock market value of the incumbents resisting the change continues to fall. With the entry of new firms that are based on new technology, the stock market capitalization rises again. The paper uses IT revolution as an explanation for post 1972 stock market fall followed by post 1985 rise in the stock market capitalization. Thus, the paper shows that with the arrival of a major innovation/technology, investors lower their valuation of the effected firms until the new technology is adopted and incorporated in the business activities. Both these papers empirically emphasize the risk of exit faced by the firms that resist innovation thus reflecting the implications of innovation on a firm's risk level and required return.

2.2 Innovation and Expected Stock Returns

The above studies focus on role of innovation in increasing the risk premium in the equity market as a whole. The role of innovation in driving economic growth and resulting economic slowdown in case of low innovation acts as a factor driving equity risk premium. Unlike these studies, the emphasis of our study is to analyze the effect of innovation on expected returns on micro level, evaluating if innovation is a factor differentiating expected returns of firms high on innovation from those with low innovation. Based on above studies, it can be established that it is the inability to incorporate innovation or convert innovation options into tangible assets that drives high risk premium associated with innovation. From this it may be inferred that firms with greater inclination towards innovation would have a lower risk of being obsolete leading to lower required returns. However, as discussed in Dicks & Fulghieri (2020), the innovation process is itself risky due to the uncertainty associated with the distribution of its success probability, thereby increasing the risk of the firms with high innovation. In this regard, there are a few studies that have focused on the role of innovation in explaining cross sectional variation of stock returns.

Garlappi (2004), describes the effect of competition and industry structure on the risk premia associated with innovation and R&D. During good market conditions, threat of preemption from the rival increases the risk premia for the firm leading the R&D race. On the other hand, during poor market conditions, the rival may forego earlier, decreasing the leader's risk premia. The study also calibrates that presence of competition in R&D in an industry result in higher and volatile risk premia. Building further on this analysis, Bena & Garlappi (2020) study the effect of strategic interaction among innovating firms on their respective expected returns. The paper presents a model showing that a firm's expected return decreases in its innovation output and increases with the innovation output of the rival. Investment in innovation exposes a firm to technological risk as a firm may not reach the desired innovation results immediately. Mere investment in innovation does not prevent its rivals from innovation. The model shows that a firm with higher innovation output will have lower exposure to this technological risk as compared to its rivals. Overall, low innovation output makes a firm riskier increasing its beta. Using patenting data from 1950-2010, the paper finds that firms that are leaders in innovation have beta lower than one while firms with lower patents have betas greater than one.

Hsu & Huang (2010) empirically test the role of future technology prospects in explaining stock returns. The paper draws motivation from consumption risk literature along with economic theories proposing importance of technology in aggregate production function. An investor's current consumption is dependent not only on the current wealth but also on expected future income. As technological growth increases productivity and future output, therefore it should be positively related with current consumption. Moreover, under Merton (1973) the economic variables that are related to consumption growth may act as systematic risk factors thus effecting asset returns. Based on these theories and adding a technology factor to ICAPM and Fama-French models, the paper empirically finds that technology prospects act as systematic risk factor effecting asset prices. The paper constructs a technology factor to track changes in future technology prospects and finds a positive risk premium for it along with highest technology beta for portfolio with highest R&D intensity. Thus Garlappi & Jena (2020) and Hsu & Huang (2008) differ from each other with respect to the effect of innovation and technological progress on firm's systematic risk and resulting expected returns.

Garleanu et al. (2012) identify innovation as a factor explaining the value premium observed in the cross-sectional stock returns. Innovation exerts increased competition on the existing firms, thereby negatively impacting their profits and human capital. The study describes this as the displacement risk. The firms that innovate more provide a hedge against displacement risk. Such firms extract a greater fraction of their value from future inventions, making them growth firms. As a result of protection against displacement risk, growth firms earn lower average returns as compared to less innovative value firms.

An explanation for the difference in the outcomes for the above studies can be found in Dicks & Fulghieri (2020). They propose that investors value an innovating firm more and are willing to pay more for its equity when there are other innovating firms in which they can invest. Thus, investors value innovation more when it is not in isolation. This creates an innovation wave accompanied by high stock market valuations. Given the high uncertainty associated with outcome of innovation, investors are more optimistic to invest in a portfolio of innovating firms thus giving them the benefits like that of risk diversification. While this study focuses on the cash flows for the high valuation of innovative firms by the investors, Pastor & Veronesi (2009) consider the effect of technological revolution on the discount rates and resulting stock values. According to their study, the stock prices of innovative firms first rise but as the innovative technology is adopted by more firms, the risk associated with that technology changes from idiosyncratic to systematic risk thereby increasing the discount rates for all the firms. This study finds that the discount rates for firms that are the early adopters of new technology rise more than of the firms which are late adopters.

There also exists some literature that studies how innovation effects stock returns only in relation to some factors like firm's investment level and financial constraints. Garlappi & Song (2020) study firm's return exposure to investment specific technology (IST) shocks. IST shocks refers to technological innovations that materialize through creation of new capital stock. In this study adoption of technological innovation enables a firm to reduce the cost of investment capital and thus increase its current market value. Thus, greater the expected future investments, higher the value created through exposure to IST shock. The study calculates a firm's IST beta based on the value of the present value of its investment as ratio of its price and finds that high investment to price ratio leads to high return exposure to investment shocks. The study finds high IST betas for firms with high book to market value justifying the presence of value premium. Thus, this study establishes the role of a firm's investment level with respect to the value that is created with adoption of an innovative technology.

Li (2011) finds that innovation as measured through R&D investment determines returns for only financially constrained firms while the effect of R&D is insignificant on returns of firms that do not face financial constraints. It finds that financial constraints lead to positive R&D-return relation. This study thus establishes that the relationship between innovation and expected returns is only relevant if financial strength of a company is considered, otherwise the relationship is insignificant.

In view of the above, there exists a wide range of literature establishing the importance of innovation for economic growth and identifying it to be a source of uncertainty and risk for an economy. At a micro level, there are studies focusing on innovation as a factor that contributes towards determining stock prices and returns. In this regard, some studies identify increased innovation as source of increased systematic risk while others establish innovative firms to be less risky. Some studies also establish the link between innovation and stock returns to be significant only in the presence of certain factors. Through this paper we try to identify the relevance of innovation for stock returns, establishing if innovation is a factor that should be incorporated in the asset pricing models explaining the average stock returns.

2.3 Asset Pricing Models

The Capital Asset Pricing Model (CAPM) by Sharpe (1965) and Lintner (1965) is the earliest asset pricing model explaining the average stock returns. CAPM implies that expected return on a security is the function of its market beta that is obtained through regression of security's return on market return. Since this earliest model of asset pricing, several other factors have been identified that affect the cross section of expected returns thus challenging CAPM. One of such factors is the size effect by Banz (1981), who identified that the returns on small stocks i.e. stocks with low market equity are higher than returns on big stocks and size adds to the explanation of average stock returns as provided by market betas. Stattman (1980) and Rosenberg et al. (1985) studied the relevance of book to market value (B/M) in explaining the stock returns and found that stocks with high B/M ratio had higher average stock returns. Basu (1983) identified earnings to price (E/P) ratio to improve explanation of average stock returns using model that included market beta and size. DeBondt and Thaler (1985) found that the stocks with low long-term past returns had higher future returns i.e. there is reversal in the long term returns. Bhandari (1988) identified a positive relation between average stock returns and leverage and found that addition of leverage to a model containing beta and size improves the explanation of the average stock returns.

Fama & French (1992) proposed that the factors like size represented by market value of equity, earning to price ratio, leverage and book to market value ratio are all scaled versions of price and thus some of these factors may be redundant with respect to explaining the stock returns. Fama & French (1992) showed that size and book to market equity provide a strong explanation of average stock returns for the period 1963-1990. Building on this, Fama & French (1993) proposed the three-factor asset pricing model in which they added two additional factors based on size and book to market equity to the original CAPM to explain the average stock returns. The two additional factors were SMB (Small minus Big i.e. return on portfolio of small market capitalization stocks minus the return on portfolio of big market capitalization stocks) and HML (high minus low i.e. return on portfolio of high book to market value stocks minus return on portfolio of low book to market stocks).

Jagadeesh and Titman (1993) introduced the momentum factor that has also been incorporated in asset pricing models as a factor to explain stock returns. Jagadeesh and Titman (1993) showed that the strategies based on buying the stocks that performed well in the past and selling the stocks that performed poorly earn significant positive returns. Fama & French (1996) showed that their three-factor model captured all the anomalies in average stock returns based on size, book to market equity, earning/price, cashflow/price, past sales growth and long-term reversal effect that were unexplained by the traditional CAPM. However, the momentum factor as identified by Jagadeesh and Titman was not explained by the three-factor model.

Incorporating this momentum factor, Carhart (1997) proposed a four-factor asset pricing model incorporating 3 factors from Fama & French (1993) along with momentum factor. Carhart (1997) showed that the four factor model reduces the pricing errors as compared to the three factor model. Further, Fama & French (2015) refined its 3-factor model by incorporating two additional factors related to profitability and investments. These two factors included RMW (robust minus weak i.e. return on portfolio of high operating profitability stocks minus the return on portfolio of low operating profitability stocks) and CMA (conservative minus aggressive i.e. return on portfolio of stocks that are conservative in investment as measured through change in total assets minus the return on portfolio of stocks with aggressive investment). Developing further on asset pricing models, Hou, Xue & Zhang (2015) proposed the 'q factor' model for asset pricing incorporating excess market return, size, investment and return on equity as the factors explaining expected stock return. Thus, since the first asset pricing model in the form of CAPM, many models and factors have been proposed with the aim to explain the expected stock returns. While some asset pricing models have brough about improvements over the other, still none of the models can completely explain the average stock returns. Fama-French 5 factor model, Hou, Xue & Zhang q factor model and Carhart 4 factor model all result in pricing errors leading to excess returns that are not explained by the factors in the respective models. As discussed above, at the macroeconomic level, innovation is identified as the source of equity risk premium and many studies have also investigated its impact on the returns at firm level. Given the existing asset pricing models do not completely explain the stock returns, this study will investigate if innovation adds value to the existing asset pricing model with respect to explaining the stock returns.

2.4 Tests to Compare Asset Pricing Models

The above discussion shows different factors and models that have been proposed explaining the average stock returns. Along with this, there are different studies that compare the asset pricing models using different asset pricing tests. Among these, the widely used tests are ratio-based measures based on measuring the pricing errors (observed based on alphas) and estimation precision of these alphas. The models with low alphas and high estimation precision succeed. This involves using t-statistic for single asset or F statistic based on Gibbons, Ross, Shanken (1989) test commonly known as GRS test. GRS test jointly tests the alphas obtained for the test assets used in the asst pricing models evaluating if the alphas are jointly equal to zero. Fama & French (2015), Fama & French (2020) and Hou, Xue & Zhang (2015) are some of the studies that use GRS test statistic to determine the effectiveness of model along with drawing comparison across models. However, as discussed in Barillas & Shanken (2018), relatively large p-values obtained in case of ratio-based measures may suggest imprecision in estimating alphas rather than establishing the adequacy of models.

Moreover, the GRS test may encounter a power problem when the test rejects the model even when the alphas are low but also have low standard errors. Fama & French (1993) and Fama & French (2016) are both rejected based on GRS test although they produce values of alphas that are not economically significant. Thus, in addition to using GRS statistic, many studies use alpha based statistics. The mostly commonly used include the average absolute value of alphas and average absolute value of statistic against each alpha. Fama & French (2015), Fama & French (2020) and Hou, Xue & Zhang (2015) use alpha based statistics in addition to GRS statistic. A low value of alpha based statistics is better for a model suggesting a low pricing error.

Studies like Barillas and Shanken (2018) use Bayesian procedure to develop asset pricing test computing model probabilities for all possible asset pricing models. Following Bayesian approach for asset testing allows comparison of both nested as well as non-nested pricing models.

Hansen and Jagannathan (1997) proposed Hansen-Jagannathan distance (HJ distance) that is also a popular measure used to test how mis-specified a model is and to compare competing models. HJ distance measures the least squares distance between the Stochastic Discount Factor (SDF) being evaluated and the admissible SDFs that accurately price the test assets. This approach tries to find the minimum variance portfolios from the candidate factors mimicking portfolios. A model with HS distance of 0 would be the correctly specified model. Building on HJ distance, different tests have been developed to compare the HJ distance of different asset pricing models instead of just comparing the values of HJ distance. In this regard, Kan and Robotti (2009) proposed a test to evaluate if the HJ distance between the two asset pricing models is same. Further, Gospodinov et al. (2013) proposed a method to jointly test the misspecifications of more than two asset pricing models. They suggest a multiple model comparison test that compares the HJ distance of a benchmark model with multiple competing models.

Chapter 3 Data

Covering the period from 1960 to 2020, the study makes use of data on innovation along with data on stock returns, stock prices, book to market value, operating profitability, investments and Fama-French 5 factors.

3.1 Comparing Measures of Innovation

The commonly used measures of innovation are a firm's Research and Development (R&D) expenses and patent data. Patents provide temporary monopoly rights to the patent holders over their inventions. Within the patent data, different subcategories of innovation involve patents filed, patents granted and patent citations. R&D expenses and patents filed are considered input-based measures of innovation while patents granted and patent citations are forms of output-based measures of innovation (Huang et al., 2021). R&D expenses as measure of innovation is considered to have limitations. First it captures only one quantitative input that does not provide any information about a company's innovation strategy. Moreover, R&D expenses are subject to accounting norms in terms of whether they should be expensed on capitalized. In addition to this, the disclosed information on R&D expenses may not be reliable and may result in measurement error problems. It is found that many firms do not disclose their R&D expenditures in Compustat database although those firms engage in innovation activity. It has been studied that about 10.5% of firms that have missing R&D information do file and receive patents. Moreover, selling, general and administrative (SG&A) expenses and R&D expenses may be reported interchangeably with some firms reporting certain expenses as SG&A which others report as R&D. Thus, using R&D expenses as a measure of innovation may bias estimations (He & Tian, 2018).

Following Mukherjee et al. (2017), Francis et al. (2019), Bena & Garlappi (2020), Cumming et al. (2020), Zhang et al. (2021), Huang et al. (2021) and Nguyen et al. (2021) this study uses patent-based measures as the main tool to measure innovation in this study. United States Patent and Trademark Office (USPTO) is the agency that looks after the issuance of patents to organizations in USA. Patents are considered as rich measure of innovation mainly because of the detailed information contained in patent data regarding the innovation like its technological area, geographical area, inventor details etc. Moreover, the patent data of USA is extensive as patents have been granted in USA since 18th century and the data dates to 1870. The data related to patents is provided on voluntary basis against the incentive of attaining temporary monopoly rights over the invention. This therefore increases the authenticity of the patent data. Another resourceful characteristic of the data on patents is that it also includes citations against each patent. Citations are an important source of determining the quality of patents as patents of high quality tend to receive greater citations. Based on this, citations are also used as measure of innovation as they reflect the quality of an innovation.

3.2 Patent Based Measures of Innovation

Using patent data as the base, different measures have been proposed that not merely rely on number of patents issued to a firm rather emphasize on the quality and value of the patents, e.g. citation based measures are one of such measures. However, Kogan et al. (2016) argue that citation-based measures only reflect scientific value of an innovation and do not represent its economic value. For example, a patent may not contribute much to scientific advancement, but it may help a company to fight competition and thus may generate private benefits. Thus, the private value created by patents may be more meaningful for a company than a patent's scientific value. Kogan et al. (2016) propose a measure of innovation that captures the economic value created by a patent defined as the present value of the monopoly rents resulting from a patent. For this purpose, they study the movements in stock prices following the days the patent is issued to a firm (three-day window including the day of patent issuance), filtering out events other than patent issue that may affect stock prices. The economic value of patent is then calculated as the product of the estimated stock return due to the issuance of patent multiplied by the market capitalization of the firm on the day prior to patent issuance. Moreover, when compared to the other measures of innovation quality i.e. patent citations, the measured economic value of patents is strongly positively related to forward citations of patents.

Given the importance of Kogan et al. (2016) measure of innovation in terms of measuring the quality and value of a patent, we use this measure as the indicator of innovation in our study. In this regard, the study uses the data on the economic value of patents as compiled in Kogan et al. (2016) (and later updated). This data is available for patents issued from 1926-2020. The data contains the patent number, firm's PERMNO, filing data of patent, issue date of patent, forward citations received by patent along with real and nominal economic values of patent is dollar terms. The study uses the nominal economic value created by a patent as the measure of innovation. Kogan et al. (2016) provide the nominal economic value of each patent granted against a PERMNO. In this study, we use the yearly nominal economic value as the sum of the economic value all patents granted against a PERMNO in a particular year. However, Kogan et al. (2016) calculates the value of patent in dollar terms, but to account for the impact of the size of the firms on the value of the patents, this study uses a relative measure of innovation. In this regard, annual economic value of the patents as ratio of the market capitalization of the stock (as of December of the respective year) is used as the measure of innovation. Over the period 1960-2020, we get total of 74,446 yearly nominal economic values against different PERMNOs.

3.3 CRSP and Compustat Data

In addition to data on the economic value of patent, the study makes use of data on monthly stock returns, stock price and shares outstanding obtained from Centre for Research in Security Prices (CRSP). This study also uses the data on book equity, operating profitability and total value of assets as obtained from Compustat. The data related to innovation and that obtained from CRSP both use PERMNO as the identifier. As the data from Compustat has to be used along with the data on innovation and stock returns, we first merged the Compustat and CRSP data. In Compustat the unique identifier used for a firm is GVKEY while in CRSP the unique company level identifier is PERMCO and unique security level identifier in PERMNO. CUSIP is an identifier that is present in both the CRSP and Compustat data and thus is used as the link between the two databases. Issued by CUSIP Service Bureau, CUSIP is a nine digit code in Compustat in which first 6 digits identify the issuer, the seventh and eight digit identify the issue and the ninth digit is the check digit. In CRSP, the CUSIP is eight digit code with first six digits identifying the issuer and the last two digits identifying the issue. However, CUSIP is not permanent and may change over time. The Compustat only shows the most recent CUSIP while CRSP has the most recent as well as historical CUSIPs.

For merging the two databases, we started with matching the eight digit historical CUSIP from CRSP with the first eight digits of Compustat CUSIP resulting in identifying the GVKEY against a PERMNO. Initially using the recent CUSIP from CRSP showed that for some securities with change in CUSIP, the PERMNO remained the same while in Compustat a new GVKEY was assigned with this change in CUSIP. Thus, matching CRSP and Compustst using recent CRSP CUSIP resulted in missing some firms in the merged data and therefore, historical CUSIPs from CRSP were used. Moreover, once the two databases were matched based on eight digits of CUSIP, further analysis of the unmatched data showed that for some the first six digits (issuer identifier) matched in the two databases while the last two digits did not match. Thus, the remaining unmatched data from the two databases was further merged using the first 6 digits of the CUSIPs. Matching was not initiated using 6 digits as for some it resulted in many to many matches. Moreover, after this matching, further analysis of the unmatched data showed that there were securities

(PERMNO) against a PERMCO that were matched with a GVKEY but at the same time there were some PERMNOs against the same PERMCO that were not matched to that same GVKEY. Analysis of this showed that for some securities again the first 6 digits from CRSP (issuer identifier) matched with the six digits (issuer identifier) from Compustat while the following two digits did not match. Thus, the data that was already matched using the 8 digits CUSIP was not available for matching using 6 digits due to which these securities were not matched even when 6 digits CUSIP was used. For this, the unmatched data from CRSP that had a PERMCO that was already matched to a GVKEY in Compustat was also matched to that GVKEY. Based on this analysis, 83.64% data from CRSP was matched with Compustat. Considering the PERMNOs in the data on innovation, there was a match of 89% with Compustat data.

In addition to the above mentioned data, the study also makes use of the data on Fama-French 5 factors that is obtained from Kenneth R. French data library[1].

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Chapter 4 Methodology

The main question that the paper wants to investigate is if innovation is one of the risk factors contributing to expected stock returns and if it should be priced when determining the expected stock returns. To analyze this, the study first analyzes the relationship between a firm's innovation level and its stock returns. As discussed above, the measure of innovation for this study is described as follow:

$$Innovation = \frac{Yearly\ Nominal\ Economic\ Value\ of\ all\ Patents\ against\ a\ stock}{Market\ Capitalization\ of\ the\ stock\ at\ the\ end\ of\ Decemeber\ of\ respective\ year}$$

Kogan et al. (2016) data on innovation provides the nominal economic value of each patent issued against a PERMNO. To calculate the annual nominal value of innovation against a PERMNO, the nominal economic value of all the patents issued to a stock in a year are summed. As discussed earlier, Kogan et al. (2016) calculates nominal economic value created by patent as the product of the estimated stock return due to patent issue multiplied by the market capitalization on the day prior to patent issuance. Therefore, to control for the size effect we measure innovation as the ratio of yearly nominal economic value to the market capitalization as of December of the respective year.

4.1 Univariate and Bivariate Portfolio Formation

To analyze the pattern between the level of innovation and expected returns, the study begins with the formation of innovation-based portfolios. In this respect, ten portfolios are formed in the June of each year t, based on the sorting on the value of innovation for *t-1*. These portfolios are formed based on all those securities for which value of innovation for *t-1* and market capitalization value for June of year *t* are available. Each of the ten innovation portfolios represent a decile i.e. each year using the value of innovation, stocks are sorted into ten equal groups. Thus, the breakpoints used for portfolio formation are based on all the stocks available in the innovation data. For these ten portfolios, market value weighted and equally weighted monthly returns are calculated to evaluate if there exists a relationship between a firm's innovation level and stock returns.

In addition to forming portfolios based on innovation alone, portfolios are also formed employing bivariate sorting. For bivariate sorting, innovation is accompanied with one of the four other variables that include size, ratio of book to market equity, profitability and investment. Using each of these variables along with innovation, 25 portfolios are formed through double sorting. Double sorting is implemented using both the independent and conditional sorting of innovation. In independent sorting the stocks are sorted into five equal groups independently based on innovation and one of the four variables mentioned above. In conditional sorting the stocks are first sorted into five groups based on one of the four variables and then within each of these five groups the stocks are further sorted into five equal groups based on innovation. Following summarizes the approach followed to form portfolios based on innovation and one of the four variables:

1. 6 and 25 portfolios on size and innovation: With reference to size and innovation, we form 6 and 25 portfolios. The portfolios are formed in the June of each year *t*. For size, the portfolios are formed making use of market equity (ME) at the end of June of year *t*. Market equity is calculated as the product of price and shares outstanding. The portfolios based on innovation are formed based on the value of innovation calculated for the year *t-1*. The portfolios are formed including all the stocks for which market equity for June of year *t* and innovation value for year *t-1* are available.
   To form the 6 size-innovation portfolios, the stocks are first sorted into two groups based on size using median market equity value as of June of year *t* as the breakpoint. Based on innovation for the year *t-1*, the securities are sorted both independently and conditionally into 3 groups representing bottom 30%, middle 40% and top 30%. For conditional sorting, each of the two groups formed based on size are further sorted into 3 groups (30%-40%-30%) based on innovation. For independent sorting, the stocks are sorted based on innovation irrespective of their size group. Similar approach is followed to form the 25 portfolios. The securities are sorted independently into 5 equal groups based on size and innovation with each group representing a quintile. For conditional sorting, the stocks are first sorted into 5 equal groups based on market equity for June of year *t* and each of these five groups is then further sorted into 5 equal groups based on innovation value for year *t-1.*
2. 25 portfolios on book to market equity ratio and innovation: These 25 portfolios are formed in June of each year *t*. Following Fama & French (2015), the book value of equity is calculated as value of stockholder's equity, plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock, the data for which is obtained from Compustat. The ratio of book to market equity is calculated as the book equity obtained for the fiscal year ending in *t-1* divided by the value of market equity as of December of year *t-1*. The portfolios sorted on innovation are formed based on the value of innovation calculated for the year *t-1*. The portfolios are formed including all the securities for which market equity for June of year *t*, innovation value and book to market equity ratio for year *t-1* are available. When forming the 25 portfolios, the securities are sorted into 5 groups based on book to market value with each group representing a quintile. The securities are also sorted independently into 5 groups based on innovation and 25 portfolios represent the intersection of 5

book to market value portfolios and 5 innovation portfolios. When sorting based on innovation, we also use conditional sorting where each of the 5 quintiles formed based on book to market value are further sorted into 5 groups based on innovation thus summing up to 25 portfolios.

3. 25 portfolios based on profitability and innovation: These portfolios are formed in June of each year *t*. Following Fama & French (2015), operating profitability is calculated as the ratio of operating profitability and book equity. Operating profitability is calculated as annual revenue minus cost of goods sold, interest expense and selling, general & administrative expenses. The portfolios in June of year *t* are formed based on operating profitability and book equity values for the fiscal year ending in *t-1*. The portfolios based on innovation are formed based on the value of innovation calculated for the year *t-1*. The portfolios are formed including all the securities for which market equity for June of year *t*, innovation value and operating profitability ratio for year *t-1* are available. Every year in June, the securities are sorted into 5 groups based on operating profitability, each group representing a quintile. The securities are also sorted independently into 5 groups based on innovation forming 25 portfolios at the intersection of each of the five profitability portfolios and five innovation portfolios. When sorting based on innovation, we also use conditional sorting where each of the 5 quintiles formed based on operating profitability are further sorted into 5 groups based on innovation making total 25 operating profitability-innovation portfolios.
4. 25 portfolios based on investment and innovation: The portfolios are formed in June of each year *t*. Following Fama & French (2015), investment is calculated as change in total assets from the fiscal year ending in *t-2* to the fiscal year ending in *t-1* divided by total assets in *t-2*. The portfolios based on innovation are formed based on the value of innovation calculated for the year *t-1*. The portfolios are formed including all the securities for which market equity for June of year *t*, innovation value and investment value for year *t-1* are available. For forming the 25 portfolios, the securities are sorted into quintiles based on the level of investment. The securities are also sorted into five equal groups based on the level of innovation thus forming 25 portfolios at the intersection of each investment portfolio and innovation portfolio. When sorting based on innovation, we also use conditional sorting where each of the 5 quintiles formed based on investment are further sorted into 5 groups based on innovation.

4.2 Test of Monotonicity

Analysis of the ten portfolios based on innovation along with 25 portfolios formed based on innovation and one of the four factors of size, book to market equity ratio, profitability and investment indicates that average monthly stock returns increase with the firm's level of innovation. For all the portfolios, the average monthly return for the portfolio with highest level of innovation is greater than the average return for the portfolios with low innovation. Based on this, we perform a test of monotonicity following the approach proposed in Patton & Timmermann (2010) to evaluate if monotonically positive relationship exists between stock returns and level of innovation.

Patton & Timmermann (2010) suggest a nonparametric approach applying bootstrap methods to test for monotonicity. Under this approach, the null hypothesis proposes a flat or weakly decreasing pattern of returns across the portfolios of interest while alternate hypothesis proposes an increasing pattern of return. For this purpose, we consider μ_i as the expected return on ranked N+1 securities over T time periods i.e. $\mu_i = \left(\frac{1}{T}\right)\sum_{t=1}^{T} r_{it}$ for all i = 0,..,N. and define the return differential as $\Delta_i = \mu_i - \mu_{i-1}$ for all i =1,....., N. In this regard, null and alternative hypotheses will be defined as:

$H_o: \Delta \leq 0 \quad versus\ H_1:\ \Delta > 0$

The above hypotheses can also be written as:

$H_o: \Delta \leq 0 \quad versus\ H_1: min_{i=1,..,N}\ \Delta_i > 0$. If the smallest value of $\Delta_i > 0$ then $\Delta_i > 0$ for all i=1,...,N. Based on this, the test statistic used is: $J_T = min_{i=1,..,N}\ \Delta_i$ which uses all the adjacent pairs of returns to test for monotonicity. Further, Patton & Timmerman (2010) also employ the bootstrap approach. For this, a new sample of returns is drawn from original sample of T time periods for N+1 securities defined as $\{r^b_{i\tau(t)}, \tau(1), \ldots, \tau(T); i = 0,1,\ldots,N\}$. Here, $\tau(t)$ is the new time index randomly drawn from the original set {1,...,T}. Moreover, b is the bootstrap number ranging from b = 1,...,B where B is chosen to be sufficiently large. Once the bootstrapped return series Δ^b is obtained for each security, the test statistic and p-value are calculated as:

$$J_T^{(b)} = min_{i=1,..,N}\ \left(\Delta_i^{(b)} - \Delta_i\right) \quad b = 1,2,\ldots,B$$

$$p = \frac{1}{B}\sum_{b=1}^{B} 1\{J_T^{(b)} > J_T\}$$

If the p-value is less than 0.05, it would rule in favor of alternative hypothesis indicating a monotonically increasing relationship.

4.3 Regression Analysis

Based on the analysis of the variation in stock returns with the innovation level, the study further evaluates if innovation factor is one of the significant risk factors requiring compensation, thereby explaining the expected stock returns. To do so, the study incorporates an innovation factor to the existing asset pricing models with the goal to analyze if the model with innovation factor better explains the expected stock returns. Earlier in the literature review, we discussed various asset pricing models that have been proposed over the years. Different analysis and studies have been conducted to compare the asset pricing models and to establish the models that perform best. In this regard, Barillas & Shanken (2018) conducted a study that tested all possible asset pricing models formed based on the subset of different factors that have been proposed over years. The best three pricing models obtained in their study always contained excess market return, profitability, book to market value ratio and momentum factor. After these best three models, Fama-French 5 factors model and Hou, Xue & Zhang q factor model performed well. Moreover, the study showed that Fama-French 5 factors model and Hou, Xue & Zhang q factor model was dominated by models that contained momentum factor. Considering this, the study uses Fama-French 5 factors model as the main benchmark asset pricing model.

The study employees time series regression to evaluate if innovation contributes towards explanation of the expected stock returns thus improving the existing asset pricing models. For this purpose, the study first develops an innovation factor to be incorporated into the existing model. Following the approach adopted in Fama-French 3 factors and 5 factors model for the construction of factors, this study makes use of innovation value as well as size of the firm for construction of innovation factor. In this respect, the innovation factor is described as follow:

$$Innovation\ factor = \frac{1}{2}(small\ high\ innovation + big\ high\ innovation) - \frac{1}{2}(small\ low\ innovation + big\ low\ innovation)$$

To form the innovation factor, we make use of the 6 size-innovation portfolios that were discussed earlier. As high innovation portfolio generates higher return than low innovation portfolio, the innovation factor involves going long the high innovation portfolio and short the low innovation portfolio. However, in this regard, high innovation portfolio is defined as the average of small and big high innovation stocks and low innovation portfolio is based on the average of both small and big low innovation stocks.

The initial analysis encompasses time series regression of the 10 innovation portfolios and 6 size-innovation portfolios against the Fama-French 5 factors to evaluate if the stock returns on these portfolios are explained by the model. Following this, further analysis is performed through time series regression of different test assets against Fama-French 5 factors with and without innovation factor, thus testing if the model is improved with the addition of the innovation factor. These models are presented as follow:

$$R_{it} - RF_t = \alpha_i + \beta_i(RM_t - RF_t) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \qquad (1)$$

$$R_{it} - RF_t = \alpha_i + \beta_i(RM_t - RF_t) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + i_i Innovation\ factor_t + \ e_{it} \quad (2)$$

Eq (1) represents the existing Fama-French 5 factors model while Eq (2) represents the Fama-French 5 factors plus innovation model that we want to test in this study. In the above equations, R_{it} is the return on security or portfolio i for period *t* and RF_t is the risk-free rate for period t. RM_t is the return on market portfolio, SMB_t is the return on portfolio of small stocks minus the return on portfolio of big stocks, HML_t is the return on portfolio of high book to market value stocks minus the return on portfolio of stocks of low book to market value, RMW_t is the difference between the returns on portfolios of stocks with robust and week profitability and CMA_t represents the difference between returns of portfolios with conservative and aggressive investments. Innovation factor in the above equation represents the newly created innovation factor that we want to evaluate with respect to asset pricing in this study.

Using Ordinary Least Squared (OLS) regression, the study uses different sets of test assets to obtain the value of $alpha\ (\alpha)$ in Equations (1) and (2). If a model captures all the variation in the stock returns, then its $alpha\ (\alpha)$ should not be significantly different from zero. To test if the $alphas\ (\alpha)$ of the test portfolios are jointly equal to zero; Gibbons, Ross & Shanken (1989) test (GRS test) is used with test statistic calculated as follow:

$$\frac{T}{N} * \frac{T-N-k}{T-N-k} * \left(1 + u_f' \Omega^{-1} u_f\right)^{-1} * \ \alpha' \sum\nolimits^{-1} \alpha \ \sim F_{N,T-N-k}$$

T represents the number of time series observations, *N* is the number of test assets for which the values of alphas are being jointly tested while *k* represents the number of factors used in the model. u_f represents the vector of factors mean with Ω representing the variance co variance matrix of factor returns. ∑ represents the variance covariance matrix of the residual terms. The GRS test statistic follows an F distribution using which the *p* value is obtained to evaluate if the model results in the values of alphas that are not different from zero. In addition to using the *p* value to evaluate the success of the model, we also use the GRS test statistic itself to compare the five factors and six factors model. In our case where we try to test if the values of alphas are not different from zero, a lower value of GRS test statistic would help to achieve this. Thus, the model with a lower value of GRS statistic would indicate an improvement over the model with the higher value of test statistic. In addition to this, following Fama & French (2015) and Fama & French (2020), we employ equal weight metrics as additional measures to compare models with and without innovation factor. The equal weight metrics include:

1. $A\,|\alpha|$ and $A\,|t(\alpha)|$: these measure the average of the absolute alphas and absolute t statistics of the alphas of all the test assets used.
2. $\frac{A\,\alpha^2}{V\bar{r}}$: This measures the average of the squared alphas of the test assets as ratio of the cross-section variance of the average returns of the test assets.
3. $\frac{A\lambda^2}{V\bar{r}}$: To adjust for noise in the estimated values of alphas, the squared standard error of each alpha is subtracted from the squared alphas to come up with the value of noise adjusted squared intercept (λ^2), that is $\lambda^2 = \alpha^2 - s^2(\alpha)$. The average of the noise adjusted squared intercept across all the test assets is then divided by the variance of the average returns of the test assets. This reflects the alpha dispersion relative to the dispersion of the average returns of test assets.

These measures are called equal weight metrics because they weigh each regression equally. A low value of all these equal weight measures is better for a model.

The test assets that we use on the left-hand side of the equations (1) and (2) include Fama-French 25 portfolios formed based on size and book to market values, 25 portfolios formed on size and operating profitability and 25 portfolios formed on size and investment. Moreover, Fama-French 30 and 49 industry portfolios are also used as test assets.

Chapter 5 Description of Sample

The analysis period considered for this study is from 1960 to 2020. Over this period the number of patents issued increased by over 6 times with the number of issued patents increasing from 15,478 in 1960 to 101,840 in 2020. A significant increase in patents issuance started since 1998. However, at the same time the increase in the number of innovating firms has not been as large as the number of patents. The number of innovating firms in 1960 were 517 rising to 899 in 2020. The number of innovating firms increased significantly from 1994 to early 2000 after which it started declining. Figure 1 summarizes the trend of patents issued since 1960.

<< Insert Figure 1 here>>

Table 1 provides descriptive statistics of the patent data used in this study. On average 45,798 patents have been issued each year since 1960. Based on all patents issued annually, the average economic value created annually through issuance of patents is around $936.528 billion. For all the patents issued since 1960, the average patent value has been around $20.44 million.

<< Insert Table 1 here>>

Table 2 provides the average market capitalization of the firms based on their level of innovation. Distributing firms into 10 groups based on their level of innovation, Table 2 summarizes the average size of the firms in each group measured based on their market equity. As can be seen, the average size of the firms in high innovation groups is bigger than the average size in the low innovation groups. The average size is much higher for the three highest innovation groups. The average market capitalization for the lowest 7 groups is around $2,419.45 million while the average market capitalization for the highest three groups is $8,905.21 million. This reflects that big firms are more involved in innovation as compared to small sized firms. Moreover, the size of the innovation rank 9 is largest followed by rank 8 and rank 10. We can observe that although big size firms are more involved in innovation but firms with highest innovation may not necessarily be the firms with highest market capitalization as evident based on the lower average market capitalization of innovation rank 10 as compared to innovation rank 9 and rank 8. Moreover, the average market capitalization of innovation rank 1 is higher than the market capitalization of following five innovation ranks reflecting that companies with lowest level of innovation are not necessarily only small sized companies but some relatively big sized companies may also be less innovative.

<< Insert Table 2 here>>

In addition to size, we also look at how innovation varies across industries. Using Standard Industrial Classification (SIC) codes, we look at the innovation level of the ten main business/industry groups as represented in Table 3. Based on the data of all the innovating firms since 1960, the highest ratio of about 78% belongs to the manufacturing sector i.e. based on all the securities that have appeared in the innovation data since 1960, the highest percentage belongs to the manufacturing sector. The second highest ratio, although much lower than the manufacturing sector, belongs to the service sector at 8.90% followed by transportation & public utilities, mining, finance & real estate, public administration and wholesale trade at 3.42%, 2.5%, 2.22%, 1.73% and 1.69% respectively. For the remaining sectors like retail trade, construction and agriculture & forestry the ratio is less than 1%.

For manufacturing and service sectors, Table 3 also provides the top five sub industries with reference to innovation. Within manufacturing; electronics and electrical equipment has the highest share with respect to innovation at 20.24%. This category includes industries dealing in electrical industrial appliances, home appliances, lighting equipment and communication equipment. The second highest share within the manufacturing sector is for chemicals and allied products that mainly include sectors like industrial organic chemicals, agriculture chemicals and pharmaceuticals. The industries dealing in industrial commercial machinery and computer equipment are also among the top five manufacturing sectors that are involved in innovation. The industrial groups dealing with measuring, analyzing and controlling instruments have fourth highest share with respect to innovation within manufacturing sector. This groups includes sectors that deal in laboratory apparatus, surgical instruments, photographic instruments and navigation & aeronautical instruments. Finally, the industry dealing in transportation equipment has the fifth highest innovation share within manufacturing sector. Motor vehicles, aircrafts, ship and boat building, railroad equipment, motorcycles and space vehicles are some of the subcategories of this sector.

Within the services sector, the highest share with respect to innovation is for business services. This category includes services like advertising, consumer credit reporting, equipment rental and leasing, computer programming, data processing and photography. Engineering, accounting, research and management services have the second highest innovation share within services sector. This category includes services like architecture, accounting, auditing, research & development and management & public relation services. In addition to these, health services and motions pictures are other service based sectors which rank among the top five innovation sectors within the service sector. The motion picture sector includes motion picture production as well as its distribution.

<< Insert Table 3 here>>

Chapter 6 Empirical Findings

The analysis of identifying the relevance of innovation in explaining the variation in stock returns begins with examining how the stock returns vary with the level of innovation. For this we observe the average monthly stock returns of the ten portfolios formed based on innovation. Table 4 provides an average of the equally weighted and market value weighted monthly returns of the ten innovation portfolios. As can be seen for both equally weighted and value weighted returns, highest innovation rank portfolio produces higher return as compared to lowest rank innovation portfolio. For equally weighted returns, the difference between the average monthly return of the lowest innovation portfolio and highest innovation portfolio is 40 basis points that translates into annual return of 4.9%. Likewise, for the value weighted returns, the difference in the average monthly return between highest and lowest innovation portfolios is 22.4 basis points translating into annual return of 2.72%. Higher stock return for high innovation portfolios is in line with the set of the literature that proposes an equity premium associated with innovation identifying it to be a source of economic uncertainty and risk. At the micro level, these results correspond with the previous studies identifying innovation as a risky process due to the uncertainty associated with the outcome, thus demanding a risk premium. Table 4 shows that highest innovation portfolio has higher return than lowest innovation portfolio, however, we do not see the return consistently increasing with the increase in innovation. For both the equal weighted and value weighted portfolios, there are 6 ups and three downs as we move from low to high innovation. We apply the test of monotonicity to analyze if the average returns increase monotonically with the level of innovation.

<< Insert Table 4 here>>

As discussed in methodology, we use the non-parametric monotonicity test by Patton & Timmermann (2010) to test for monotonicity. We applied the test of monotonicity on the value weighted monthly returns of the ten innovation portfolios to test if the returns increase monotonically with innovation level. Figure 2 shows how the average returns vary across the ten innovation portfolios. The p-value obtained against the monotonicity test is 0.6480 indicating that the alternative hypothesis of monotonically increasing returns is not accepted.

<< Insert Figure 2 here>>

To analyze more in depth the variation of stock returns with respect to innovation, we analyze the stock returns across portfolios formed based on innovation and other factors like size, book to market value, profitability, and investment.

6.1 Size and Innovation Sorted Portfolios

Size is one of the factors determining the variation in stock returns as identified by Banz (1981) and later incorporated in Fama-French 3 factors and 5 factors models. As already discussed in methodology, we form 6 and 25 portfolios based on size and innovation. Table 5 provides the average value weighted monthly returns against the 6 size-innovation portfolios. Consistent with Fama & French (2015), the size effect is visible with respect to the 6 portfolios with average monthly return higher for small size as compared to the big size for each of the three innovation categories. As observed with the 10 innovation portfolios, the average monthly return mostly increases with the level of innovation with exception for the conditional sorting of innovation where return on rank 2 innovation portfolio is lower than return on rank 1 portfolio within big size category. Moreover, the innovation effect is more prominent in small size stocks. As can be seen in Table 5, the average difference between high and low innovation for small size stocks is 0.4582% (0.3517% for conditional sort) as compared to difference of 0.0716% (0.1183% for conditional sort) for big size firms. This reflects a higher innovation premium for the small size firms. The innovation premium for small size firms is both statistically and economically significant with *t* value of 3.34 and 2.90 for independent and conditional sorting respectively. Overall, the average difference between the return of high innovation portfolios and return of low innovation portfolios is 26.5 basis points for independent sorting and 23.5 basis points for conditional sorting of innovation over the period 1961-2020.

<< Insert Table 5 here >>

Similar trend can be observed in case of 25 portfolios where the average monthly return mostly decreases as we move up the size ladder. Main exception to this is in case of lowest innovation rank, where return on smallest size is lower than the return on following two size ranks for independent sorting of innovation. For conditional sorting of innovation too, the return on smallest size portfolio within lowest innovation rank is lower than the return on portfolio of rank 2. However, the return still remains higher than the return on the biggest two size portfolios. The size rank 4 portfolio also has a higher return than the size rank 3 portfolio for innovation ranks 3 and 4 in case of conditional sort and innovation rank 3 in case of independent sort. Overall, the return on big size portfolios is lower than the average return on portfolios of small sized firms. As observed with the 10 innovation portfolios and 6 size-innovation portfolios, the average monthly return for the 25 portfolios mostly increases with the level of innovation except for some portfolios where the average return shows some decrease with increase in innovation. As observed with 10 innovation portfolios, the increase in average returns with increase in innovation level is not consistent. However, as compared to the average return for lowest innovation portfolios, we can see a higher return for highest innovation portfolio within each size group. Moreover, as observed earlier the innovation effect is more prominent in small size stocks. The difference between the average returns of high and low innovation firms decreases as we move up the size scale. The high-low innovation difference for smallest size rank is 93.3 basis points that reduces to 13 basis points for highest size rank when we consider independent sorting of innovation again reflecting the presence of innovation premium mainly for small size firms. Based on the average returns for size-innovation portfolios, innovation is a source of risk for small size firms as compared to large size firms thereby leading to a premium for the small size firms that have high levels of innovation.

Further, combining the size and innovation effect for the 25 size-innovation portfolios, we can see that the difference in the average monthly return of small size-high innovation firms and big size-low innovation firms is 1.13% or 14.4% annually.

<< Insert Table 6 here>>

6.2 Book to Market and Innovation Sorted Portfolios

As suggested in Stattman (1980) and Fama-French 3 factors and 5 factors models, book to market value (B/M) also explains the average stock returns. Therefore, we also form 25 portfolios based on sorting against B/M and innovation. Table 7 provides the average value weighted monthly returns of these 25 portfolios. Under the value effect, the high book to market value portfolios (the value stocks) generate higher return than low B/M portfolios (the growth stocks). The value effect can be observed across almost all the B/M portfolios within each innovation sort. With some exceptions, the average returns increase as the book to market value increases. The innovation effect as observed earlier, can be viewed here as well, however, it is more associated with extreme high and low innovation groups within each B/M portfolio.

The middle three innovation quintiles within each B/M group do not show a consistent behavior. Thus, the innovation effect for each B/M portfolio is the high average return for highest innovation quintile and low average return for lowest innovation quintile. The difference between the average return of highest and lowest innovation portfolio for lowest B/M quintile is 14.5 basis points increasing to 34 basis points for highest B/M quintile.

<< Insert Table 7 here>>

6.3 Investment and Innovation Sorted Portfolios

Following the similar approach as adopted for 25 size-innovation and B/M-innovation portfolios, we also form 25 portfolios based on double sorting using firm's level of investment and innovation. As can be seen in Table 8, average value weighted monthly return decreases as we move up the investment quintiles. Consistent with results in Fama and French (2015), high investment quintiles mostly produce lower return than low investment quintiles. With respect to innovation, the behavior is not completely consistent with the one seen so far in the previous portfolios formed based on size and B/M. The highest innovation quintile producing higher return than lowest innovation quintile is visible in the three highest investment quintiles only. The lowest two investment quintiles (specifically with independent sorting) have highest innovation quintile produce lower return than lowest innovation quintile. It appears that these firms are involved in innovation but are conservative with respect to investment spending that may result in the reduction of the risk associated with the process of innovation. Such firms may be those that innovate but do not commit too many resources to it thus reducing the risk in case innovation is not successful and resulting in lower average returns. Moreover, for the highest three investment quintiles, the innovation effect is prominent for the lowest innovation quintile and highest innovation quintiles with highest innovation portfolios producing higher return than lowest innovation portfolio. As with B/M-innovation portfolios, the middle three innovation quintiles do not show a consistent behavior in this regard.

<< Insert Table 8 here>>

6.4 Profitability and Innovation Sorted Portfolios

We further analyze how innovation effects average returns when we introduce profitability as another variable. Table 9 provides the average value weighted monthly returns of the portfolios formed on double sorting against innovation and profitability. The relationship of high profitability and higher average return as proposed in Novy-Marx (2013) and further discussed in Fama and French (2015) is not visible for all the portfolios in Table 9. We can see that average return for highest profitability quintile is higher than average return for lowest profitability portfolio for lower innovation quintiles. However, this is not the case for the higher innovation quintiles (highest two for conditional sorting and 3rd and 5th quintile for independent sorting). The major difference is for the highest innovation quintile where the average return on low profitability portfolio is much higher than average return for high profitability portfolio. As discussed earlier, high uncertainty associated with the outcome of innovation may result in higher required return for high innovation level. For the highest innovation quintile with low profitability, it appears that firms with innovation may not be yielding profitable outcomes increasing the uncertainty associated with innovation and thus leading to higher required returns. At the same time, high level of innovation with high profitability may reduce the uncertainty associated with innovation thus leading to lower required return for high profitability-high innovation quintiles as compared to low profitability-high innovation portfolio.

<< Insert Table 9 here>>

6.5 Six Size-Innovation Portfolios against Fama-French 5 Factors

Using the six size-innovation portfolios formed earlier as the test assets, we apply the Fama-French 5 factors model, evaluating how effectively the average monthly returns of these six portfolios are explained by the five factors. Table 10 provides the results of the regression using 6 size-innovation portfolios formed with innovation sorted independently as well as sorted conditionally on size. If a model explains the average returns, then the values of the alphas should not be significantly different from zero. We can see that for high innovation portfolios, both for small and big size firms, the *t* values for the alphas reflect that they are significantly different from zero. If we look at the innovation portfolios within each size, we can observe the relevance of the innovation effect. In view of the size effect the small sized firms produce higher returns than big size firms. In this respect, small size firms producing alphas is justified, however, as seen in Table 10, the high innovation portfolio within big size also produces significant positive alpha. If we observe the coefficient values for alphas in Table 10 we can see positive alphas for all three innovation portfolios within small size both with independent and conditional sorting, but we also see some positive alphas for big size firms. For big size we see positive significant alpha for big-high innovation for conditional sort and for big-medium (t value suggests it to be insignificant) and big-high portfolios (significant alpha) for independent sort. Moreover, for small size, the small-low innovation portfolio does not have significant alpha. Within each size group, high innovation is producing higher alpha than low innovation. For big size firms, the difference between the alpha of high and low innovation is about 14 basis points (18 basis points for conditional sort). For small size, high innovation produces alpha that is 52.4 basis points (42.4 for conditional sort) higher than low innovation. Thus, based on this analysis, controlling for size, high innovation is generating higher alphas than low innovation suggesting the presence of innovation premium. Moreover, this premium is higher for small sized firms.

<< Insert Table 10 here>>

As discussed earlier, GRS test helps to identify if the values of the alphas of all the test assets are jointly equal to zero. Table 26 shows the GRS test results for this regression. As can be seen, the GRS test statistic is 4.29 with *p* value of 0 rounded to three decimal places. This reflects that alphas are significantly different from zero and the returns on the six portfolios formed on basis of size and innovation are not fully explained by the five factors model.

6.6 Ten Innovation Portfolios against Fama-French 5 factors

The analysis performed for 6 size-innovation portfolios is also performed using the 10 innovation portfolios formed earlier. The excess monthly returns of each of these portfolios are regressed using Fama-French 5 factors model. The purpose of this is to evaluate if the model explains the average returns of these portfolios by measuring if alphas are jointly equal to zero. Table 11 provides the outcome of this regression. As reflected by the t-statistic, the alphas of the high innovation portfolios (highest two deciles) are statistically significant. Based on the values of alphas, if we long the highest innovation portfolio and short-sell the lowest innovation portfolio, we can earn a return of 0.30 basis points monthly or 3.6% annually in excess of the return predicted by Fama-French 5 factors model which is economically significant. If we look at the exposure of these 10 portfolios to the Fama-French 5 factors, we see that the high innovation portfolios have negative exposure to SMB while low innovation portfolios have a positive exposure to the factor. This shows that the high innovation firms are big sized firms. However, with respect to other factors, we cannot see a clear pattern of the exposure of the high and low innovation portfolios to the factors. As shown in Table 26, GRS statistic for this regression analysis is 1.71 with *p* value of 0.0737. At significance levels of 1% and 5%, these results reflect that the values are not significantly different from zero. At significance level of 10%, it shows that the alphas are significantly different from zero.

<< Insert Table 11 here>>

Based on the 10 innovation portfolios, we can see that for high innovation portfolios the model does not completely capture the variation in the average returns as reflected in their high alphas. For the 6 size-innovation portfolios as well, alpha is significant for high innovation portfolios for both small and big sized firms. Seeing higher alphas produced by high innovation, we next perform our analysis by adding an additional factor to the Fama-French 5 factors model. This additional factor reflects innovation and as discussed in methodology, is formed based on difference between high and low innovation portfolios. The remaining analysis is based on regressing different sets of test assets using models with and without the innovation factor and evaluating if the addition of innovation factor improves the model. As discussed previously, one of the ways of analyzing this is through GRS test. In addition to testing if the alphas of the test assets are jointly equal to zero, we can compare the GRS test statistic across the models. The model with lower value of GRS statistic brings about an improvement as compared to the model with higher GRS statistic. We also compare the models with and without innovation using the equal weight metrics.

6.7 Fama-French Five Factors plus Innovation Factor

As discussed above, innovation is relevant with respect to the variation in the expected stock returns. In this section, we will perform analysis using asset pricing model with and without the innovation factor. For this purpose, following test assets will be used:

10 innovation portfolios[1]: The ten innovation portfolios formed previously using innovation as the variable for sorting will be one set of test assets to be used.

25 Size-BM Portfolios[1]: Obtained from Fama-French database, these include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on the ratio of book equity to market equity (BE/ME).

25 Size-Operating Profitability (OP) Portfolios[1]: Obtained from Fama-French database, these include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on the operating profitability.

25 Size-Investment Portfolios[1]: Obtained from Fama-French database, these include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on the investment that is calculated as the ratio of change in assets to total assets in the previous year.

30 industry Portfolios[1]: Obtained from Fama-French database, these include 30 portfolios that are formed based on 4 digit SIC code.

49 Industry Portfolios[1]: Obtained from Fama-French database, these include 49 portfolios formed based on SIC codes.

As innovation factor will be added to the existing 5 factors Fama-French model, we first analyze the correlation between the innovation factor and the five Fama-French factors. Table 12 provides the summary statistics for Fama-French 5 factors plus innovation factor. As can be observed, the correlation of innovation factor with all the other 5 factors is low. CMA factor that reflects the level of investment also has a low correlation with innovation factor showing that a firm's investment level may not reflect its inclination towards innovation. Moreover, as discussed above in sample statistics, high innovation firms have high average market capitalization. However, the correlation matrix shows a low but positive correlation of 0.16-0.18 between innovation factor and SMB. It appears that innovation positively correlates with size as a risk factor with high risk associated with both small size firms as well as high innovation firms. Further, the summary statistics show that the innovation factor has a mean value of 0.0027 that translates into yearly average of 3.31% with t-value of 3.26 showing it to be statistically as well as economically significant. After market risk premium, innovation factor has the highest average value as compared to other Fama-French factors.

<< Insert Table 12 here>>

6.8 Regression Analysis

Previously we regressed the 10 innovation portfolios using the Fama-French 5 factors model. Now, we see how the effectiveness of the model is impacted once we add innovation factor to the model. Table 13 provides the results of the regression with innovation factor formed based on independent sorting of innovation and size as well as on conditional sorting of innovation against size. As shown in the above analysis regressing 10 innovation portfolios on five factors, the *p* value reflects that alphas are different from zero only at 10% significance level. With 6 factor model, the GRS statistic is lower than the five factors model at 1.09 (1.10 for conditional sorting) with *p* value of 0.36. This shows that under the 6 factors model the alphas are jointly equal to zero at all significance levels. In addition to a lower value for GRS statistic with 6 factors, all other equal weight metrics i.e. $A\,|\alpha|$, $A\,|t(\alpha)|$, $\frac{A\,\alpha^2}{V\bar{r}}$ and $\frac{A\lambda^2}{V\bar{r}}$ have lower values as compared to 5 factors model.

<< Insert Table 13 here>>

We perform similar analysis using 25 Size-BM portfolios as test assets which are regressed against Fama-French 5 factors and then against 5 factors plus innovation factor. Table 14 provides the results of the regression on Fama-French 5 factors. As can be seen in the table, in line with Fama and French (2015), the exposure to SMB reduces as we move from small size portfolios to big size portfolios and all the portfolios within size big have negative exposure to SMB reflecting their big size. The exposure to HML is also justified as low B/M portfolios have negative exposure to HML reflecting their growth orientation. Moreover, within each B/M portfolio, we can see that firms' growth orientation reduces as size increases. The firms with lowest B/M mostly have negative exposure to RMW. These would represent the growth firms which are not yet profitable. Within this quintile, negative exposure to RMW decreases as size increases with big growth firms exposed positively to RMW. In line with Fama & French (2015), the portfolio in smallest size rank and lowest B/M rank has the most negative exposure to RMW. At the same time, this portfolio has negative exposure to CMA showing it to be aggressive in investment. As discussed in Fama & French (2015), these represent the unprofitable firms that grow rapidly. As reflected from the *t* values, the 5 factors model produces 9 significant alphas (t value > ±1.64).

<< Insert Table 14 here>>

Table 15 provides the results of the regression of 25 Size-BM portfolios on Fama-French 5 factors plus innovation. If we look at the loading of each of the 25 portfolios against innovation factor, we can see that all the five portfolios within the smallest size group have positive exposure to innovation factor and is statistically significant at 10% or lower except for one portfolio i.e. B/M rank 3. The coefficient against innovation factor for the smallest size portfolios do not follow a consistent pattern, however the low B/M portfolios (B/M low and B/M rank 2) within smallest size group have higher loading on innovation factor as compared to high B/M portfolios within this category. As low B/M portfolios represent growth firms, we can see that all smallest size companies have positive exposure to innovation factor and small growth companies are more exposed to innovation than small value firms. The middle three size groups show negative exposure to innovation factor except for the high B/M firms in size 2 and size 3 which have a positive but statistically insignificant positive exposure. For the big size firms, the lowest B/M firms have positive significant exposure to innovation factor. This category represents the big growth firms with positive loading on innovation. The three middle BM groups within big size have negative exposure to innovation factor and big highest B/M portfolio has positive but insignificant loading against innovation. Overall, the results show that smallest size firms have positive exposure to innovation with small growth firms more positively exposed to innovation than small value firms. Moreover, big growth-oriented firms also have a positive exposure to innovation. Out of the 25 portfolios, 16 portfolios have a statistically significant (*t* value of greater than ±1.64) exposure to innovation factor. Looking at the values of alpha, the 6 factors model generates 4 statistically significant alphas as compared to 9 significant alphas seen previously in case of 5 factors model.

<< Insert Table 15 here>>

Now to compare the Fama-French 5 factors model with the 6 factors model, we consider the GRS statistic. Table 26 shows that the GRS statistic drops from 2.95 in case of 5 factors model to 2.7 for the model with 6 factors. However, the *p* value for both the models is 0 rounded to three decimal places reflecting that both the models do not completely capture the variation in expected stock returns. But lower GRS value shows that 6 factors model has improvement over 5 factors model. The value of absolute alpha for 6 factors model reduces about 0.6 basis points as compared to the value of average absolute alpha for 5 factors model. The reduction in the value of absolute alpha is low. However, as discussed in Fama & French (2015), the Fama-French 5 factors model that incorporated two additional factors also did not reduce the absolute alpha much for 25 size-BM portfolios. It produced a decrease in absolute value of alpha of about 0.8 basis points in comparison to the 3 factors model. In addition to absolute alpha, the values of the other equal weight metrics like $A\,|t(\alpha)|$, $\frac{A\,\alpha^2}{V\bar{r}}$ and $\frac{A\lambda^2}{V\bar{r}}$ also decrease for 6 factors model showing an improvement over the 5 factors model.

25 portfolios formed based on size and operating profitability are used as another set of test assets to compare the 5 factors and 6 factors model. Table 16 provides the results of the analysis of 25 Size-Operating Profitability portfolios regressed against Fama-French 5 factors. As these portfolios are formed with size as one of the sorting variables, the portfolios in the highest size quintile have negative exposure to SMB and within each OP quintile, exposure to SMB reduces as we move from smallest to biggest size. Small low operating profitability portfolios (OP rank low with size rank small and 2) have significant negative loading on HML reflecting these to be growth-oriented firms. The portfolios with big size stocks and highest operating profitability (size big with OP high) also have significant negative exposure to HML showing such stocks to be inclined towards growth as well. Most of the middle three OP portfolios within each size quintile have positive loading on HML. As the portfolios are sorted based on operating profitability, we can see all portfolios to have significant exposure to RMW with lowest OP portfolios carrying negative exposure and high OP portfolios with positive exposure. With reference to the alphas produced by the model, only 4 are statistically significant (t value > ±1.64).

<<Insert Table 16 here>>

Table 17 provides the results of the regression of 25 Size-OP portfolios against 6 factors with innovation sorted independently as well as conditionally. Analyzing the loading of each of the portfolios on the innovation factor shows that for the portfolios sorted based on size and operating profitability, exposure to innovation factor has a link with the growth-value orientation as reflected through the exposure to HML factor. A negative exposure to HML would reflect a company to be growth oriented with low book to market ratio. As can be seen in Table 17, all the portfolios with negative exposure to HML i.e. growth oriented portfolios have a positive exposure to innovation factor i.e. they have high level of innovation. However, the pattern of movement of coefficients against innovation factor and HML factor is not very consistent. For example, smallest size and lowest operating profitability portfolio has highest positive exposure to innovation factor of 0.28 (t=7.24) but this portfolio, although has negative exposure to HML at -0.11 (t= -3.38), but this is not the highest negative exposure. The highest negative exposure to HML is for the big size firms with highest operating profitability at -0.13 (t= -6.44). This portfolio has a positive exposure to innovation factor at 0.14 (t= 5.44) but not the highest exposure. However, we can see growth firms to have positive exposure to innovation, reflecting these firms to be more innovative than value firms with high book to market values. Within the lowest operating profitability quintile, smallest size portfolio has highest positive exposure to innovation as mentioned above. This portfolio is like the one discussed above while discussing Size-BM portfolios, small sized unprofitable firms that grow rapidly and the positive exposure on innovation may reflect that innovation may be one of the means to grow. Within this operating profitability quintile, the big size firms have significant negative exposure to innovation. If we look at the exposure of this portfolio against other factors, we can see that this portfolio represents value stocks (positive loading on HML) with aggressive investment but low innovation. Most of the other profitability quintiles have negative loading on innovation except for the big sized high profitability portfolio. Big size, high operating profitability and growth orientation (negative exposure to HML) characterize this portfolio and justifies its positive loading on innovation factor. Within the 25 size-OP portfolios, 17 portfolios have statistically significant loading (*t* value of greater than ±1.64) against innovation factor.

<<Insert Table 17 here>>

Comparing the 5 and 6 factors models for 25 size-OP portfolios, as shown in Table 26, the GRS statistic drops from 2.04 for 5 factors model to around 1.98 for 6 factors model, however, the *p* values for both the models come to 0 rounded to three decimal places. As compared to 25 size-BM portfolios, the decrease in absolute value of alpha for 6 factors model is slightly higher at about 0.8 basis points. The measures of $A\,|t(\alpha)|$ and $\frac{A\,\alpha^2}{V\bar{r}}$ also decline for 6 factors model. However, the value of $\frac{A\lambda^2}{V\bar{r}}$ is slightly higher for 6 factors model with innovation sorted conditionally at 0.1010 as compared to 0.1007 for 5 factors model. But with independent sorting of innovation, this drops to 0.0943. Overall, GRS test statistic and equal weight metrics decline in 6 factors model as compared to 5 factors model. With respect to number of significant alphas, the six factors model like the 5 factors model produces four significant alphas.

Size and investment based portfolios is another set of test assets that is employed to evaluate if the six factors model improves the explanation of expected returns. Table 18 provides the results of the regression of 25 size-investment portfolios against Fama-French 5 factors. As these portfolios are sorted with investment as one of the variables, the high investment quintiles have negative exposure to CMA. The highest investment quintile also has negative exposure to HML showing that high investment firms are growth oriented. With respect to RMW, the lowest investment quintile within small size (size small and size 2) has significant negative exposure reflecting low profitability of small firms with low investment. Moreover, as in Fama & French (2015), the highest investment quintile also has negative loading on RMW showing low profitability for high investment firms as well. The 5 factors portfolio results in 10 statistically significant values of alphas (*t* value of greater than ±1.64).

<<Insert Table 18 here>>

Table 19 provides the regression results for 25 size-investment portfolios against the Fama-French 5 factors plus innovation factor. If we look at the loadings of the portfolios on innovation factor, we cannot identify a particular pattern. This is especially true for the smallest size and lowest investment portfolio that has a high positive loading of 0.31 (t= 6.02) on innovation factor. These appear as growth firms with negative loading on HML, although the statistical significance against HML exposure is low. However, with small size and low investment their loading on innovation factor is high. Smallest size firms with high investment also have a positive loading on innovation that appears logical given their aggressive investment. The portfolios within size ranks 2,3 and 4 mostly have negative exposure to innovation factor. Within the big size companies, low investment portfolios have negative exposure to innovation factor except the lowest investment portfolio that has positive but statistically insignificant loading on innovation factor. The high investment portfolios within the big size category have a positive and significant exposure to innovation factor reflecting that big and high investment companies are involved in innovation. The number of portfolios that have significant exposure to innovation factor is much lower in case of size-investment portfolios as compared to the size-BM and size-OP portfolios discussed above. 11 portfolios show a statistically significant exposure to innovation factor in case of size-investment portfolios (*t* value of greater than ±1.64).

<< Insert Table 19 here>>

The GRS statistic for the 25 size-Inv portfolios, as shown in Table 26, reduces from 3.28 in case of Fama-French 5 factors to 3.03 (3.05 for conditional sorting) in case of Fama-French 5 factors plus innovation. The drop is the GRS statistic rules in favor of 6 factors model, however the *p* value still remains at zero rounded to three decimal places showing that alphas are significantly different from zero. If we look at the absolute value of alpha for the two models, the value almost remains the same at 8.2 basis points. The average absolute t value for 5 factors model is lower at 1.42 for five factors as compared to 1.47 for 6 factors model. However, the other two metrics i.e. $\frac{A\,\alpha^2}{V\bar{r}}$ and $\frac{A\lambda^2}{V\bar{r}}$ are still lower for 6 factors model. The six factors model produces 9 significant alphas as compared to 10 for 5 factors model.

6.9 Robustness Check

The GRS statistic for the three test assets discussed above decreases in case of six factors model. The average absolute value of alpha and average absolute t value also reduces for the model with innovation factor in case of 25 size-BM and 25 size-OP portfolios. However, for 25 size-Investment portfolios the absolute alpha does not change for 6 factors model and absolute t value slightly increases.

To further assess the performance of the 6 factors model, we use test assets formed based on industrial classification. In this regard, Fama-French 30 and 49 industry portfolios are used. The industrial classification for these portfolios in available in Appendix A. Table 20 provides the regression results of the 30 industry portfolios against Fama-French 5 factors. Most of the industrial portfolios have a positive loading on SMB although many of them may not be identified as small sized businesses. Games, books, apparel, textiles, construction, construction, steel, fabricated products, electrical equipment, autos, aircraft & railroad equipment, mines, coal, services, business equipment, transport, wholesale, retail, and meals all have significant positive exposure against SMB. Sectors like consumer goods, health care, services and business equipment appear as growth oriented with significant negative exposure to HML. Most of the industrial groups have positive exposure to RMW except for steel, telecom, services and business equipment which have significant negative loading on RMW reflecting low profitability. Games, services, business equipment and financial sector show aggressive investment with statistically significant negative exposure to CMA. With respect to alphas, the 5 factors model results in 13 statistically significant alphas (t value > ± 1.64).

<< Insert Table 20 here >>

Table 21 provides the regression results for the 30 industry portfolios regressed 6 factors with innovation sorted independently. If we look at the loading of various industries on innovation factor, we can see that games, consumer goods, chemicals, steel, fabricated products & machinery, electrical equipment, autos, aircraft and railroad equipment, services and business equipment are the main industries which have positive loading against innovation. Among these, the exposure of industries like business equipment and services is statistically significant. As compared to this, industries like food, liquor, apparel, construction, utilities, transportation, wholesale, retail, and financial sector have significant negative exposure to innovation factor.

<<Insert Table 21 here>>

As shown in Table 22, with innovation factor formed based on conditional sorting of innovation, the loadings of various industries on innovation factor remains the same as with independent sorting. However, with conditional sorting, fabricated products & machinery also has positive significant exposure to innovation factor in addition to business equipment and services as seen with independent sorting of innovation. Moreover, chemicals have negative but insignificant exposure to innovation and printing & publishing has significant negative exposure to innovation.

<< Insert Table 22 here>>

Comparison of the 5 factors and 6 factors model for 30 industry portfolios based on GRS statistic in Table 26, shows that the statistic drops from 2.67 for 5 factors model to 2.18 for 6 factors model. Of all the test assets used so far, the 30 industry portfolios show the highest drop in absolute value of alpha of 1.4 basis points. Moreover, $A\ |t(\alpha)|$, $\frac{A\ \alpha^2}{V\bar{r}}$ and $\frac{A\lambda^2}{V\bar{r}}$ also drop for the 6 factors model.

Fama-French 49 industry portfolios provide greater industrial depth as compared to the 30 industry portfolios and have been used as another test asset for robustness check of the results obtained so far. Table 23 provides the regression output for the 49 industry portfolios regressed against 5 factors. As with 30 industry portfolios, majority of the 49 industry portfolios have significant positive exposure to SMB factor. Drugs, utilities, telecom and banks are the industrial sectors with negative loading on SMB. Tobacco products, consumer goods, healthcare, medical equipment, drugs, business services, hardware, software, chips and lab equipment appear as growth-oriented industries with significant negative loading on HML. Steel, telecom, hardware, chips and financial sector are some of the industries with significant negative exposure on RMW reflecting low profitability. Entertainment, hardware, chips, banks and financial trading are the industries with aggressive investment as they show statistically significant negative exposure to CMA. Moreover, the five factors model produces 22 statistically significant alphas.

<< Insert Table 23 here >>

Table 24 provides the regression output for the 49 industrial portfolios regressed on 6 factors with innovation sorted independently. The analysis based on 30 industry portfolios reflected a positive but insignificant loading of games industry against innovation. Analysis using 49 industry portfolios shows that within this industry, both recreation sector including toys and entertainment sector have positive loading against innovation factor. However, the exposure is statistically insignificant as reflected in the *t* values. Moreover, sectors like medical equipment, drugs and chemicals all have positive but insignificant exposure to innovation factor. Fabricated products show a negative exposure to innovation factor while machinery has a positive exposure to it. Electrical equipment, autos, aircraft, mining, hardware, software, chips and lab equipment are the other sectors with positive exposure to innovation factor. Of these, machinery, hardware, chips and lab equipment have statistically significant positive loading against innovation. Industries like agriculture, food, liquor, clothing, utilities, wholesale & retail and financial sector continue to show negative exposure to innovation factor.

<< InsertTable 24 here >>

Table 25 provides the regression results for the 49 industry portfolios against the 6 factors with innovation factor constructed through conditional sorting of innovation. With respect to loading on innovations factor, almost similar trend is observed as with the independent sorting of innovation. Machinery, hardware, chips and lab equipment are the sectors with positive significant loading on innovation factor.

<< Insert Table 25 here >>

Just as with 30 industry portfolios, the analysis of 49 portfolios against 6 factors shows improved GRS statistic with its value dropping from 4.13 for 5 factors to 3.79 for 6 factors. However, as with other test assets, the *p* value comes at 0 rounded to three decimal places reflecting that neither 5 factors nor 6 factors model completely explain the expected stock returns. Moreover, as with other test assets, the 6 factors model results in lower value for the average absolute alpha that drops by 1.9 basis points along with reduced value for $A\,|t(\alpha)|$, $\frac{A\,\alpha^2}{V\bar{r}}$ and $\frac{A\lambda^2}{V\bar{r}}$. The six factors model generates 18 significant alphas as compared to 22 for Fama-French 5 factors model.

Overall, based on the five different sets of test assets used, we can see that the GRS statistic for the 6 factors model is lower than the Fama-French 5 factors model. As with five factors model, the *p* values for the 6 factors model reflect that the alphas for the test assets are not jointly equal to zero thus rejecting the model. However, lower GRS statistics for 6 factors model supports an improvement over the 5 factors model. The 6 factors model also results in a reduction in the average absolute values of alphas, that is more pronounced for the portfolios formed based on industrial classification. With respect to loading on innovation factor, we have seen that most of the portfolios in the lowest size quintile (smallest size) have a positive exposure even when they rank lowest on operating profitability and investment. Moreover, we also see some pattern between innovation and growth, whereby growth-oriented firms show positive loading against innovation factor.

<<Insert Table 26 here>>

6.9.1 Analysis on Firm Level

All the analysis above is based on the value of the innovation that is associated with the security issued by a firm as identified by its PERMNO in CRSP. A firm can have different classes of shares existing at the same time, each identified by a different PERMNO. Therefore, as robustness check, we also performed the analysis based on the innovation at firm level. For this, we used permanent company identifier (PERMCO) from CRSP as the main identifier to determine the value of innovation. To determine PERMCO innovation, the yearly nominal economic value of all securities (PERMNOs) within that PERMCO was added. The innovation value determined for a PERMCO was assigned to all the securities for that PERMCO, including those securities to which nominal economic value of innovation was not assigned in the Kogan et al. (2016) data. Using PERMCO as the main identifier to determine the nominal economic value of innovation of each security, the rest of the analysis with respect to formation of innovation sorted portfolios, innovation factor and regression using Fama-French 5 factors plus innovation factor was performed as discussed in the sections above. The results of analysis on firm level were similar to the main results that have been discussed so far.

The innovation factor constructed as $\frac{1}{2}(\text{small high innovation} + \text{big high innovation}) - \frac{1}{2}(\text{small low innovation} + \text{big low innovation})$ has the average monthly return of 28.77 basis points over the period 1963-2020 as compared to 27 basis points for the innovation factor calculated in the main analysis. Moreover, the regression analysis based on incorporating this innovation factor in the Fama-Frech 5 factors model produced similar results. Table 27 provides the GRS statistic along with equal weight metrics obtained as a result of regression of different test assets against 5 factors plus this innovation factor. The GRS statistic along with the equal weight metrics remain lower for 6 factors model except for average absolute *t* value for 25 size-investment portfolios as was the case previously. The GRS statistic for all the test assets for the 6 factors model in Table 27 is lower than GRS statistic in Table 26 except for 25 size-investment portfolios, but it remains lower than GRS statistic for 5 factors model. The metrics like $A\ |(\alpha)|$, $A\ |t(\alpha)|$, $\frac{A\ \alpha^2}{V\bar{r}}$ and $\frac{A\lambda^2}{V\bar{r}}$ almost remain the same for all test assets for 6 factors model in Table 26 and Table 27.

<<Insert Table 27 here>>

Chapter 7 Conclusion

This study makes an attempt to identify the relevance of innovation in explaining the average stock returns. The economists have emphasized the role of innovation in economic growth with innovation included as an important factor in the economic growth models. At the macroeconomic level, given its significance for growth, innovation is therefore identified as a source of economic uncertainty resulting in risk premium in asset pricing. In addition to identifying the relevance of innovation at macro level, there exist several studies that investigate how innovation effects the average stock returns. Review of literature shows that some studies identify innovation as a source of risk given the uncertainty associated with the distribution of its success probability, thus requiring a risk premium from highly innovating firms. On the other hand, it has also been identified that firms with high innovation output may be less exposed to technological risk thus making the non-innovating firms riskier resulting in higher required returns. This study tries to analyze how innovation effects the average returns and if it could be one of the factors explaining the stock returns. Over years different factors have been identified to explain the average stock returns resulting in different asset pricing models. While some models explain the stock returns better than the others, still the pricing errors remain. Through the introduction of innovation factor in the existing asset pricing model, the study analyzes if innovation is relevant for asset pricing.

Using patents as the main identifier of innovation, the study uses Kogan et al. (2016) data that measures the economic value of patent. Sorting stocks into portfolios depending on their level of innovation, the results from this study indicate that the average returns of the highly innovative firms are higher than the average returns of the least innovative firms. The average monthly difference between the returns of the high innovation and low innovation firms is about 22 basis points that is statistically as well as economically significant. In addition to this, the variation in the average stock returns is also studied using bi-variate sorting where stocks are sorted based on innovation along with a second variable like size, book to market value ratio, operating profitability. For most of these portfolios we find a higher average return for highest innovation portfolios as compared to low innovation portfolios. The main exception to this is the low investment stocks where high innovation stocks generated lower return than low innovation stocks. It appears that firms with high innovation accompanied with low investment may reduce the risk associated with the innovation process thereby resulting in lower required return.

We identify that average stock returns vary with level of innovation and there is an innovation premium with high innovation stocks earning higher return than low innovation stocks. This innovation premium is particularly high and significant for small size firms suggesting that innovation mainly increases risk for small size firms. Using Fama-French 5 factors model as the reference asset pricing model, we regress the portfolios sorted based on innovation and find that the highest two innovation portfolios generate significant positive alphas. On average, 30 basis points can be earned on monthly basis over the return predicted by 5 factors model if we buy the highest innovation portfolio and short sell the lowest innovation portfolio. Moreover, if we control for size, the high innovation portfolios within both small and big size produce positive significant alpha again reflecting a premium for innovation that is higher for small sized stocks as compared to big sized stocks.

In light of the above, we attempt to identify if innovation can contribute as one of the factors explaining the variation in the average stock returns. We create an innovation factor as the difference between the return on high and low innovation portfolios controlling for size. The average monthly return of this innovation factor is 27 basis points over the period 1963-2020. Using Fama-French 5 factors model as the reference model, we include the innovation factor as the 6^{th} factor and test the model using different sets of test assets.

The innovation factor appears significant for most of the 25 Fama-French portfolios formed based on size & book to market value and on size & operating profitability while for 25 portfolios formed based on size & investment, it appears significant for only 11 portfolios. Moreover, for all these test assets, the smallest size portfolios mostly have a high positive exposure to innovation factor reflecting these to be high in innovation. However, we do not identify a consistent pattern on variation in loading on innovation factor in relation to variables like size, investment and operating profitability. For 25 portfolios formed based on size and operating profitability, the regression results show that portfolios with negative exposure to HML factor i.e. growth oriented stocks have a positive exposure to innovation factor. Moreover, big-growth oriented stocks, big-high profitability stocks and big-aggressive investment stocks also show a positive exposure to innovation reflecting such firms to be innovative. Further, as robustness check, we also use industrial portfolios as test assets. Within the industrial groups, we see that the sectors dealing in machinery, electrical equipment, autos, aircraft, coal and mining, hardware, software, chips and lab equipment have positive exposure to innovation factor.

An important aspect of this thesis is to explore if innovation factor improves the asset pricing model with respect to explaining the average stock returns. For this purpose, we use the GRS test and alpha based measures to compare the Fama-French 5 factors model 6 factors model containing the innovation factor. Based on the GRS test statistic, the 6 factors model like the 5 factors is rejected. The six factors model yields values of alphas that are jointly significantly different from zero and thus the returns are not fully explained by the 6 factors. However, the value of GRS test statistics for all the test assets reduces for the 6 factors model showing an improvement over the Fama-French 5 factors model. Moreover, metrics like average absolute alpha, average absolute *t* value and ratio of average squared alphas to variance of cross section average return of test assets mostly reduce for 6 factors model as compared to 5 factors model again favoring the 6 factors model. The reduction in the average absolute value of alpha is less than a basis point for 25 size-BM and 25 size-operating profitability portfolios while absolute alpha for 6 factors model remains the same for 25 size-investment portfolios. For the industrial portfolios, the average absolute alpha reduces by 1.4-1.9 basis points.

This study finds that innovation is relevant with respect to average stock returns with high innovation resulting in high average returns mainly for small size stocks. This indicates high risk associated with small size firms that are more innovative thus requiring a risk premium to invest in such stocks. With reference to innovation as being a determinant explaining average stock returns when added to the existing asset pricing model, the test results are not supportive. However, addition of innovation factor shows an improvement in the existing asset pricing model.

Bibliography

An, H., Chen, C. R., Wu, Q., & Zhang, T. (2021). Corporate Innovation: Do Diverse Boards Help? *Journal of Financial and Quantitative Analysis*, 56:1, 155-182.

Banz, R. W. (1981). The Relationship between Return and Market Value of Common Stocks. *Journal of Financial Economics*, 9:1, 3-18.

Barillas, F., & Shanken, J. (2018). Comparing Asset Pricing Models. *The Journal of Finance*, 73:2, 715-754.

Basu, S. (1983). The Relationship between Earnings Yield, Market Value and Return for NYSE Common Stocks: Further Evidence. *Journal of Financial Economics*, 12, 129-156.

Bena, J., & Garlappi, L. (2019). Corporate Innovation and Returns. *The Review of Corportae Finance Studies*, 9, 340-383.

Bhandari, L. C. (1988). Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence. *Journal of Finance*, 43:2, 507-528.

Black, F. (1972). Capital Maket Equlibrium with Restricted Borrowing. *Journal of Business*, 45:3, 444-455.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52:1, 57-82.

Cumming, D., Ji, S., Peter, R., & Tarsalewska, M. (2020). Market Manipulation and Innovation. *Journal of Banking and Finance*, 120.

DeBondt, W. F., & Thaler, R. H. (1985). Does the stock market overreact? *The Journal of Finance*, 40:3, 793-805.

Dicks, D., & Fulghieri, P. (2021). Uncertainty, Investor Sentiment and Innovation. *The Review of Financial Studies*, 34, 1236-1279.

Fama, E. F., & French, K. R. (1992). The Cross Section of Expected Stock Returns. *The Journal of Finance*, 47:2, 427-465.

Fama, E. F., & French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33:1, 3-56.

Fama, E. F., & French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. *The Journal of Finance*, 51:1, 55-84.

Fama, E. F., & French, K. R. (2015). A Five Factor Asset Pricing Model. *Journal of Financial Economics*, 116, 1-22.

Fama, E. F., & French, K. R. (2020). Comparing Cross Section and Time Series Factor Models. *The Review of Financial Sudies*, 33, 1891-1926.

Francis, B. B., Hasan, I., Sharma, Z., & Waisman, M. (2019). Motivating High Impact Innovation: Evidence from Managerial Compensation Contracts. *Financial Markets, Institutions and Instruments*, 28, 291-318.

Garlappi, L. (2004). Risk Premia and Preemption in R&D Ventures. *Journal of Financial and Quantitative Analysis*, 39, 843-872.

Garlappi, L., & Song, Z. (2020). Investment Shocks and Asset Prices: An Investment Based-Approach. *Journal of Financial and Quantitative Analysis*, 55:8, 2665-2699.

Garleanu, N., Kogan, L., & Panageas, S. (2012). Displacement risk and asset returns. *Journal of Financial Economics*, 105, 491-510.

Garleanu, N., Panageas, S., & Yu, J. (2012). Technological Growth and Asset Pricing. *The Journal of Finance*, 67:4, 1265-1292.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica*, 57:5, 1121-1152.

Gospodinov, N., Kan, R., & Robotti, C. (2013). Chi Squared tests for evaluation and comparison of asset pricing models. *Journal of Econometrics*, 173, 108-125.

Hall, B. H., Jaffe, A. B., & Tratenberg, M. (2001). The NBER Patent Citations Data File: Lessons, Insights and Methdological Tools. *NBER Working Paper Series*.

Hansen, L. P., & Jagannathan, R. (1997). Assessing specification errors in stochastic discount factors models. *The Journal of Finance*, 52:2, 557-590.

He, J., & Tian, X. (2018). Finance and Corporate Innovation: A Survey. *Asia Pacific Journal of Financial Studies*, 47, 165-212.

Hobijn, B., & Jovanovic, B. (2001). The Information Technology Revolution and the Stock Market: Evidence. *The American Economic Review*, 91:5, 1203-1220.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting Anomalies: Investment Approach. *The Review of Financial Studies*, 28:3, 650-705.

Hsu, P.-H. (2009). Technological Innovations and Aggregate Risk Premiums. *Journal of Financial Economics*, 94:2, 264-279.

Hsu, P.-H., & Huang, D. (2010). Technology Prospects and the Cross Section of Returns. *The Journal of Empirical Finance*, 17, 39-53.

Huang, H. J., Habib, A., Sun, S. L., Liu, Y., & Guo, H. (2021). Financial Reporting and Corporate Innovation: A Review of International Literature. *Accounting and Finance*, 61:4, 5439-5499.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48:1, 65-91.

Jinnai, R. (2015). Innovation, Produsct Cycle and Asset Prices. *Review of Economic Dynamics*, 18, 484-504.

Jovanovic, B., & MacDonald, G. M. (1994). The Life Cycle of a Competitive Industry. *Journal of Political Economy*, 102:2, 322-347.

Kan, R., & Robotti, C. (2009). Model Comparison using the Hansen-Jagannathan Distance. *The Review of Financial Studies*, 22, 3449-3490.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological Innovation, Resource Allocation and Growth. *The Quarterly Journal of Economics*, 132:2, 665-712.

Kung, H., & Schmid, L. (2015). Innovation, Growth and Asset Prices. *THe Journal of Finance*, 70:3, 1001-1037.

Li, D. (2011). Financial Constraints, R&D Investment and Stock Returns. *The Review of Financial Studies*, 24:9, 2974-3007.

Lintner, J. (1965). The Valuation of Risk Assets amd the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *Review of Economics and Statistics*, 47:1, 13-37.

Mukherjee, A., Singh, M., & Zaldokas, A. (2017). Do Corporate Taxes Hinder Innovation? *Journal of Financial Economics*, 124, 195-221.

Nguyen, L., Vu, L., & Yin, X. (2021). The Bright Side of Co-Opted Boards: Evidence from Firm Innovation. *The Financial Review*, 56, 29-53.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *The Journal of Financial Economics*, 108, 1-28.

Pastor, L., & Veronesi, P. (2009). Technological Revolutions and Stock Prices. *American Economic Review*, 9:4, 1451-1483.

Patton, A. J., & Timmermann, A. (2010). Monotonicity in Asset Returns: New Tests with Applications to the Term Structure, the CAPM and Portfolio Sorts. *The Journal of Financial Economics*, 98, 605-625.

Romer, P. M. (1990). Endogenous Technological Change. *The Journal of Political Economy*, 98:5, 71-102.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive Evidence of Market Inefficiency. *Journal of Portfolio Management*, 11:3, 9-17.

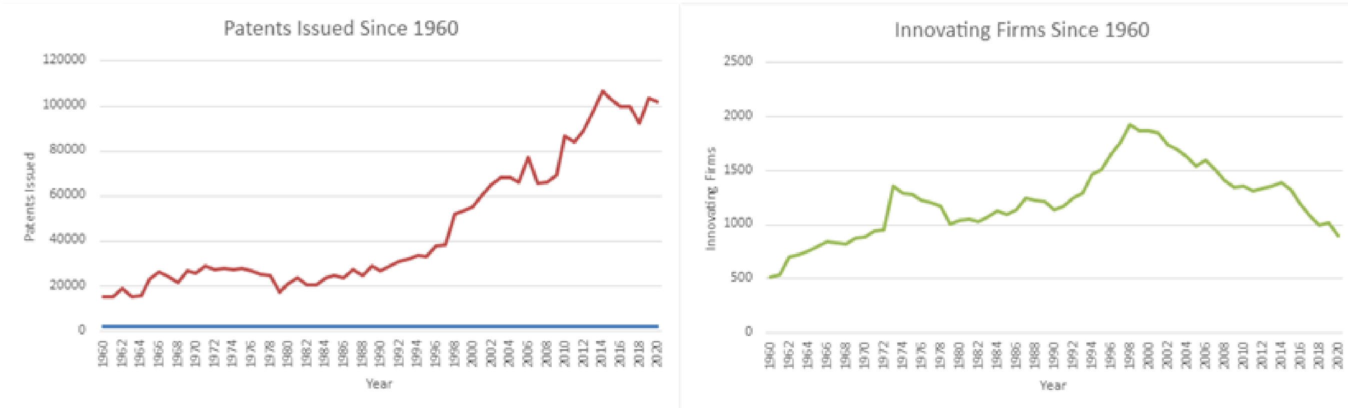
Shah, R., Gao, Z., & Mittal, H. (2015). *Innovation, Entrepreneurship, and the Economy in the US, China, and India.* Elsevier Academic Press.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equillibrium under Conditions of Risk. *Journal of Finance*, 19:3, 425-442.

Solow, R. M. (1957). Technical Change and the Aggregate Productvition Function. *The Review of Economics and Statistics*, 39:3, 312-320.

Stattman, D. (1980). Book Values and Stock Returns. *The Chicago MBA: A Journal of Selected Papers*, 4, 25-45.

Figure 1: The number of patents issued and number of innovating firms since 1960



Based on the data issued by United States Patent and Trademark Organization (USPTO) and as compiled by Kogan et al. (2016), the figure represents the number of patents that have been granted to US firms each year since 1960. The number of innovating firms represents the number of unique firms granted patents each year since 1960.

Table 1: Descriptive statistics of innovating firms, patents issued and economic value of patents.

Variable	Mean	STD	Min	Max
Average No. of Innovating Firms (per year)	1,220.43	333.09	517.00	1,924.00
Average No. of Patents Issued (per year)	45,798.72	29,109.66	15,227.00	106,655.00
Average Yearly Nominal Economic Value of patents	936,528.29	1,213,039.91	24,744.00	5,953,703.45
Average Patent Nominal Economic Value since 1960	20.44	61.01	0	6,128.54

The descriptive statistics are based on the patents data compiled by Kogan et al. (2016) for US based firms. The statistics are calculated based on the sample period 1960-2020. Statistics for innovating firms represent the number of unique US firms that are granted patent each year and the number of patents reflect the total patents granted to all the firms in a year. Nominal economic value of patent as calculated by Kogan et al. (2016) is the product of the estimated stock return due to the issuance of patent multiplied by the market capitalization of the firm on the day prior to patent issuance and is quoted in million US dollars. Statistics on yearly nominal economic value are based on total nominal economic value of all patents issued in a year since 1960 and those on patent economic value are based on economic value of each patent issued since 1960.

Table 2: Average market capitalization for innovation deciles

Inn Rank	Avg Market Cap
1	3,474.01
2	1,897.28
3	1,697.61
4	1,683.78
5	1,917.42
6	2,459.39
7	3,806.64
8	8,120.18
9	11,832.88
10	6,762.58

The table provides the average market capitalization of each of the ten innovation deciles. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in the December of respective year. Using the calculated innovation value as the sorting variable, 10 portfolios are formed each year in June starting from 1961 using innovation value for the previous year (t-1). Those securities are included in the portfolios each year (t) for which market capitalization for June of year t is available. Market capitalization for June is used to calculate average market capitalization of each of the ten portfolios for each year from 1961 to 2020. Average market capitalization is then calculated for each portfolio over the sample period. The values of market capitalization are in million US dollars.

Table 3: Industry wise distribution of innovating firms

Industry	% of all Innovating Firms since 1960	Sub Sector	% Within Main Sector
Manufacturing	78.07%	Electronics and other Electrical Equipment	20.24%
		Chemicals & Allied Products	17.07%
		Industrial, Commercial Machinery and Computer Equipment	16.37%
		Measuring, Analyzing and Controlling Instruments	13.13%
		Transportation Equipment	6.14%
Services	8.90%	Business Services	62.96%
		Engineering, Accounting, Research and Management Services	18.99%
		Health Services	4.74%
		Miscellaneous Services	3.74%
		Motion Pictures	3.41%
Transportation and Public Utilities	3.42%		
Mining	2.50%		
Finance, Insurance and Real Estate	2.22%		
Public Administration	1.73%		
Wholesale Trade	1.69%		
Retail Trade	0.91%		
Construction	0.45%		
Agriculture, Forestry and Fishing	0.11%		

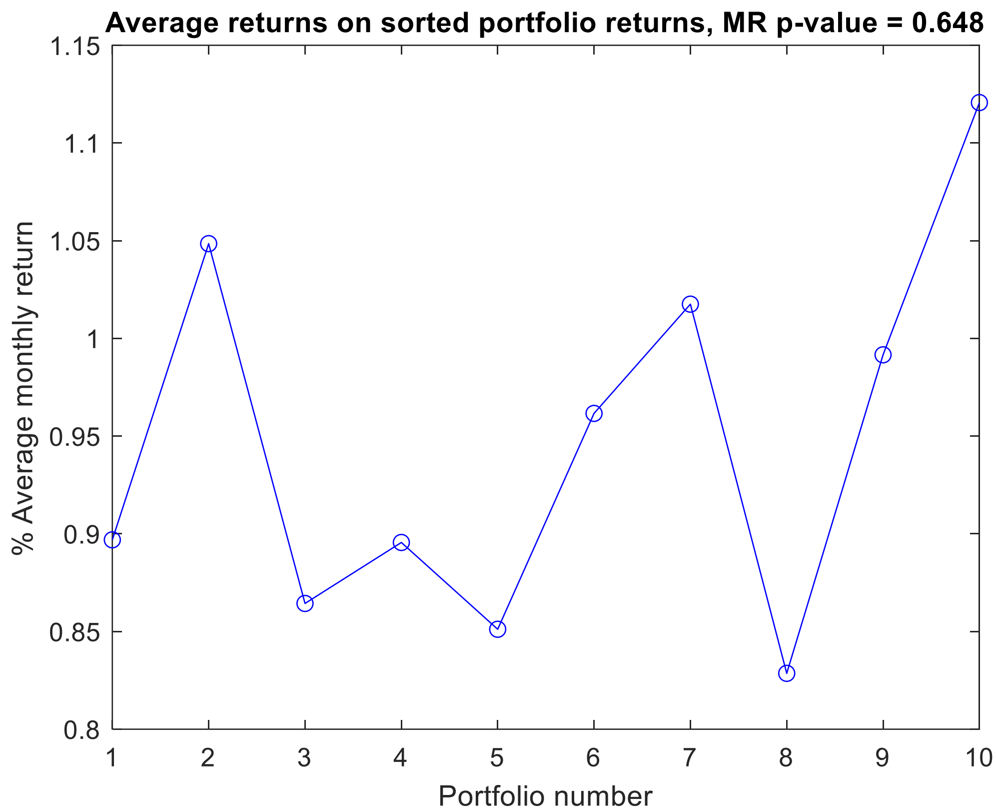
The table provides the industry wise distribution of innovating firms. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year as obtained from Kogan et al. (2016) to the market capitalization against the PERMNO in December of respective year. Using the first two digits of Standard Industrial Classification (SIC) codes https://siccode.com/sic-code-lookup-directory, all the firms in the innovation data are matched with their SIC codes after which total number of firms in each industry classification is calculated over the period 1960-2020. For two industrial groups, manufacturing and services, top five sub-industries are also mentioned with respect to innovation.

Table 4: Average monthly equally weighted and value weighted returns against ten innovation portfolios

Equally Weighted										
Innovation Portfolios	**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**
Average Monthly Return	0.0111	0.0125	0.0126	0.0124	0.0138	0.0135	0.0138	0.0135	0.0138	0.0151
Value Weighted										
Innovation Portfolios	**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**
Average Monthly Return	0.0090	0.0105	0.0086	0.0090	0.0085	0.0096	0.0102	0.0083	0.0099	0.0112

The 10 portfolios low to high innovation are formed based on the level of innovation. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). Using the calculated innovation value as the sorting variable, 10 portfolios are formed each year in June starting from 1961 using innovation value for the previous year (t-1). Those securities are included in the portfolios each year (t) for which market capitalization for June of year t is available. Using PERMNO as the main firm identifier, for each of the innovation portfolios equally weighted and market value weighted monthly return is calculated using stock return data from CRSP. The table provides the average of these equally weighted and market value weighted monthly returns over the period 1961-2020.

Figure 2: Average monthly value weighted returns against 10 innovation portfolios



The figure shows the average monthly value weighted returns against 10 innovation portfolios with 1 representing lowest innovation portfolio and 10 representing highest innovation portfolio. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). Using the calculated innovation value as the sorting variable, 10 portfolios are formed each year in June starting from 1961 using innovation value for the previous year (t-1). Those securities are included in the portfolios each year (t) for which market capitalization for June of year t is available. Using PERMNO as the main firm identifier, for each of the innovation portfolios equally weighted and market value weighted monthly return is calculated using stock return data from CRSP. The figure shows the trend of the average of these value weighted monthly returns over the period 1961-2020. Following the test of monotonicity proposed in Patton & Timmermann (2010), the return on the 10 portfolios is tested for increasing monotonic relationship between returns and level of innovation. The test yield a p value of 0.648 ruling against the alternative hypothesis of increasing monotonic relationship between innovation and average returns.

Table 5: Average value weighted monthly return on 6 portfolios formed based on size and innovation

Innovation Independent		
Portfolios	**Size Rank 1**	**Size Rank 2**
Inn Rank 1	0.0121	0.0090
Inn Rank 2	0.0128	0.0092
Inn Rank 3	0.0167	0.0098
Innovation Conditional on Size		
Portfolios	**Size Rank 1**	**Size Rank 2**
Inn Rank 1	0.0122	0.0091
Inn Rank 2	0.0125	0.0084
Inn Rank 3	0.0157	0.0102

The table provides the average value weighted monthly returns of 6 portfolios formed based on size and innovation. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). Size is calculated as June market equity. 2*3 portfolios are formed every year in June. Using market equity for June of year t, all the innovating firms are sorted into two size groups using median size value as the breakpoint. Using calculated innovation value as the sorting variable, all the innovating firms are sorted into three groups representing bottom 30%, middle 40% and top 30%. For conditional sorting, the sorting based on innovation is done within each of the two size groups. Only those securities are included in the portfolios of June of t for which we have innovation value for t-1 and market equity for June of t. Value weighted returns are calculated for each month for each of the six portfolios based on which average return is calculated for each portfolio over the period 1961-2020.

Table 6: Average monthly value weighted returns of 25 Size-Innovation Portfolios

		Innovation Independent			
Portfolios	**Size Rank 1**	**Size Rank 2**	**Size Rank 3**	**Size Rank 4**	**Size Rank 5**
Inn Rank 1	0.0109	0.0128	0.0122	0.0107	0.0089
Inn Rank 2	0.0154	0.0117	0.0109	0.0103	0.0083
Inn Rank 3	0.0172	0.0133	0.0110	0.0113	0.0085
Inn Rank 4	0.0192	0.0153	0.0129	0.0128	0.0082
Inn Rank 5	0.0202	0.0179	0.0155	0.0144	0.0102
		Innovation Conditional on Size			
Portfolios	**Size Rank 1**	**Size Rank 2**	**Size Rank 3**	**Size Rank 4**	**Size Rank 5**
Inn Rank 1	0.0128	0.0130	0.0122	0.0106	0.0087
Inn Rank 2	0.0157	0.0118	0.0109	0.0104	0.0082
Inn Rank 3	0.0156	0.0137	0.0109	0.0111	0.0082
Inn Rank 4	0.0196	0.0129	0.0123	0.0133	0.0096
Inn Rank 5	0.0195	0.0174	0.0148	0.0144	0.0106

The table provides the average value weighted monthly returns of 25 portfolios formed based on size and innovation. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). Size is calculated as June market equity. 25 portfolios are formed every year in June. Using market equity for June of year t, all the innovating firms are sorted into quintiles using market equity. Using calculated innovation value as the sorting variable, all the innovating firms are also sorted into five equal groups forming 25 portfolios at the intersection of each of the five size portfolios and five innovation portfolios. For innovation, conditional sorting is also employed in which each of the five size portfolios are sorted into 5 innovation quintiles thus forming 25 portfolios with innovation conditional on size. Only those securities are included in the portfolios of June of t for which we have innovation value for t-1 and market equity for June of t. Value weighted returns are calculated for each month for each of the 25 portfolios based on which average return is calculated for each portfolio over the period 1961-2020.

Table 7: Average monthly value weighted returns of 25 Book to Market-Innovation Portfolios

Innovation Independent					
Portfolios	**BM Rank 1**	**BM Rank 2**	**BM Rank 3**	**BM Rank 4**	**BM Rank 5**
Inn Rank 1	0.0090	0.0091	0.0097	0.0108	0.0110
Inn Rank 2	0.0082	0.0093	0.0104	0.0090	0.0130
Inn Rank 3	0.0078	0.0097	0.0103	0.0111	0.0125
Inn Rank 4	0.0084	0.0088	0.0098	0.0105	0.0112
Inn Rank 5	0.0104	0.0105	0.0112	0.0115	0.0144
Innovation Conditional on B/M					
Portfolios	**BM Rank 1**	**BM Rank 2**	**BM Rank 3**	**BM Rank 4**	**BM Rank 5**
Inn Rank 1	0.0084	0.0090	0.0093	0.0108	0.0112
Inn Rank 2	0.0092	0.0095	0.0106	0.0093	0.0135
Inn Rank 3	0.0083	0.0094	0.0110	0.0098	0.0124
Inn Rank 4	0.0091	0.0083	0.0099	0.0108	0.0119
Inn Rank 5	0.0100	0.0107	0.0106	0.0110	0.0140

The table provides the average value weighted monthly returns of 25 portfolios formed based on size and book to market value. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). The book value of equity is calculated as value of stockholder's equity, plus balance sheet deferred taxes and investment tax credit minus the book value of preferred stock. The portfolios based on book to market equity ratio formed in June of year t use book equity for the fiscal year ending in year t-1 divided by the market equity value at the end of December of year t-1. The portfolios based on innovation are formed based on the value of innovation calculated for the year t-1. The portfolios are formed including all the securities for which market equity for June of year t, innovation value and book to market equity ratio for year t-1 are available. When forming the 25 portfolios, the securities are sorted into 5 groups based on size and book to market value, each group representing a quintile. The securities are also sorted independently into 5 groups based on innovation and 25 portfolios define the intersection of five book to market value portfolio and five innovation portfolios. When sorting based on innovation, we also use conditional sorting where each of the 5 quintiles formed based on book to market value are further sorted into 5 groups based on innovation, firming total 25 portfolios. Value weighted returns are calculated for each month for each of the 25 portfolios based on which average return is calculated for each portfolio over the period 1961-2020.

Table 8: Average monthly value weighted returns of 25 Investment-Innovation Portfolios

Innovation Independent					
Portfolios	**Inv Rank 1**	**Inv Rank 2**	**Inv Rank 3**	**Inv Rank 4**	**Inv Rank 5**
Inn Rank 1	0.0135	0.0122	0.0096	0.0090	0.0081
Inn Rank 2	0.0113	0.0105	0.0096	0.0094	0.0082
Inn Rank 3	0.0148	0.0105	0.0098	0.0109	0.0084
Inn Rank 4	0.0130	0.0107	0.0099	0.0086	0.0092
Inn Rank 5	0.0128	0.0115	0.0105	0.0118	0.0100
Innovation Conditional on Investment					
Portfolios	**Inv Rank 1**	**Inv Rank 2**	**Inv Rank 3**	**Inv Rank 4**	**Inv Rank 5**
Inn Rank 1	0.0130	0.0117	0.0097	0.0093	0.0072
Inn Rank 2	0.0120	0.0108	0.0095	0.0091	0.0096
Inn Rank 3	0.0143	0.0106	0.0100	0.0110	0.0079
Inn Rank 4	0.0131	0.0100	0.0099	0.0099	0.0112
Inn Rank 5	0.0131	0.0115	0.0106	0.0115	0.0097

The table provides the average value weighted monthly returns of 25 portfolios formed based on investment and innovation. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). Investment is calculated as change in total assets from the fiscal year ending in t-2 to the fiscal year ending in t-1 divided total assets in t-2. The portfolios based on innovation are formed based on the value of innovation calculated for the year t-1. The portfolios are formed including all the securities for which market equity for June of year t, innovation value and investment value for year t-1 are available. For forming the 25 portfolios, the securities are sorted into quintiles based on the level of investment. The securities are also sorted into five equal groups based on the level of innovation thus forming 25 portfolios at the intersection of each investment portfolio and innovation portfolio. When sorting based on innovation, we also use conditional sorting where each of the 5 quintiles formed based on investment are further sorted into 5 groups based on innovation forming total 25 portfolios. Value weighted returns are calculated for each month for each of the 25 portfolios based on which average return is calculated for each portfolio over the period 1961-2020.

Table 9: Average monthly value weighted returns of 25 Operating Profitability-Innovation Portfolios

		Innovation Independent			
Portfolios	**OP Rank 1**	**OP Rank 2**	**OP Rank 3**	**OP Rank 4**	**OP Rank 5**
Inn Rank 1	0.0084	0.0099	0.0098	0.0091	0.0102
Inn Rank 2	0.0079	0.0063	0.0082	0.0092	0.0117
Inn Rank 3	0.0106	0.0087	0.0108	0.0094	0.0103
Inn Rank 4	0.0110	0.0100	0.0085	0.0068	0.0112
Inn Rank 5	0.0169	0.0110	0.0097	0.0108	0.0104
		Innovation Conditional on OP			
Portfolios	**OP Rank 1**	**OP Rank 2**	**OP Rank 3**	**OP Rank 4**	**OP Rank 5**
Inn Rank 1	0.0082	0.0094	0.0097	0.0090	0.0099
Inn Rank 2	0.0084	0.0078	0.0077	0.0089	0.0117
Inn Rank 3	0.0084	0.0074	0.0105	0.0097	0.0108
Inn Rank 4	0.0119	0.0116	0.0084	0.0070	0.0107
Inn Rank 5	0.0169	0.0106	0.0095	0.0108	0.0107

The table provides the average value weighted monthly returns of 25 portfolios formed based on investment and innovation. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). Operating profitability is calculated as the ratio of operating profitability and book equity. Operating profitability is calculated as annual revenue minus cost of goods sold, interest expense and selling, general & administrative expenses. The portfolios in June of year t are formed based on operating profitability and book equity values for the fiscal year ending in t-1. The portfolios based on innovation are formed based on the value of innovation calculated for the year t-1. The portfolios are formed including all the securities for which market equity for June of year t, innovation value and operating profitability ratio for year t-1 are available. Every year in June, the securities are sorted into 5 groups based on operating profitability, each group representing a quintile. The securities are also sorted independently into 5 groups based on innovation forming 25 portfolios as the intersection of each of the five profitability portfolios and five innovation portfolios. When sorting based on innovation, we also use conditional sorting where each of the 5 quintiles formed based on operating profitability are further sorted into 5 groups based on innovation. Value weighted returns are calculated for each month for each of the 25 portfolios based on which average return is calculated for each portfolio over the period 1961-2020.

Table 10: Regression results of 6 size-innovation portfolios against Fama-French 5 Factors

Portfolios	Small-Low Inn	Small-Medium Inn	Small-High Inn	Big-Low Inn	Big-Medium Inn	Big-High Inn
Panel A: Portfolios formed on innovation sorted independently						
			Coeff			
MR	1.0145	1.0708	1.1663	1.0062	1.0439	1.0080
SMB	0.9780	1.0767	1.1855	-0.0022	-0.0431	-0.1984
HML	-0.0327	-0.1229	-0.0679	0.0124	0.0225	-0.0663
RMW	-0.1949	-0.5009	-0.8293	0.0215	-0.0959	-0.0436
CMA	0.0353	0.0581	-0.0138	-0.0451	-0.0559	-0.0099
alpha	0.0012	0.0023	0.0064	-0.0002	0.0003	0.0012
			t value			
MR	42.8869	38.0084	27.0570	61.2171	52.4386	79.5063
SMB	25.7999	24.0240	16.5778	-0.0589	-1.3357	-9.7546
HML	-0.7215	-2.1543	-0.6675	0.3321	0.4481	-2.7094
RMW	-2.5875	-7.3386	-5.8448	0.2702	-1.3716	-1.0023
CMA	0.4239	0.5672	-0.1048	-0.6299	-0.8990	-0.1896
alpha	1.5435	2.4792	3.4957	-0.2944	0.5158	2.8235
Panel B: Portfolios formed on innovation sorted conditionally on size						
			Coeff			
MR	1.0018	1.0739	1.1353	1.0098	1.0361	1.0072
SMB	0.9735	1.0570	1.1670	0.0031	-0.1194	-0.2002
HML	-0.0451	-0.1264	-0.0885	0.0123	-0.0297	-0.0511
RMW	-0.1880	-0.4835	-0.7647	0.0249	-0.1264	-0.0334
CMA	0.0428	0.0816	-0.0111	-0.0323	-0.0897	-0.0092
alpha	0.0012	0.0021	0.0054	-0.0002	-0.0001	0.0016
			t value			
MR	40.7182	40.9943	30.3971	64.0456	56.2635	68.3955
SMB	27.0739	23.7997	19.2027	0.0903	-3.2146	-9.7229
HML	-1.0178	-2.0941	-1.0844	0.3364	-0.6722	-1.8562
RMW	-2.5517	-7.3353	-6.6883	0.3327	-1.4783	-0.8300
CMA	0.4863	0.8143	-0.0906	-0.4764	-1.2029	-0.1643
alpha	1.5400	2.1937	3.6049	-0.3562	-0.1832	3.4407

Regressed the excess monthly return on 6 size-innovation portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) over the period July 1963-Dec 2020. 6 size-innovation portfolios are formed every year in June. The securities are sorted into two size groups based on their market equity as of June of year t. Securities are sorted independently into three groups (bottom 30%, middle 40% and top 30%) based on the level of innovation in year t-1 (Panel A). Based on innovation, the securities are also sorted into three groups (bottom 30%, middle 40% and top 30%) conditionally on size (Panel B). Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 11: Regression results of 10 innovation portfolios against Fama-French 5 factors

Portfolios	Inn low	2	3	4	5	6	7	8	9	Inn high
					Coeff					
MR	0.9875	1.0448	1.0150	1.0891	1.0473	1.0411	1.0354	1.0439	0.9561	1.1197
SMB	0.0209	0.1691	0.0649	0.0373	0.0756	0.0583	-0.0381	-0.1876	-0.2449	-0.0825
HML	0.0498	-0.0030	-0.0356	0.1944	-0.0062	0.0037	-0.0837	-0.0946	-0.1045	0.0069
RMW	0.1199	-0.0142	-0.1436	0.0357	-0.2201	-0.0705	-0.0931	-0.0450	0.0358	-0.2294
CMA	-0.0136	-0.1383	0.0182	-0.2593	-0.2150	0.1301	0.0559	-0.0763	-0.0167	-0.0080
alpha	-0.0008	0.0012	-0.0002	-0.0005	0.0001	0.0000	0.0012	-0.0002	0.0015	0.0022
					t value					
MR	46.1665	36.0159	37.1112	29.4718	34.9300	37.2175	46.9242	43.3868	61.5595	39.5656
SMB	0.5588	3.5872	0.9923	0.6289	1.0180	1.3657	-1.2728	-3.8673	-10.9017	-1.9349
HML	1.2531	-0.0565	-0.4370	1.8479	-0.0782	0.0555	-1.5888	-1.6574	-3.5941	0.1113
RMW	1.6824	-0.1844	-0.9555	0.3329	-1.3569	-0.7214	-2.1282	-0.3807	0.7473	-2.8914
CMA	-0.1732	-1.5667	0.1410	-2.1331	-1.6040	1.5346	0.8857	-0.6668	-0.2786	-0.0724
alpha	-1.1221	1.5688	-0.1474	-0.5442	0.1309	-0.0127	1.4687	-0.1943	2.7374	2.4496

Regressed the excess monthly return on 10 innovation portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) over the period July 1963-Dec 2020. The ten innovation portfolios are formed in June of each year in t, whereby securities are sorted into deciles using innovation value for t-1. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 12: Summary statistics of Fama-French 5 factors plus innovation factor

Panel A: Averages, Standard Deviations and t statistics for monthly returns

	MR	SMB	HML	RMW	CMA	Inn Factor Cond	Inn Factor Ind
Mean	0.0057	0.0023	0.0025	0.0025	0.0026	0.0024	0.0027
Std Dev	0.0447	0.0303	0.0286	0.0218	0.0197	0.0199	0.0219
t statistic	3.3386	2.0215	2.2663	2.9853	3.4470	3.1865	3.2600

Panel B: Correlation between factors

	MR	SMB	HML	RMW	CMA	Inn Factor
MR	1.0000					
SMB	0.2894	1.0000				
HML	-0.2144	-0.0312	1.0000			
RMW	-0.2040	-0.3432	0.0814	1.0000		
CMA	-0.3774	-0.1002	0.6756	-0.0348	1.0000	
Inn Factor Ind	0.2379	0.1583	-0.1467	-0.3807	-0.1098	1.0000
Inn Factor Cond	0.2486	0.1758	-0.1410	-0.3889	-0.1045	1.0000

Summary statistics based on monthly returns of Fama-French 5 factors and innovation factor over the period July 1963-Dec 2020. The Fama-French 5 factors are as calculated and updated at Kenneth R. French data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) and include MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment). Innovation factor is created using data on innovation obtained from Kogan et al. (2016). Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. In June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are also sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1. 6 size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. With Inn Factor Cond, same process is applied but the for the 6 size-innovation portfolios, three innovation portfolios are formed conditional on size.

Table 13: Regression results of 10 innovation portfolios against Fama-French 5 factors plus innovation factor

Portfolios	Inn low	2	3	4	5	6	7	8	9	Inn high
Panel A: Innovation factor constructed based on independent sorting of innovation										
					Coeff					
MR	1.0181	1.0625	1.0457	1.0930	1.0597	1.0516	1.0299	1.0523	0.9425	1.0808
SMB	0.0231	0.1704	0.0671	0.0376	0.0765	0.0591	-0.0385	-0.1870	-0.2459	-0.0854
HML	0.0272	-0.0161	-0.0585	0.1915	-0.0153	-0.0041	-0.0796	-0.1009	-0.0944	0.0357
RMW	-0.0195	-0.0949	-0.2838	0.0177	-0.2765	-0.1185	-0.0679	-0.0833	0.0978	-0.0523
CMA	-0.0163	-0.1399	0.0154	-0.2597	-0.2161	0.1292	0.0564	-0.0770	-0.0155	-0.0045
INN	-0.3986	-0.2308	-0.4009	-0.0514	-0.1612	-0.1375	0.0719	-0.1095	0.1772	0.5064
alpha	0.0005	0.0019	0.0012	-0.0004	0.0007	0.0004	0.0009	0.0002	0.0010	0.0005
					t value					
MR	48.5252	35.8315	35.2888	29.0161	32.7916	36.1514	47.5495	44.9897	64.8586	40.4240
SMB	0.8065	3.7340	1.1839	0.6398	1.0784	1.4807	-1.2725	-4.0202	-10.2405	-2.3879
HML	0.6929	-0.2858	-0.7705	1.8371	-0.1951	-0.0654	-1.4830	-1.8505	-3.1577	0.6608
RMW	-0.3510	-1.2381	-2.0072	0.1952	-1.7189	-1.5097	-1.5307	-0.7120	1.5395	-0.8223
CMA	-0.2516	-1.5369	0.1291	-2.1207	-1.6225	1.5214	0.8969	-0.6977	-0.2437	-0.0503
INN	-7.3352	-3.7215	-4.3137	-0.7002	-1.7104	-1.9580	1.8561	-1.8495	3.8549	7.5190
alpha	0.6639	2.4925	1.0974	-0.3861	0.6346	0.4665	1.2413	0.2238	1.5812	0.5970
Panel B: Innovation factor constructed based on sorting of innovation conditional on size										
					Coeff					
MR	1.0173	1.0633	1.0435	1.0987	1.0605	1.0496	1.0315	1.0554	0.9434	1.0812
SMB	0.0186	0.1677	0.0627	0.0366	0.0746	0.0577	-0.0378	-0.1885	-0.2440	-0.0797
HML	0.0256	-0.0181	-0.0589	0.1865	-0.0169	-0.0032	-0.0805	-0.1040	-0.0941	0.0383
RMW	-0.0245	-0.1042	-0.2819	-0.0109	-0.2839	-0.1116	-0.0740	-0.1007	0.0976	-0.0424
CMA	-0.0206	-0.1427	0.0115	-0.2616	-0.2181	0.1281	0.0569	-0.0790	-0.0137	0.0011
INN	-0.4546	-0.2836	-0.4358	-0.1468	-0.2010	-0.1295	0.0601	-0.1755	0.1948	0.5887
alpha	0.0005	0.0020	0.0012	-0.0001	0.0007	0.0004	0.0010	0.0004	0.0010	0.0004
					t value					
MR	49.9974	35.6641	34.2500	29.6802	33.0537	36.0818	47.6197	46.3204	65.3769	41.8475
SMB	0.6820	3.7143	1.0967	0.6256	1.0478	1.4072	-1.2621	-4.0991	-10.1189	-2.2079
HML	0.7066	-0.3291	-0.7722	1.8039	-0.2143	-0.0500	-1.5080	-1.9437	-3.1058	0.7376
RMW	-0.4673	-1.3968	-1.9603	-0.1193	-1.7522	-1.3821	-1.6707	-0.8785	1.4756	-0.7065
CMA	-0.3351	-1.5573	0.0958	-2.1129	-1.6332	1.4989	0.9032	-0.7299	-0.2121	0.0123
INN	-8.6820	-4.0340	-3.9256	-1.9433	-1.9193	-1.6787	1.4373	-2.5227	3.8787	8.1903
alpha	0.7577	2.6102	1.0732	-0.1057	0.7035	0.3985	1.2842	0.4161	1.5329	0.4735

Regressed the excess monthly return on 10 innovation portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) plus newly created innovation factor (INN) over the period July 1963-Dec 2020. The ten innovation portfolios are formed in June of each year in t, whereby securities are sorted into deciles using innovation value for t-1. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). To create innovation factor, in June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are also sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1. 6 size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. With innovation factor conditional on size, same process is applied but the for the 6 size-innovation portfolios, three innovation portfolios are formed conditional on size. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 14: Regression results of 25 Size-BM portfolios on Fama-French five factors

B/M	Low	2	3	4	High	Low	2	3	4	High
			MR					**t(MR)**		
Small	1.0543	0.9410	0.9280	0.8853	0.9634	40.2967	50.5658	68.1371	53.6817	47.3315
2	1.1002	1.0115	0.9809	0.9598	1.0837	63.1700	71.1881	51.9073	65.3092	57.8474
3	1.0710	1.0280	0.9891	1.0003	1.0993	69.4981	60.6170	42.7066	62.2047	48.5484
4	1.0506	1.0870	1.0564	1.0329	1.1507	57.5576	46.7589	47.6296	44.4966	35.4793
Big	0.9848	1.0060	0.9676	1.0251	1.0803	71.4522	53.3267	40.7501	39.8326	29.8287
			SMB					**t(SMB)**		
Small	1.2507	1.2157	1.0747	1.0659	1.0687	28.7443	28.8668	42.8834	44.0877	36.7826
2	0.9767	0.9370	0.8067	0.7523	0.8852	30.6008	31.1354	25.1047	37.7587	39.2230
3	0.7106	0.6300	0.4942	0.4704	0.6146	26.6342	24.9656	14.2002	17.7432	13.5806
4	0.3547	0.2838	0.2351	0.2476	0.3070	12.8865	7.2218	6.2848	8.9301	7.3419
Big	-0.1913	-0.1319	-0.1956	-0.1772	-0.1572	-11.0741	-4.6011	-5.5755	-6.5108	-2.3774
			HML					**t(HML)**		
Small	-0.4138	-0.1767	0.1262	0.2833	0.4716	-8.7190	-3.5649	5.2941	8.0348	15.3495
2	-0.4357	-0.0317	0.2832	0.4100	0.6332	-10.4349	-1.1048	6.1250	17.4540	26.2875
3	-0.3734	0.0390	0.3186	0.5132	0.6806	-12.4196	1.1499	5.6453	9.9927	9.9489
4	-0.4134	0.0616	0.3338	0.5262	0.7668	-12.9964	1.1854	5.6904	7.7287	12.7326
Big	-0.3026	0.0220	0.2473	0.7147	1.0422	-13.8351	0.6349	5.5319	13.6138	14.8912
			RMW					**t(RMW)**		
Small	-0.4902	-0.3950	-0.0523	-0.0434	0.0128	-8.6486	-4.7413	-1.7520	-0.8599	0.2777
2	-0.1646	0.0841	0.2340	0.0929	0.0432	-2.7231	1.3684	3.4000	2.8350	1.3555
3	-0.1266	0.1328	0.2005	0.1345	0.1893	-4.5562	2.6233	3.1178	2.3536	2.3373
4	-0.1443	0.2084	0.2272	0.0714	0.0394	-2.7749	2.7834	2.9552	1.3422	0.5290
Big	0.1935	0.1741	0.0688	0.0576	-0.1688	8.2576	3.7816	1.1229	0.7860	-1.4618
			CMA					**t(CMA)**		
Small	-0.1484	0.0135	0.0403	0.0686	0.1200	-1.8501	0.2773	0.9456	1.6210	2.1665
2	-0.1597	0.0354	-0.0034	0.0921	0.0274	-2.5861	0.6633	-0.0689	2.1471	0.7537
3	-0.2921	0.0221	0.0545	0.0602	0.1001	-6.0729	0.4192	1.0875	0.9852	1.4346
4	-0.1145	0.1938	0.1236	0.0427	0.0036	-1.9861	2.9116	1.9968	0.5145	0.0374
Big	-0.0558	0.1762	0.1548	-0.0492	-0.3976	-1.5007	3.9413	2.7394	-0.6586	-3.0801
			alpha					**t(alpha)**		
Small	-0.0028	0.0016	-0.0001	0.0016	0.0011	-3.5053	1.9729	-0.1574	2.8132	2.0345
2	-0.0008	0.0000	-0.0001	0.0002	0.0000	-1.4808	0.0535	-0.1876	0.3984	-0.0251
3	0.0002	0.0004	-0.0007	0.0002	-0.0003	0.4304	0.6868	-1.1298	0.4060	-0.4118
4	0.0018	-0.0014	-0.0012	0.0003	-0.0007	2.3750	-1.9995	-1.7095	0.3823	-0.9941
Big	0.0010	-0.0008	-0.0004	-0.0022	-0.0005	2.3901	-1.4853	-0.6183	-3.0457	-0.5806

Regressed the excess monthly return on 25 Size-BM portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment) over the period July 1963-Dec 2020. 25 Size-BM portfolios as obtained from Fama-French database, include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on the ratio of book equity to market equity (BE/ME). The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 15: Regression results of 25 Size-BM portfolios on Fama-French 5 factors plus Innovation factor

Panel A: Innovation factor formed based on independent sorting of innovation

B/M	Low	2	3	4	High	Low	2	3	4	High
			MR					**t(MR)**		
Small	1.0419	0.9266	0.9250	0.8800	0.9564	39.2258	44.7253	62.1419	51.8245	44.8607
2	1.1053	1.0124	0.9902	0.9675	1.0815	63.2330	67.3353	51.8687	66.9750	60.5101
3	1.0771	1.0336	0.9996	1.0057	1.0983	69.9547	61.2120	42.9899	61.2818	45.6093
4	1.0507	1.0958	1.0671	1.0365	1.1537	52.6085	48.0690	50.1927	44.8113	35.7829
Big	0.9755	1.0127	0.9838	1.0303	1.0786	75.9250	52.4252	42.0786	39.0805	29.0389
			SMB					**t(SMB)**		
Small	1.2498	1.2146	1.0745	1.0655	1.0681	29.0659	33.7130	43.0650	46.8608	35.1501
2	0.9771	0.9371	0.8074	0.7529	0.8851	30.2613	31.1685	27.1192	39.4393	39.0492
3	0.7111	0.6304	0.4950	0.4708	0.6145	26.0228	24.6503	15.3391	18.1648	13.5138
4	0.3547	0.2845	0.2359	0.2478	0.3072	12.9266	7.5014	6.4923	8.9372	7.4006
Big	-0.1920	-0.1315	-0.1945	-0.1768	-0.1573	-12.3756	-4.7170	-5.9353	-6.4814	-2.3815
			HML					**t(HML)**		
Small	-0.4046	-0.1661	0.1285	0.2872	0.4768	-8.1673	-3.8797	5.3177	8.5611	15.0878
2	-0.4395	-0.0323	0.2763	0.4043	0.6348	-10.6606	-1.1008	6.6332	17.5228	26.0366
3	-0.3780	0.0349	0.3108	0.5092	0.6813	-12.3486	1.0626	5.9017	10.2871	10.0990
4	-0.4135	0.0551	0.3258	0.5236	0.7646	-13.4168	1.1188	5.8337	7.7023	12.9969
Big	-0.2957	0.0170	0.2353	0.7108	1.0435	-13.9853	0.4946	5.8593	13.8484	14.6969
			RMW					**t(RMW)**		
Small	-0.4339	-0.3295	-0.0383	-0.0190	0.0448	-7.9762	-6.0631	-1.1310	-0.4678	0.7852
2	-0.1879	0.0803	0.1914	0.0581	0.0531	-3.0785	1.1519	3.3831	2.0587	1.4674
3	-0.1547	0.1074	0.1526	0.1095	0.1936	-5.4864	2.0758	2.8464	2.0874	2.6316
4	-0.1446	0.1682	0.1781	0.0552	0.0256	-3.6924	2.0683	2.2952	0.9770	0.3831
Big	0.2359	0.1433	-0.0050	0.0341	-0.1610	11.0643	2.8765	-0.1056	0.4382	-1.5303
			CMA					**t(CMA)**		
Small	-0.1473	0.0148	0.0406	0.0691	0.1207	-1.8486	0.3146	0.9578	1.5720	2.0893
2	-0.1602	0.0353	-0.0042	0.0914	0.0275	-2.4886	0.6554	-0.0793	2.1544	0.7624
3	-0.2927	0.0216	0.0536	0.0597	0.1002	-5.9469	0.3945	1.0247	0.9454	1.4343
4	-0.1145	0.1930	0.1226	0.0424	0.0034	-1.9867	2.8352	1.8886	0.5017	0.0343
Big	-0.0550	0.1756	0.1534	-0.0496	-0.3974	-1.6232	3.7279	3.1573	-0.6416	-3.0987
			INN					**t(INN)**		
Small	0.1611	0.1871	0.0400	0.0697	0.0914	3.3505	2.8465	1.0316	1.8108	2.3329
2	-0.0667	-0.0108	-0.1218	-0.0995	0.0285	-1.6489	-0.2704	-2.9057	-4.3122	0.8747
3	-0.0804	-0.0725	-0.1370	-0.0713	0.0124	-2.7326	-2.0541	-3.4058	-2.1676	0.2425
4	-0.0009	-0.1148	-0.1403	-0.0463	-0.0393	-0.0153	-2.7221	-3.7403	-1.1344	-0.7793
Big	0.1211	-0.0881	-0.2110	-0.0674	0.0223	6.6432	-2.6714	-4.6458	-1.5684	0.2509
			alpha					**t(alpha)**		
Small	-0.0033	0.0010	-0.0002	0.0014	0.0008	-4.1735	1.5332	-0.4249	2.7178	1.4862
2	-0.0006	0.0001	0.0003	0.0005	-0.0001	-1.1074	0.1225	0.5852	1.1431	-0.1965
3	0.0005	0.0006	-0.0002	0.0005	-0.0003	0.9046	1.0850	-0.4204	0.8532	-0.4827
4	0.0018	-0.0010	-0.0007	0.0004	-0.0006	2.5997	-1.4741	-1.0472	0.5972	-0.8127
Big	0.0006	-0.0005	0.0003	-0.0020	-0.0006	1.5061	-0.9148	0.4244	-2.8348	-0.6475

Panel B: Innovation factor formed based on innovation sorted conditionally on size

B/M	Low	2	3	4	High	Low	2	3	4	High
			MR					**t(MR)**		
Small	1.0419	0.9277	0.9251	0.8798	0.9564	39.8314	45.3679	63.4033	52.5074	45.6649
2	1.1040	1.0121	0.9886	0.9662	1.0822	62.8906	67.3510	51.1338	66.2204	59.2266
3	1.0775	1.0339	0.9984	1.0055	1.0982	70.9786	61.2227	42.4769	61.8936	46.5036
4	1.0530	1.0954	1.0674	1.0384	1.1543	53.7713	47.9177	50.0027	45.4443	35.9930
Big	0.9768	1.0105	0.9814	1.0300	1.0762	76.5841	52.0014	41.2216	38.9300	29.1574

Table 15 continued

B/M	Low	2	3	4	High	Low	2	3	4	High
			SMB					**t(SMB)**		
Small	1.2516	1.2166	1.0749	1.0663	1.0692	29.6738	33.0738	42.8939	46.7164	35.0891
2	0.9765	0.9370	0.8061	0.7519	0.8853	30.0996	30.9636	26.1926	39.3553	39.0372
3	0.7101	0.6295	0.4935	0.4700	0.6147	26.0244	24.5170	14.9665	18.0008	13.4378
4	0.3545	0.2832	0.2343	0.2471	0.3067	12.7606	7.3649	6.3636	8.8535	7.3523
Big	-0.1907	-0.1323	-0.1967	-0.1775	-0.1569	-12.2159	-4.6591	-5.9394	-6.4099	-2.4033
			HML					**t(HML)**		
Small	-0.4036	-0.1659	0.1286	0.2878	0.4773	-8.2447	-3.8193	5.3422	8.4993	15.0733
2	-0.4389	-0.0322	0.2769	0.4047	0.6344	-10.5504	-1.0925	6.4881	17.4694	26.0475
3	-0.3787	0.0342	0.3110	0.5090	0.6814	-12.3852	1.0436	5.8356	10.2284	10.0883
4	-0.4154	0.0548	0.3248	0.5217	0.7639	-13.2087	1.0969	5.7643	7.6526	12.9947
Big	-0.2960	0.0183	0.2361	0.7107	1.0456	-14.0043	0.5270	5.8216	13.9015	14.6966
			RMW					**t(RMW)**		
Small	-0.4299	-0.3308	-0.0381	-0.0164	0.0469	-7.9528	-5.6584	-1.1134	-0.3917	0.7979
2	-0.1832	0.0812	0.1965	0.0618	0.0502	-3.0514	1.1591	3.3236	2.1262	1.4368
3	-0.1582	0.1043	0.1551	0.1091	0.1943	-5.5933	1.9746	2.7799	2.0254	2.5958
4	-0.1559	0.1676	0.1738	0.0446	0.0220	-3.6100	2.0108	2.1814	0.7594	0.3263
Big	0.2324	0.1520	0.0018	0.0338	-0.1491	11.0009	2.9752	0.0365	0.4308	-1.4709
			CMA					**t(CMA)**		
Small	-0.1454	0.0166	0.0410	0.0699	0.1217	-1.8397	0.3453	0.9682	1.5750	2.0848
2	-0.1606	0.0353	-0.0052	0.0906	0.0277	-2.4992	0.6529	-0.0973	2.1407	0.7675
3	-0.2937	0.0207	0.0523	0.0589	0.1003	-5.9030	0.3744	0.9931	0.9302	1.4359
4	-0.1151	0.1918	0.1210	0.0414	0.0028	-1.9882	2.7968	1.8388	0.4826	0.0282
Big	-0.0539	0.1751	0.1516	-0.0503	-0.3966	-1.5800	3.7379	3.1131	-0.6477	-3.1393
			INN					**t(INN)**		
Small	0.1901	0.2023	0.0450	0.0852	0.1074	3.6455	3.0249	1.1182	2.1735	2.5630
2	-0.0586	-0.0088	-0.1183	-0.0980	0.0222	-1.1778	-0.1868	-2.6380	-3.8598	0.6967
3	-0.0996	-0.0897	-0.1429	-0.0799	0.0159	-2.9642	-2.2712	-3.3257	-2.1424	0.2873
4	-0.0366	-0.1284	-0.1680	-0.0844	-0.0547	-0.6749	-2.6769	-3.9759	-1.7969	-0.9162
Big	0.1223	-0.0699	-0.2107	-0.0750	0.0622	6.4053	-1.6626	-3.9220	-1.4527	0.5940
			alpha					**t(alpha)**		
Small	-0.0033	0.0010	-0.0002	0.0014	0.0008	-4.2253	1.5061	-0.4344	2.6459	1.4366
2	-0.0007	0.0001	0.0002	0.0005	-0.0001	-1.1738	0.1024	0.4888	1.0599	-0.1472
3	0.0005	0.0007	-0.0002	0.0005	-0.0003	0.9694	1.1396	-0.4609	0.8654	-0.4915
4	0.0019	-0.0010	-0.0007	0.0005	-0.0006	2.7044	-1.4538	-0.9901	0.7474	-0.7631
Big	0.0007	-0.0006	0.0002	-0.0020	-0.0007	1.5723	-1.0552	0.3305	-2.8723	-0.7702

Regressed the excess monthly return on 25 Size-BM portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) plus newly created innovation factor (INN) over the period July 1963-Dec 2020. 25 Size-BM portfolios as obtained from Fama-French database, include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on the ratio of book equity to market equity (BE/ME). Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). To create innovation factor, in June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1 (Panel A). Stocks are also sorted based on innovation sorted conditionally on size. Within each size group, the stocks are sorted into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1 (Panel B). 6 size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 16: Regression results of 25 Size-OP portfolios on Fama-French five factors

OP	Low	2	3	4	High	Low	2	3	4	High
			MR					**t(MR)**		
Small	0.9853	0.8971	0.9343	0.9615	1.1042	49.7158	43.8922	51.7890	50.7477	47.2067
2	1.1011	1.0189	0.9445	0.9978	1.1276	67.1714	57.5239	73.4785	64.5241	43.8640
3	1.0716	0.9778	0.9739	1.0446	1.1118	55.7881	52.7146	54.4850	66.7955	59.0016
4	1.0862	1.0419	1.0124	1.0762	1.0669	51.3809	57.9200	53.1297	56.3921	55.7439
Big	1.0772	1.0212	0.9975	0.9895	0.9678	40.2213	51.5026	60.3709	74.9241	82.1734
			SMB					**t(SMB)**		
Small	1.2373	1.0800	0.9861	1.0481	1.1884	38.0029	31.3564	29.2514	29.3505	30.7099
2	0.9104	0.8339	0.8117	0.8712	0.9740	33.8451	26.1504	38.0501	37.4128	24.9490
3	0.5896	0.5729	0.5318	0.5739	0.7136	18.4054	23.4711	23.7893	18.5553	24.7707
4	0.2711	0.2479	0.2534	0.2379	0.4396	7.7962	8.2923	11.5282	5.7238	15.1458
Big	-0.2795	-0.2186	-0.2593	-0.1966	-0.1439	-7.4829	-8.1517	-11.4673	-11.1031	-6.7522
			HML					**t(HML)**		
Small	-0.1301	0.2715	0.2949	0.3146	0.1843	-3.3407	6.4112	7.0445	6.5773	3.2576
2	-0.1364	0.1845	0.2407	0.2281	0.1687	-3.5107	4.5066	9.7275	8.2375	2.7722
3	-0.0671	0.1901	0.2127	0.2086	0.1328	-1.3707	5.1080	5.1107	4.9662	2.9105
4	-0.0126	0.1455	0.2151	0.1475	-0.0183	-0.2773	3.3947	6.5886	2.7119	-0.5108
Big	0.2346	0.1728	0.1318	-0.0206	-0.1454	4.0934	4.3095	2.9178	-0.8763	-5.9892
			RMW					**t(RMW)**		
Small	-0.5969	0.1269	0.2873	0.3685	0.3830	-11.5344	2.3346	4.4589	5.4081	5.9694
2	-0.5756	0.1238	0.2311	0.3812	0.5594	-9.7172	2.6890	4.5900	10.7591	8.3880
3	-0.7667	0.0470	0.1586	0.3689	0.5448	-13.6050	0.9255	4.9197	7.0228	8.4139
4	-0.7444	-0.2153	0.1689	0.3829	0.3401	-13.2805	-3.6729	3.3617	5.8294	5.1511
Big	-0.7657	-0.2670	-0.1033	0.1299	0.3529	-11.2493	-6.2083	-2.2622	4.4578	12.0179
			CMA					**t(CMA)**		
Small	0.1045	-0.0320	0.0438	-0.0366	-0.0617	1.7988	-0.5449	0.8097	-0.6531	-0.7473
2	0.0258	0.0954	0.0376	-0.0557	-0.0889	0.4901	1.9242	0.7900	-1.1929	-1.5436
3	-0.1348	0.0720	0.0110	0.0272	-0.1248	-2.0477	1.1889	0.1959	0.5150	-2.1809
4	-0.0500	0.0876	0.0292	0.1285	0.0082	-0.6877	1.2992	0.4933	2.1203	0.1148
Big	-0.2391	0.0756	0.0149	0.0134	-0.0036	-2.9936	1.4160	0.2470	0.3702	-0.0874
			alpha					**t(alpha)**		
Small	-0.0009	0.0009	-0.0006	-0.0003	-0.0020	-1.1378	1.4311	-0.9534	-0.4573	-2.8375
2	0.0000	-0.0009	-0.0004	-0.0009	-0.0006	-0.0816	-1.6565	-0.8045	-1.5042	-0.9624
3	0.0011	-0.0001	-0.0002	-0.0009	-0.0001	1.6520	-0.2103	-0.3641	-1.4355	-0.2261
4	0.0017	0.0004	-0.0002	-0.0009	0.0004	2.2780	0.5752	-0.3125	-1.4342	0.5758
Big	0.0002	-0.0008	0.0001	0.0001	0.0007	0.2983	-1.4702	0.2402	0.2220	1.5567

Regressed the excess monthly return on 25 Size-OP portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment) over the period July 1963-Dec 2020. 25 Size-OP portfolios as obtained from Fama-French database, include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on operating profitability. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 17: Regression results of 25 Size-OP portfolios on Fama-French 5 factors plus innovation factor

Panel A: Innovation factor formed based on independent sorting of innovation

OP	Low	2	3	4	High	Low	2	3	4	High
			MR					**t(MR)**		
Small	0.9632	0.9050	0.9440	0.9724	1.1065	51.1937	46.2111	50.3358	50.8341	46.9752
2	1.0969	1.0274	0.9551	1.0076	1.1345	63.7822	57.9166	78.8622	66.7623	44.0394
3	1.0683	0.9829	0.9826	1.0547	1.1176	53.0906	53.9326	57.2989	67.5406	58.2523
4	1.0816	1.0440	1.0195	1.0879	1.0666	49.2305	57.6794	55.8994	57.8619	54.7370
Big	1.0906	1.0262	0.9995	0.9880	0.9564	42.5219	50.8192	61.3806	73.2637	89.4797
			SMB					**t(SMB)**		
Small	1.2357	1.0806	0.9868	1.0489	1.1886	45.3935	32.9958	32.2569	32.2877	31.3279
2	0.9101	0.8346	0.8125	0.8720	0.9745	34.1927	28.2182	39.9320	39.2385	25.9517
3	0.5893	0.5733	0.5324	0.5746	0.7141	18.4235	23.3810	23.5679	19.7672	25.9218
4	0.2707	0.2481	0.2539	0.2388	0.4396	7.7620	8.2864	11.7345	6.0661	15.2003
Big	-0.2785	-0.2182	-0.2591	-0.1967	-0.1448	-8.2666	-8.2177	-11.7258	-11.0294	-8.5735
			HML					**t(HML)**		
Small	-0.1137	0.2656	0.2878	0.3065	0.1825	-3.3809	6.6846	7.7155	7.1687	3.2456
2	-0.1333	0.1782	0.2328	0.2208	0.1636	-3.3941	4.7006	10.2909	8.3471	2.7887
3	-0.0646	0.1863	0.2062	0.2011	0.1285	-1.3371	5.0854	5.1731	5.3175	2.9393
4	-0.0093	0.1439	0.2098	0.1389	-0.0182	-0.2062	3.3740	6.5805	2.7621	-0.5050
Big	0.2247	0.1691	0.1303	-0.0195	-0.1369	4.1524	4.2600	2.8854	-0.8468	-6.4497
			RMW					**t(RMW)**		
Small	-0.4965	0.0908	0.2435	0.3189	0.3722	-13.6309	2.0420	5.3565	6.2441	5.9231
2	-0.5567	0.0853	0.1826	0.3367	0.5279	-10.1543	1.9835	2.8648	10.9256	8.5952
3	-0.7517	0.0237	0.1188	0.3228	0.5184	-14.6102	0.4201	3.4747	6.7187	8.6977
4	-0.7238	-0.2250	0.1363	0.3299	0.3413	-12.7214	-3.9258	2.3886	5.2554	5.0987
Big	-0.8266	-0.2897	-0.1124	0.1365	0.4049	-14.9891	-7.2792	-2.5530	5.1395	17.5440
			CMA					**t(CMA)**		
Small	0.1065	-0.0327	0.0429	-0.0376	-0.0619	1.9063	-0.5753	0.8716	-0.7501	-0.7574
2	0.0261	0.0946	0.0367	-0.0566	-0.0895	0.5186	1.9075	0.7277	-1.2192	-1.5642
3	-0.1345	0.0715	0.0102	0.0263	-0.1253	-2.0928	1.1529	0.1808	0.4920	-2.1421
4	-0.0496	0.0874	0.0286	0.1275	0.0082	-0.6975	1.2861	0.4673	2.0682	0.1152
Big	-0.2403	0.0752	0.0147	0.0135	-0.0026	-3.1936	1.3994	0.2425	0.3672	-0.0731
			INN					**t(INN)**		
Small	0.2871	-0.1032	-0.1255	-0.1419	-0.0309	7.2447	-2.9507	-2.8494	-3.2686	-0.5508
2	0.0540	-0.1101	-0.1387	-0.1274	-0.0900	1.1430	-3.8691	-3.9186	-3.9420	-2.4871
3	0.0429	-0.0667	-0.1139	-0.1316	-0.0755	0.9084	-2.1078	-4.4125	-4.2051	-2.1283
4	0.0591	-0.0277	-0.0931	-0.1516	0.0032	1.3317	-0.5292	-3.0756	-4.7016	0.0661
Big	-0.1741	-0.0649	-0.0261	0.0189	0.1486	-4.3430	-2.0284	-0.7736	0.6507	5.4492
			alpha					**t(alpha)**		
Small	-0.0018	0.0012	-0.0002	0.0001	-0.0019	-2.6618	2.0899	-0.2931	0.2133	-2.7493
2	-0.0002	-0.0005	0.0001	-0.0005	-0.0003	-0.3867	-0.9640	0.1860	-0.8707	-0.5350
3	0.0010	0.0001	0.0002	-0.0005	0.0001	1.4557	0.1537	0.3486	-0.8201	0.1603
4	0.0015	0.0005	0.0001	-0.0004	0.0004	2.0422	0.7407	0.2225	-0.6526	0.5909
Big	0.0008	-0.0006	0.0002	0.0000	0.0002	1.0579	-1.0767	0.3936	0.1005	0.4258

Panel B: Innovation factor formed based on innovation sorted conditionally on size

OP	Low	2	3	4	High	Low	2	3	4	High
			MR					**t(MR)**		
Small	0.9643	0.9033	0.9417	0.9716	1.1066	51.6788	45.3596	49.7540	51.1321	47.1120
2	1.0963	1.0263	0.9546	1.0070	1.1338	64.6315	57.1594	78.6324	67.5582	43.6339
3	1.0687	0.9838	0.9825	1.0542	1.1174	53.5921	54.2237	57.6910	67.9054	58.6514
4	1.0845	1.0452	1.0208	1.0880	1.0679	49.7460	58.5936	56.4235	57.2582	55.0015
Big	1.0899	1.0262	0.9975	0.9887	0.9566	42.3081	51.1439	62.4475	73.6986	91.3793

Table 17 continued

OP	Low	2	3	4	High	Low	2	3	4	High
			SMB					**t(SMB)**		
Small	1.2389	1.0795	0.9856	1.0474	1.1882	46.3667	32.3891	31.1012	31.5356	31.1851
2	0.9107	0.8334	0.8110	0.8706	0.9735	34.3207	27.7471	39.7475	38.9302	25.5462
3	0.5898	0.5724	0.5312	0.5731	0.7132	18.3716	23.3740	23.5326	19.5093	25.5814
4	0.2712	0.2477	0.2528	0.2370	0.4395	7.7718	8.2370	11.6293	5.9545	14.9863
Big	-0.2805	-0.2190	-0.2593	-0.1965	-0.1431	-8.1302	-8.2356	-11.4520	-11.0600	-8.4680
			HML					**t(HML)**		
Small	-0.1130	0.2665	0.2889	0.3064	0.1823	-3.3901	6.5590	7.4887	7.0619	3.2386
2	-0.1325	0.1785	0.2324	0.2206	0.1637	-3.3838	4.6070	10.1800	8.3372	2.7677
3	-0.0647	0.1852	0.2056	0.2008	0.1282	-1.3393	5.0624	5.1426	5.2429	2.9147
4	-0.0112	0.1428	0.2083	0.1379	-0.0192	-0.2487	3.3439	6.5276	2.7049	-0.5289
Big	0.2242	0.1687	0.1317	-0.0199	-0.1362	4.1607	4.2421	2.9175	-0.8630	-6.4292
			RMW					**t(RMW)**		
Small	-0.4951	0.0971	0.2516	0.3194	0.3713	-13.0641	2.0652	5.0872	6.0464	5.8628
2	-0.5523	0.0880	0.1819	0.3367	0.5296	-10.1629	2.0185	2.8382	10.9252	8.4824
3	-0.7525	0.0178	0.1169	0.3222	0.5177	-14.5283	0.3112	3.3027	6.4838	8.5361
4	-0.7362	-0.2312	0.1282	0.3258	0.3353	-12.7434	-3.8446	2.1823	4.9912	4.7993
Big	-0.8274	-0.2911	-0.1034	0.1339	0.4073	-14.3275	-7.2893	-2.3695	4.9363	18.0160
			CMA					**t(CMA)**		
Small	0.1095	-0.0335	0.0421	-0.0390	-0.0623	1.9462	-0.5888	0.8452	-0.7830	-0.7631
2	0.0269	0.0936	0.0352	-0.0579	-0.0903	0.5427	1.8791	0.6915	-1.2459	-1.5712
3	-0.1341	0.0706	0.0090	0.0250	-0.1261	-2.0903	1.1267	0.1590	0.4608	-2.1376
4	-0.0496	0.0868	0.0272	0.1258	0.0079	-0.6895	1.2646	0.4396	2.0183	0.1107
Big	-0.2421	0.0744	0.0149	0.0136	-0.0009	-3.2371	1.3891	0.2469	0.3698	-0.0276
			INN					**t(INN)**		
Small	0.3206	-0.0939	-0.1126	-0.1548	-0.0369	7.3965	-2.6230	-2.4387	-3.5039	-0.6458
2	0.0734	-0.1128	-0.1550	-0.1402	-0.0940	1.4461	-3.4738	-4.0051	-4.0803	-2.3839
3	0.0449	-0.0921	-0.1314	-0.1470	-0.0851	0.8688	-2.4981	-4.4954	-4.2727	-2.1210
4	0.0258	-0.0501	-0.1282	-0.1799	-0.0153	0.5276	-0.9211	-3.8181	-4.4963	-0.3023
Big	-0.1942	-0.0761	-0.0003	0.0124	0.1712	-4.9110	-2.1473	-0.0068	0.3958	6.0379
			alpha					**t(alpha)**		
Small	-0.0019	0.0012	-0.0002	0.0001	-0.0019	-2.6546	1.9885	-0.4230	0.2107	-2.7231
2	-0.0003	-0.0006	0.0001	-0.0005	-0.0004	-0.4567	-1.0057	0.2081	-0.8500	-0.5558
3	0.0010	0.0002	0.0002	-0.0005	0.0001	1.4629	0.2504	0.3948	-0.7974	0.1724
4	0.0016	0.0005	0.0002	-0.0003	0.0005	2.1821	0.8173	0.3641	-0.5800	0.6679
Big	0.0008	-0.0005	0.0001	0.0001	0.0002	1.0648	-1.0449	0.2332	0.1515	0.3622

Regressed the excess monthly return on 25 Size-OP portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) plus newly created innovation factor (INN) over the period July 1963-Dec 2020. 25 Size-OP portfolios as obtained from Fama-French database, include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on the operating profitability. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). To create innovation factor, in June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1 (Panel A). Based on innovation the stocks are also sorted conditionally. Within each size group, the stocks are sorted into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1 (Panel B). Six size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 18: Regression results of 25 Size-Inv portfolios on Fama-French five factors

Inv	Low	2	3	4	High	Low	2	3	4	High
			MR					**t(MR)**		
Small	1.0164	0.9032	0.8948	0.9291	1.0202	45.3325	65.7597	52.7776	61.0500	52.2871
2	1.1167	0.9757	0.9290	1.0104	1.0957	82.2394	58.8123	65.9943	73.2538	71.1120
3	1.0969	0.9607	0.9674	1.0027	1.0994	45.2460	61.7189	57.1251	56.7166	75.8405
4	1.1682	1.0499	1.0031	1.0082	1.0947	55.6086	46.5835	56.6324	49.9431	51.7053
Big	1.0659	0.9639	0.9710	0.9840	1.0479	54.5810	64.4163	81.6117	66.4893	60.5880
			SMB					**t(SMB)**		
Small	1.2794	1.0278	1.0279	1.0800	1.2040	39.7934	41.8568	46.5538	48.0351	33.9611
2	0.9229	0.7727	0.8348	0.8553	0.9544	41.3269	24.1504	33.0857	40.3758	33.9604
3	0.6314	0.5496	0.5039	0.6107	0.6842	18.1702	25.5471	21.3829	24.5645	27.9440
4	0.2625	0.1903	0.2663	0.3005	0.4283	5.8610	5.5744	10.6148	9.5806	14.3043
Big	-0.1118	-0.2046	-0.1803	-0.1995	-0.1890	-3.2081	-9.0379	-8.6052	-8.9348	-8.2996
			HML					**t(HML)**		
Small	-0.0742	0.1742	0.2059	0.1473	-0.0154	-1.6014	5.7060	6.4711	4.9043	-0.3534
2	0.0574	0.2697	0.1898	0.2524	-0.1120	2.1866	5.8220	6.5958	9.2762	-3.0768
3	0.1278	0.2088	0.2253	0.1879	-0.0523	3.1751	5.9705	5.5447	5.2298	-1.4905
4	0.1086	0.2504	0.2104	0.0973	-0.1808	1.6488	4.7004	5.2100	2.5976	-5.1297
Big	-0.1217	-0.0115	0.1115	-0.0050	-0.0553	-2.5519	-0.4328	4.8396	-0.1441	-1.6022
			RMW					**t(RMW)**		
Small	-0.5186	-0.0009	0.0794	0.0670	-0.2189	-6.9057	-0.0254	1.6575	2.0591	-4.7725
2	-0.1790	0.1897	0.1043	0.2272	-0.1512	-6.2446	3.3073	2.9900	6.3402	-2.8044
3	-0.0595	0.0847	0.2165	0.1430	-0.1232	-0.8429	1.9854	5.4734	3.2474	-2.2537
4	0.0205	0.1286	0.1255	0.1265	-0.2595	0.2949	2.5212	3.0065	1.5961	-5.1486
Big	0.0582	0.0545	0.1452	0.1425	-0.0209	0.9170	1.6682	4.0286	3.5483	-0.7469
			CMA					**t(CMA)**		
Small	0.3312	0.1991	0.1002	0.0180	-0.2989	5.3337	4.4103	2.0628	0.3397	-4.8944
2	0.4321	0.1873	0.1427	-0.0875	-0.4129	12.1710	4.0167	3.6971	-2.2325	-8.0255
3	0.3532	0.2861	0.1204	-0.1488	-0.5010	6.8925	5.6400	2.4110	-2.6281	-11.1976
4	0.5159	0.2656	0.1117	-0.0209	-0.4207	7.6782	4.0754	1.8377	-0.2987	-6.4720
Big	0.8167	0.4960	0.1285	-0.1208	-0.7002	11.6658	13.2471	3.0271	-2.2028	-13.4751
			alpha					**t(alpha)**		
Small	0.0018	0.0012	0.0012	0.0003	-0.0031	1.9161	2.3699	2.0506	0.5579	-5.0543
2	-0.0004	0.0001	0.0009	0.0002	-0.0013	-0.8994	0.2044	2.0195	0.4121	-2.6290
3	0.0003	0.0007	-0.0001	0.0005	-0.0001	0.4400	1.1838	-0.2571	0.9446	-0.1239
4	-0.0011	-0.0005	0.0002	0.0009	0.0015	-1.7058	-0.8381	0.3468	1.4003	1.9082
Big	-0.0005	-0.0005	-0.0007	0.0005	0.0019	-0.6688	-1.2516	-2.0032	0.9573	3.3631

Regressed the excess monthly return on 25 Size-Inv portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment) over the period July 1963-Dec 2020. 25 Size-Inv portfolios as obtained from Fama-French database, include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on investment that is represented as change in total assets over year t-2 and t-1 divided by total assets in t-2. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 19:Regression results of 25 Size-Inv portfolios on Fama-French 5 factors plus innovation factor

Panel A: Innovation factor formed based on independent sorting of innovation

Inv	Low	2	3	4	High	Low	2	3	4	High
			MR					t(MR)		
Small	0.9919	0.9020	0.8983	0.9312	1.0151	48.9029	62.2972	51.0796	61.8187	48.5102
2	1.1156	0.9842	0.9321	1.0166	1.1009	79.1925	57.5368	61.7732	73.6847	69.5705
3	1.0990	0.9637	0.9760	1.0052	1.1090	42.3620	61.2720	58.8160	55.3247	74.8716
4	1.1726	1.0591	1.0096	1.0111	1.0912	54.9448	48.2342	56.4568	46.8167	49.7220
Big	1.0622	0.9666	0.9714	0.9776	1.0421	51.7299	65.1995	79.8692	66.0436	57.3432
			SMB					t(SMB)		
Small	1.2776	1.0277	1.0281	1.0801	1.2037	49.0279	42.0862	45.6716	48.3920	33.7221
2	0.9229	0.7734	0.8350	0.8558	0.9548	40.9710	26.2882	32.1791	42.3553	33.9901
3	0.6315	0.5498	0.5045	0.6109	0.6849	18.4162	25.0549	22.9080	23.9960	28.9608
4	0.2628	0.1910	0.2668	0.3008	0.4281	6.0536	5.8878	10.7460	9.4564	14.6474
Big	-0.1120	-0.2044	-0.1803	-0.2000	-0.1895	-3.2243	-8.8838	-8.5648	-9.6683	-7.7913
			HML					t(HML)		
Small	-0.0560	0.1751	0.2033	0.1458	-0.0117	-1.4731	5.7498	6.4520	4.8639	-0.2642
2	0.0582	0.2635	0.1876	0.2479	-0.1158	2.1744	6.0351	6.5314	9.4663	-3.2745
3	0.1263	0.2065	0.2188	0.1860	-0.0594	3.2576	5.8576	5.6428	5.2097	-1.8585
4	0.1053	0.2436	0.2055	0.0951	-0.1781	1.6495	4.7222	5.1599	2.5475	-5.4036
Big	-0.1190	-0.0135	0.1111	-0.0002	-0.0510	-2.4560	-0.5024	4.7691	-0.0076	-1.4477
			RMW					t(RMW)		
Small	-0.4068	0.0049	0.0634	0.0578	-0.1961	-6.9189	0.1419	1.4779	1.7279	-4.2981
2	-0.1741	0.1510	0.0903	0.1992	-0.1747	-5.3088	3.1411	2.4027	6.0039	-3.4531
3	-0.0690	0.0710	0.1770	0.1313	-0.1667	-1.0833	1.4837	5.0436	3.0577	-3.5307
4	0.0002	0.0869	0.0959	0.1129	-0.2433	0.0033	1.5455	2.1586	1.3737	-5.7548
Big	0.0749	0.0423	0.1430	0.1715	0.0057	1.2372	1.0766	3.5002	5.1517	0.1746
			CMA					t(CMA)		
Small	0.3334	0.1992	0.0998	0.0178	-0.2984	4.8480	4.3640	2.1235	0.3379	-4.8952
2	0.4322	0.1866	0.1424	-0.0880	-0.4133	12.1405	4.0348	3.6412	-2.2253	-7.7057
3	0.3530	0.2858	0.1196	-0.1490	-0.5018	6.8378	5.5528	2.4065	-2.5931	-10.4858
4	0.5155	0.2648	0.1111	-0.0212	-0.4204	7.6552	4.0091	1.8319	-0.2989	-6.5710
Big	0.8170	0.4958	0.1284	-0.1202	-0.6997	11.9058	13.1431	3.0112	-2.2597	-13.1762
			INN					t(INN)		
Small	0.3198	0.0164	-0.0456	-0.0264	0.0653	6.0258	0.5721	-1.0961	-0.8234	1.8697
2	0.0141	-0.1106	-0.0398	-0.0801	-0.0671	0.4731	-3.1404	-1.1385	-2.8948	-1.8621
3	-0.0271	-0.0390	-0.1129	-0.0334	-0.1244	-0.4686	-1.1869	-4.8646	-0.9509	-2.7537
4	-0.0579	-0.1190	-0.0848	-0.0388	0.0463	-1.4961	-3.1192	-2.3546	-0.6849	1.0177
Big	0.0478	-0.0349	-0.0062	0.0828	0.0761	0.9743	-1.1779	-0.2480	2.8308	2.4867
			alpha					t(alpha)		
Small	0.0008	0.0011	0.0014	0.0004	-0.0033	1.0111	2.3116	2.4055	0.7477	-5.3639
2	-0.0005	0.0005	0.0011	0.0005	-0.0011	-0.9799	0.9119	2.2565	1.0441	-2.3484
3	0.0004	0.0008	0.0002	0.0006	0.0003	0.6149	1.3939	0.4845	1.1702	0.5800
4	-0.0009	-0.0001	0.0005	0.0011	0.0014	-1.4529	-0.1777	0.8863	1.6757	1.8232
Big	-0.0006	-0.0004	-0.0007	0.0002	0.0016	-0.8661	-0.9359	-1.8542	0.4540	2.9184

Panel B: Innovation factor formed based on innovation sorted conditionally on size

Inv	Low	2	3	4	High	Low	2	3	4	High
			MR					t(MR)		
Small	0.9943	0.9017	0.8972	0.9301	1.0149	47.2829	63.0929	51.3801	61.8754	49.5319
2	1.1164	0.9818	0.9322	1.0168	1.0997	79.0551	57.0574	63.2408	73.3743	68.5881
3	1.0988	0.9640	0.9758	1.0068	1.1080	42.8819	61.6547	58.4622	56.5213	74.3677
4	1.1723	1.0601	1.0105	1.0129	1.0939	55.1272	48.7785	56.5374	48.0175	49.6571
Big	1.0618	0.9658	0.9712	0.9775	1.0418	52.0829	64.8681	80.0764	67.4179	57.6098

Table 19 continued										
Inv	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
			SMB					**t(SMB)**		
Small	1.2811	1.0279	1.0277	1.0799	1.2044	48.1873	42.0374	45.7229	48.0240	33.8943
2	0.9230	0.7723	0.8345	0.8548	0.9541	41.1370	25.3290	32.0493	42.4577	33.5670
3	0.6312	0.5493	0.5032	0.6104	0.6836	18.2182	25.0162	22.8695	23.6195	28.4125
4	0.2621	0.1895	0.2658	0.3002	0.4284	6.0005	5.8386	10.7005	9.2404	14.3458
Big	-0.1114	-0.2047	-0.1803	-0.1990	-0.1886	-3.2146	-8.9182	-8.5664	-9.7001	-7.6924
			HML					**t(HML)**		
Small	-0.0561	0.1755	0.2040	0.1466	-0.0111	-1.4207	5.7569	6.4613	4.8574	-0.2506
2	0.0577	0.2648	0.1872	0.2473	-0.1152	2.1729	5.9473	6.4584	9.5447	-3.2003
3	0.1262	0.2061	0.2184	0.1845	-0.0593	3.2354	5.8618	5.6106	5.0914	-1.8262
4	0.1052	0.2421	0.2044	0.0934	-0.1801	1.6368	4.6803	5.1283	2.4711	-5.2598
Big	-0.1183	-0.0130	0.1113	0.0003	-0.0503	-2.4531	-0.4849	4.7634	0.0090	-1.4243
			RMW					**t(RMW)**		
Small	-0.4111	0.0066	0.0678	0.0625	-0.1934	-6.5763	0.1893	1.5774	1.8366	-4.1252
2	-0.1777	0.1601	0.0888	0.1965	-0.1705	-5.5561	3.1914	2.2790	5.8477	-3.2788
3	-0.0687	0.0688	0.1754	0.1228	-0.1648	-1.0466	1.3969	4.9114	2.6492	-3.3777
4	0.0004	0.0794	0.0898	0.1033	-0.2557	0.0069	1.3790	1.9663	1.1913	-5.6770
Big	0.0780	0.0451	0.1441	0.1738	0.0087	1.2858	1.1595	3.5093	5.2723	0.2556
			CMA					**t(CMA)**		
Small	0.3364	0.1995	0.0996	0.0178	-0.2977	4.8111	4.3450	2.1112	0.3363	-4.8897
2	0.4322	0.1859	0.1420	-0.0890	-0.4138	12.1588	3.9827	3.6224	-2.2530	-7.7064
3	0.3527	0.2853	0.1184	-0.1498	-0.5030	6.8190	5.5221	2.3718	-2.5738	-10.3654
4	0.5149	0.2633	0.1100	-0.0221	-0.4205	7.6143	3.9351	1.8183	-0.3074	-6.5077
Big	0.8177	0.4956	0.1284	-0.1193	-0.6988	12.0054	13.1235	3.0084	-2.2466	-13.0637
			INN					**t(INN)**		
Small	0.3387	0.0236	-0.0364	-0.0143	0.0806	5.7619	0.7687	-0.8542	-0.4124	2.1746
2	0.0043	-0.0933	-0.0486	-0.0966	-0.0607	0.1397	-2.5218	-1.3887	-3.0192	-1.4569
3	-0.0290	-0.0500	-0.1295	-0.0637	-0.1309	-0.4646	-1.2756	-4.7735	-1.8538	-2.5244
4	-0.0631	-0.1547	-0.1123	-0.0731	0.0120	-1.4674	-3.4560	-2.8652	-1.2941	0.2531
Big	0.0625	-0.0295	-0.0036	0.0985	0.0931	1.1603	-0.9135	-0.1250	3.1720	2.7576
			alpha					**t(alpha)**		
Small	0.0008	0.0011	0.0013	0.0003	-0.0033	1.0331	2.2851	2.3270	0.6566	-5.4018
2	-0.0005	0.0004	0.0011	0.0005	-0.0011	-0.9179	0.7508	2.2820	1.1031	-2.4307
3	0.0004	0.0008	0.0003	0.0007	0.0003	0.5973	1.4306	0.5241	1.3027	0.5464
4	-0.0009	0.0000	0.0005	0.0012	0.0015	-1.4526	-0.0501	0.9996	1.7636	1.9820
Big	-0.0006	-0.0004	-0.0007	0.0002	0.0016	-0.9098	-1.0057	-1.8839	0.4000	2.8632

Regressed the excess monthly return on 25 Size-Inv portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) plus newly created innovation factor (INN) over the period July 1963-Dec 2020. 25 Size-Inv portfolios as obtained from Fama-French database, include 25 portfolios formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on investment that is represented as change in total assets over year t-2 and t-1 divided by total assets in t-2. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). To create innovation factor, in June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1 (Panel A). Based on innovation the stocks are also sorted conditionally. Within each size group, the stocks are sorted into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1 (Panel B). 6 size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 20: Regression results of 30 industry portfolios on Fama French five factors

Industry	Food	Beer	Smoke	Games	Books	Hshld	Clths	Hlth	Chems	Txtls	Cnstr	Steel	FabPr	ElcEq	Autos
MR	0.8264	0.8546	0.8542	1.2171	1.1058	0.8818	1.0886	0.8803	1.1493	1.1585	1.2369	1.2589	1.1691	1.2225	1.2972
t(MR)	21.595	17.631	16.468	25.333	24.654	21.686	20.760	23.605	38.727	16.166	41.785	24.245	32.485	35.075	15.789
SMB	-0.0423	0.0255	-0.0978	0.5414	0.3830	-0.0157	0.5526	-0.1253	0.0393	0.7825	0.3952	0.3128	0.3109	0.1387	0.2063
t(SMB)	-0.914	0.353	-0.961	7.061	7.499	-0.252	5.716	-2.118	0.908	10.016	8.078	4.394	5.714	2.139	2.496
HML	-0.0478	-0.1241	-0.1567	0.1334	0.2404	-0.1701	0.3138	-0.4126	0.2098	0.5775	0.2865	0.3056	0.0446	0.0323	0.4246
t(HML)	-0.764	-1.416	-1.699	1.254	3.851	-2.053	2.278	-4.838	3.470	3.272	4.790	3.204	0.703	0.424	3.676
RMW	0.5768	0.6304	0.6701	0.3030	0.4452	0.5824	0.6618	0.3272	0.3140	0.5625	0.4322	-0.4637	-0.0442	0.1976	0.2104
t(RMW)	8.353	8.013	5.324	2.425	7.361	7.880	4.270	3.117	4.460	4.628	5.174	-4.256	-0.634	2.279	1.359
CMA	0.3892	0.3989	0.7918	-0.2354	0.0275	0.2781	-0.1287	0.2979	0.2456	0.0884	0.1545	0.1041	0.0464	0.0022	0.2734
t(CMA)	5.108	3.217	5.450	-1.871	0.301	2.351	-0.892	1.958	2.538	0.475	1.733	0.718	0.504	0.019	1.518
alpha	-0.0003	0.0004	0.0014	-0.0004	-0.0037	-0.0012	-0.0018	0.0019	-0.0028	-0.0052	-0.0041	-0.0043	-0.0010	0.0002	-0.0037
t(alpha)	-0.334	0.272	0.716	-0.230	-2.932	-1.123	-1.115	1.680	-2.271	-3.031	-3.649	-2.382	-0.750	0.221	-2.058

Industry	Carry	Mines	Coal	Oil	Util	Telcm	Servs	BusEq	Paper	Trans	Whlsl	Rtail	Meals	Fin	Other
MR	1.1844	0.9490	1.1565	1.0043	0.6375	0.8413	1.0767	1.0700	1.0461	1.0983	1.0165	1.0045	1.0611	1.1381	1.0850
t(MR)	27.592	13.929	12.954	16.960	17.913	22.234	33.771	25.813	31.567	31.862	34.559	27.027	21.863	41.621	28.090
SMB	0.3167	0.3847	0.4627	-0.0705	-0.1547	-0.2585	0.3212	0.1072	0.0582	0.3056	0.5952	0.1604	0.4474	-0.0497	0.2621
t(SMB)	5.040	3.851	2.579	-0.879	-3.132	-5.043	5.370	1.892	1.371	5.401	10.580	2.647	6.066	-1.012	4.340
HML	0.2859	0.0937	0.1577	0.2372	0.2147	0.0952	-0.2829	-0.3442	0.0975	0.2608	-0.0126	-0.0533	0.0326	0.6092	0.0877
t(HML)	2.924	0.692	0.663	1.545	2.527	1.554	-3.977	-4.813	1.651	3.483	-0.199	-0.515	0.371	8.629	1.021
RMW	0.5263	0.0513	0.0978	0.2462	0.1321	-0.2487	-0.2051	-0.4877	0.4184	0.4198	0.4216	0.4310	0.8128	0.0386	0.2422
t(RMW)	4.476	0.337	0.324	2.378	1.782	-2.853	-2.775	-5.120	5.032	4.377	6.171	6.048	6.497	0.561	3.225
CMA	0.0225	0.2814	0.2979	0.3751	0.3021	0.1184	-0.4993	-0.4367	0.3125	0.0200	0.0864	0.0368	0.0359	-0.2266	0.1036
t(CMA)	0.156	1.317	0.861	2.391	2.319	1.002	-4.597	-3.149	3.744	0.234	0.899	0.305	0.289	-2.599	0.985
alpha	-0.0018	-0.0015	-0.0033	-0.0022	-0.0003	0.0010	0.0036	0.0040	-0.0027	-0.0027	-0.0019	0.0003	-0.0008	-0.0012	-0.0045
t(alpha)	-1.141	-0.614	-0.780	-1.222	-0.291	0.826	3.432	3.285	-2.685	-2.202	-1.831	0.232	-0.508	-1.412	-3.833

Regressed the excess monthly return on 30 industry portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment) over the period July 1963-Dec 2020. 30 industry portfolios as obtained from Fama-French database, include 30 portfolios formed based on classification of stocks into 30 industrial groups based on their four digit SIC codes. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 21:Regression results of 30 industry portfolios on Fama-French 5 factors plus innovation factor (Independent)

	Food	Beer	Smoke	Games	Books	Hshld	Clths	Hlth	Chems	Txtls	Cnstr	Steel	FabPr	ElcEq	Autos
MR	0.8423	0.8684	0.8570	1.2090	1.1150	0.8796	1.1051	0.8809	1.1482	1.1641	1.2451	1.2554	1.1619	1.2194	1.2856
t(MR)	21.5023	17.8115	16.6928	24.0905	25.3674	22.4994	20.6476	23.4135	38.4540	17.8896	42.4832	24.3889	31.8827	34.4236	15.5813
SMB	-0.0411	0.0266	-0.0976	0.5408	0.3837	-0.0158	0.5538	-0.1253	0.0392	0.7829	0.3958	0.3126	0.3103	0.1385	0.2054
t(SMB)	-0.8923	0.3650	-0.9507	6.9757	7.5781	-0.2561	5.9397	-2.1151	0.9037	10.2374	8.3468	4.3453	5.5538	2.1077	2.4395
HML	-0.0596	-0.1344	-0.1588	0.1394	0.2336	-0.1685	0.3015	-0.4130	0.2106	0.5734	0.2804	0.3082	0.0500	0.0347	0.4332
t(HML)	-0.9671	-1.4609	-1.6993	1.2994	3.6002	-2.0240	2.2642	-4.7944	3.4722	3.1767	4.8763	3.2359	0.7652	0.4491	3.7596
RMW	0.5042	0.5675	0.6571	0.3398	0.4033	0.5924	0.5864	0.3248	0.3186	0.5370	0.3947	-0.4476	-0.0114	0.2119	0.2632
t(RMW)	6.1576	5.8074	4.9900	2.5985	5.8219	7.2548	4.2429	2.8068	4.4911	4.0773	4.7081	-3.6211	-0.1537	2.1604	1.5368
CMA	0.3878	0.3976	0.7915	-0.2347	0.0267	0.2783	-0.1302	0.2979	0.2457	0.0879	0.1537	0.1045	0.0471	0.0024	0.2745
t(CMA)	5.0275	3.2367	5.4425	-1.8590	0.2956	2.3594	-0.8799	1.9545	2.5427	0.4743	1.7110	0.7179	0.5077	0.0210	1.5195
INN	-0.2076	-0.1798	-0.0373	0.1054	-0.1197	0.0285	-0.2155	-0.0068	0.0132	-0.0729	-0.1071	0.0461	0.0938	0.0410	0.1510
t(IMN)	-3.3095	-1.7822	-0.3491	0.9718	-1.5236	0.4296	-2.4636	-0.0820	0.2177	-0.4566	-1.8644	0.4922	1.6323	0.5809	1.2242
alpha	0.0003	0.0010	0.0016	-0.0007	-0.0033	-0.0013	-0.0011	0.0019	-0.0029	-0.0050	-0.0037	-0.0044	-0.0013	0.0001	-0.0042
t(alpha)	0.3155	0.6716	0.7575	-0.4442	-2.6095	-1.2026	-0.7155	1.6387	-2.3265	-2.8211	-3.3431	-2.4240	-0.9712	0.1004	-2.3802

	Carry	Mines	Coal	Oil	Util	Telcm	Servs	BusEq	Paper	Trans	Whlsl	Rtail	Meals	Fin	Other
MR	1.1830	0.9588	1.1599	1.0156	0.6565	0.8441	1.0680	1.0162	1.0474	1.1094	1.0331	1.0159	1.0704	1.1680	1.0928
t(MR)	27.0555	13.8673	12.5197	17.0442	18.2066	22.3328	33.0230	27.6220	31.7332	31.5033	35.2081	26.9050	22.0094	45.3909	27.8696
SMB	0.3166	0.3854	0.4629	-0.0696	-0.1534	-0.2583	0.3206	0.1033	0.0583	0.3064	0.5964	0.1612	0.4481	-0.0475	0.2627
t(SMB)	5.0186	3.9011	2.5848	-0.8854	-3.1155	-4.9887	5.3683	1.8900	1.3812	5.6040	10.8589	2.6626	6.1433	-1.1424	4.2557
HML	0.2870	0.0865	0.1552	0.2288	0.2007	0.0932	-0.2764	-0.3043	0.0965	0.2526	-0.0248	-0.0618	0.0258	0.5870	0.0819
t(HML)	2.9677	0.6549	0.6520	1.4933	2.3383	1.5039	-3.8445	-4.6915	1.6356	3.5127	-0.4166	-0.5944	0.2967	9.4228	0.9689
RMW	0.5329	0.0067	0.0823	0.1947	0.0459	-0.2614	-0.1655	-0.2425	0.4122	0.3692	0.3463	0.3791	0.7706	-0.0977	0.2068
t(RMW)	4.3897	0.0455	0.2341	1.7323	0.4879	-3.1753	-2.2528	-2.0610	4.5436	3.8390	5.9674	5.3447	6.5271	-1.3817	2.6113
CMA	0.0227	0.2805	0.2976	0.3741	0.3004	0.1181	-0.4985	-0.4318	0.3124	0.0190	0.0850	0.0358	0.0350	-0.2293	0.1029
t(CMA)	0.1573	1.3142	0.8571	2.4236	2.2410	1.0002	-4.6704	-3.5178	3.7224	0.2224	0.8871	0.2906	0.2747	-2.7467	0.9614
INN	0.0190	-0.1274	-0.0444	-0.1473	-0.2464	-0.0364	0.1132	0.7010	-0.0176	-0.1446	-0.2152	-0.1486	-0.1208	-0.3897	-0.1012
t(IMN)	0.2059	-1.0505	-0.1877	-1.4548	-3.5050	-0.6568	2.1115	8.5511	-0.2505	-1.9366	-3.5692	-2.4743	-1.2710	-8.0466	-1.2065
alpha	-0.0019	-0.0011	-0.0032	-0.0017	0.0005	0.0011	0.0032	0.0016	-0.0027	-0.0022	-0.0012	0.0008	-0.0004	0.0000	-0.0041
t(alpha)	-1.1952	-0.4489	-0.7203	-0.9206	0.4291	0.9129	3.0129	1.5614	-2.5374	-1.8554	-1.1502	0.6450	-0.2716	0.0439	-3.6464

Regressed the excess monthly return on 30 industry portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) plus newly created innovation factor (INN) over the period July 1963-Dec 2020. 30 industry portfolios as obtained from Fama-French database, include 30 portfolios formed based on classification of stocks into 30 industrial groups based on their four digit SIC codes. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). To create innovation factor, in June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are also sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1. 6 size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 22:Regression results of 30 industry portfolios on Fama-French 5 factors plus innovation factor (Conditional on Size)

	Food	Beer	Smoke	Games	Books	Hshld	Clths	Hlth	Chems	Txtls	Cnstr	Steel	FabPr	ElcEq	Autos
MR	0.8433	0.8708	0.8621	1.2114	1.1176	0.8815	1.1012	0.8804	1.1493	1.1663	1.2455	1.2584	1.1622	1.2203	1.2891
	21.5187	17.8757	16.6600	24.0749	25.5961	22.5218	20.5513	23.5688	38.4753	17.3004	42.8193	24.1784	31.5006	34.2412	15.5494
SMB	-0.0435	0.0243	-0.0984	0.5418	0.3822	-0.0157	0.5516	-0.1254	0.0393	0.7819	0.3945	0.3129	0.3114	0.1389	0.2069
	-0.9403	0.3345	-0.9444	6.9891	7.4930	-0.2521	5.8369	-2.1148	0.9081	10.2015	8.2476	4.3864	5.5722	2.1199	2.4609
HML	-0.0616	-0.1374	-0.1632	0.1380	0.2307	-0.1699	0.3034	-0.4127	0.2098	0.5711	0.2795	0.3060	0.0503	0.0341	0.4312
	-1.0036	-1.5074	-1.7547	1.2928	3.6088	-2.0294	2.2612	-4.7935	3.4718	3.2015	4.8434	3.2044	0.7707	0.4428	3.7362
RMW	0.4950	0.5514	0.6315	0.3304	0.3877	0.5838	0.6003	0.3267	0.3137	0.5246	0.3903	-0.4612	-0.0108	0.2082	0.2497
	5.8936	5.6937	4.6814	2.5982	5.8488	7.0808	4.2331	2.8436	4.3416	4.2110	4.5529	-3.7681	-0.1494	2.1610	1.5040
CMA	0.3852	0.3950	0.7899	-0.2341	0.0247	0.2782	-0.1317	0.2979	0.2456	0.0866	0.1524	0.1043	0.0480	0.0027	0.2753
	4.9655	3.2508	5.4285	-1.8548	0.2765	2.3544	-0.8894	1.9558	2.5368	0.4676	1.6922	0.7170	0.5181	0.0230	1.5256
INN	-0.2577	-0.2489	-0.1215	0.0865	-0.1811	0.0041	-0.1937	-0.0013	-0.0010	-0.1195	-0.1321	0.0078	0.1052	0.0335	0.1237
	-3.7226	-2.4418	-1.0624	0.7609	-2.3490	0.0589	-2.0532	-0.0153	-0.0148	-0.8238	-1.9911	0.0734	1.6657	0.4202	1.0352
alpha	0.0004	0.0011	0.0018	-0.0006	-0.0032	-0.0012	-0.0013	0.0019	-0.0028	-0.0048	-0.0037	-0.0043	-0.0013	0.0001	-0.0041
	0.4030	0.7884	0.8894	-0.3954	-2.5188	-1.1238	-0.7867	1.6184	-2.2933	-2.8141	-3.3065	-2.3573	-0.9865	0.1309	-2.3337

	Carry	Mines	Coal	Oil	Util	Telcm	Servs	BusEq	Paper	Trans	Whlsl	Rtail	Meals	Fin	Other
MR	1.1826	0.9598	1.1517	1.0132	0.6564	0.8422	1.0682	1.0188	1.0500	1.1076	1.0331	1.0150	1.0714	1.1665	1.0939
	27.0482	13.9296	12.4700	17.0216	18.4537	22.6278	33.6061	28.0343	31.8416	30.9871	35.5428	26.7744	22.0078	44.5241	27.6162
SMB	0.3169	0.3839	0.4630	-0.0711	-0.1561	-0.2586	0.3218	0.1110	0.0579	0.3049	0.5939	0.1596	0.4466	-0.0518	0.2614
	5.0070	3.8744	2.5742	-0.9030	-3.2044	-5.0345	5.4346	1.9765	1.3753	5.4947	10.7760	2.6157	6.0796	-1.1912	4.2235
HML	0.2873	0.0849	0.1616	0.2299	0.1994	0.0945	-0.2760	-0.3024	0.0943	0.2532	-0.0261	-0.0619	0.0242	0.5860	0.0804
	2.9621	0.6411	0.6789	1.5018	2.3300	1.5357	-3.8649	-4.8029	1.6063	3.4847	-0.4362	-0.5948	0.2786	9.3596	0.9573
RMW	0.5350	-0.0014	0.1211	0.2029	0.0408	-0.2531	-0.1641	-0.2393	0.3993	0.3746	0.3410	0.3802	0.7627	-0.0993	0.1990
	4.5086	-0.0093	0.3454	1.8265	0.4270	-3.0817	-2.2197	-1.9900	4.2584	3.8706	5.8118	5.3342	6.3879	-1.3760	2.5441
CMA	0.0229	0.2788	0.2990	0.3730	0.2976	0.1182	-0.4973	-0.4246	0.3115	0.0178	0.0825	0.0344	0.0334	-0.2333	0.1015
	0.1596	1.3103	0.8618	2.4125	2.2138	0.9988	-4.6864	-3.4931	3.6720	0.2086	0.8671	0.2783	0.2597	-2.7985	0.9445
INN	0.0275	-0.1658	0.0732	-0.1363	-0.2875	-0.0139	0.1291	0.7824	-0.0602	-0.1423	-0.2537	-0.1602	-0.1579	-0.4343	-0.1360
	0.2890	-1.2204	0.2663	-1.2550	-3.6996	-0.2147	2.1691	8.0175	-0.7876	-1.7498	-3.8890	-2.3313	-1.6098	-7.5832	-1.4920
alpha	-0.0019	-0.0010	-0.0036	-0.0018	0.0005	0.0010	0.0032	0.0016	-0.0026	-0.0022	-0.0011	0.0008	-0.0004	0.0001	-0.0041
	-1.2035	-0.4199	-0.7980	-0.9756	0.4790	0.8411	3.0146	1.5134	-2.3878	-1.8977	-1.0938	0.6439	-0.2263	0.0735	-3.6139

Regressed the excess monthly return on 30 industry portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) plus newly created innovation factor (INN) over the period July 1963-Dec 2020. 30 industry portfolios as obtained from Fama-French database, include 30 portfolios formed based on classification of stocks into 30 industrial groups based on their four digit SIC codes. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). To create innovation factor, in June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. Within each size group, the stocks are sorted into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1. This results in 6 size-innovation portfolios. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 23:Regression results of 49 industry portfolios on Fama-French five factors

	Agric	Food	Soda	Beer	Smoke	Toys	Fun	Books	Hshld	Clths	Hlth	MedEq	Drugs	Chems	Rubbr	Txtls	BldMt
MR	0.8092	0.8112	0.9284	0.8546	0.8542	1.1409	1.2538	1.0937	0.8818	1.0886	1.4247	0.8722	0.8693	1.1493	1.0183	1.1585	1.2475
t(MR)	15.3543	21.9752	12.0022	17.6312	16.4683	26.4599	21.8392	24.4435	21.6860	20.7603	5.6946	24.2843	20.7616	38.7266	25.4255	16.1657	35.5809
SMB	0.4583	-0.0358	-0.0135	0.0255	-0.0978	0.6795	0.5099	0.3753	-0.0157	0.5526	0.0411	0.1484	-0.2261	0.0393	0.7048	0.7825	0.3793
t(SMB)	5.2966	-0.7043	-0.1565	0.3528	-0.9610	9.3761	5.9425	7.0303	-0.2522	5.7157	0.0698	2.4728	-3.4009	0.9085	12.5606	10.0165	7.4550
HML	-0.0151	-0.0492	0.0531	-0.1241	-0.1567	0.0414	0.1448	0.2142	-0.1701	0.3138	-1.0423	-0.2999	-0.4376	0.2098	0.1032	0.5775	0.3036
t(HML)	-0.1287	-0.6906	0.3728	-1.4162	-1.6989	0.4034	1.2417	3.4643	-2.0526	2.2784	-2.2215	-3.2817	-4.8155	3.4700	1.0697	3.2722	5.2639
RMW	0.1720	0.5534	0.6064	0.6304	0.6701	0.6656	0.2336	0.4532	0.5824	0.6618	1.5368	0.2899	0.2907	0.3140	0.4336	0.5625	0.4812
t(RMW)	1.5279	7.8914	4.2565	8.0132	5.3236	6.2209	1.6468	7.0894	7.8803	4.2698	3.0883	2.5052	2.7136	4.4598	5.9334	4.6285	6.1586
CMA	0.0528	0.4575	0.2638	0.3989	0.7918	0.0611	-0.2635	0.0154	0.2781	-0.1287	1.9219	0.0229	0.3445	0.2456	0.1234	0.0884	0.2071
t(CMA)	0.3569	5.2434	1.2717	3.2173	5.4498	0.4185	-1.9025	0.1609	2.3511	-0.8924	2.1507	0.1468	2.1832	2.5379	1.1047	0.4746	2.3944
alpha	0.0001	-0.0004	0.0003	0.0004	0.0014	-0.0044	0.0017	-0.0031	-0.0012	-0.0018	-0.1129	0.0028	0.0023	-0.0028	-0.0017	-0.0052	-0.0039
t(alpha)	0.0389	-0.3909	0.1551	0.2715	0.7156	-2.1730	0.8608	-2.3505	-1.1231	-1.1149	-3.5899	2.0061	1.9027	-2.2710	-1.3527	-3.0313	-3.5764

	Cnstr	Steel	FabPr	Mach	ElcEq	Autos	Aero	Ships	Guns	Gold	Mines	Coal	Oil	Util	Telcm	PerSv	BusSv
MR	1.2453	1.2589	1.0159	1.1757	1.2225	1.2972	1.1853	1.2131	0.8992	0.5510	1.1240	1.1565	1.0043	0.6375	0.8413	1.0704	1.0645
t(MR)	27.6503	24.2453	21.2821	32.4044	35.0750	15.7893	23.5990	20.7056	13.8207	4.6240	18.4089	12.9543	16.9598	17.9127	22.2343	17.9124	51.9498
SMB	0.5908	0.3128	0.7033	0.2988	0.1387	0.2063	0.3636	0.3237	0.3674	0.3915	0.3835	0.4627	-0.0705	-0.1547	-0.2585	0.6622	0.4505
t(SMB)	6.7927	4.3938	6.2414	5.5903	2.1388	2.4957	4.8297	3.2437	3.7992	2.8027	4.1384	2.5790	-0.8786	-3.1320	-5.0425	7.4693	11.7255
HML	0.2211	0.3056	0.2810	0.0408	0.0323	0.4246	0.2904	0.2514	0.2382	-0.2817	0.2282	0.1577	0.2372	0.2147	0.0952	0.0213	-0.1071
t(HML)	2.0875	3.2036	2.2706	0.6424	0.4245	3.6765	2.7658	2.2531	2.0146	-1.3040	1.8911	0.6628	1.5446	2.5273	1.5540	0.1532	-2.1018
RMW	0.3933	-0.4637	0.2449	-0.0504	0.1976	0.2104	0.5487	0.5226	0.7384	0.0534	0.1105	0.0978	0.2462	0.1321	-0.2487	0.6583	0.1965
t(RMW)	3.0543	-4.2561	1.8978	-0.7302	2.2787	1.3589	4.3921	3.2641	5.4204	0.2173	0.8298	0.3243	2.3780	1.7820	-2.8525	5.0309	2.5884
CMA	-0.0593	0.1041	-0.2225	0.0565	0.0022	0.2734	-0.0237	0.4083	0.1670	0.4709	0.1969	0.2979	0.3751	0.3021	0.1184	0.0511	-0.0663
t(CMA)	-0.4232	0.7182	-1.4947	0.6119	0.0186	1.5182	-0.1475	2.5736	0.9388	1.2080	1.1432	0.8615	2.3908	2.3193	1.0023	0.3178	-0.9489
alpha	-0.0032	-0.0043	-0.0039	-0.0009	0.0002	-0.0037	-0.0016	-0.0039	-0.0006	0.0017	-0.0011	-0.0033	-0.0022	-0.0003	0.0010	-0.0062	-0.0001
t(alpha)	-1.7562	-2.3822	-1.7411	-0.6962	0.2210	-2.0577	-0.8777	-1.8979	-0.3156	0.4839	-0.4296	-0.7797	-1.2219	-0.2911	0.8262	-3.3065	-0.1416

	Hardw	Softw	Chips	LabEq	Paper	Boxes	Trans	Whlsl	Rtail	Meals	Banks	Insur	RlEst	Fin	Other
MR	1.0091	1.1641	1.1920	1.1114	1.0818	0.9859	1.0995	1.0165	1.0045	1.0611	1.1690	1.0491	1.1566	1.1800	1.1538
t(MR)	21.0321	7.7350	25.7063	27.0880	29.1786	23.1721	31.6968	34.5595	27.0269	21.8629	29.4348	22.8489	22.4850	36.3953	24.2819
SMB	0.0143	1.0974	0.2289	0.4438	0.0688	0.0091	0.3041	0.5952	0.1604	0.4474	-0.1144	-0.0925	0.9809	0.0080	0.3363
t(SMB)	0.2091	3.8235	3.3495	7.7381	1.4765	0.1333	5.3708	10.5802	2.6474	6.0661	-2.2013	-1.1026	12.2902	0.1832	3.7843
HML	-0.2859	-0.6995	-0.3421	-0.4719	0.1435	0.1149	0.2614	-0.0126	-0.0533	0.0326	0.7928	0.3837	0.6113	0.4246	0.0887
t(HML)	-3.3402	-2.3297	-3.7467	-7.9696	2.2502	1.3199	3.4951	-0.1987	-0.5152	0.3711	9.2597	3.4573	5.8516	6.6651	0.8232
RMW	-0.5328	0.3620	-0.5107	-0.0647	0.3660	0.2886	0.4203	0.4216	0.4310	0.8128	0.0755	0.1345	0.4573	-0.4343	0.2164
t(RMW)	-4.7409	1.2989	-4.8782	-0.8606	3.9192	2.9091	4.3635	6.1708	6.0479	6.4971	1.0292	1.0623	5.2273	-8.0413	2.3573

Table 23 Continued

	Hardw	Softw	Chips	LabEq	Paper	Boxes	Trans	Whlsl	Rtail	Meals	Banks	Insur	RlEst	Fin	Other
CMA	-0.5567	-0.5652	-0.2945	0.0117	0.4066	-0.0864	0.0200	0.0864	0.0368	0.0359	-0.3132	0.0645	-0.1245	-0.3916	0.0620
t(CMA)	-3.3556	-1.2561	-1.9518	0.0919	4.3807	-0.7464	0.2333	0.8993	0.3046	0.2892	-2.7072	0.4440	-1.0779	-4.7912	0.4004
alpha	0.0039	-0.0354	0.0035	0.0019	-0.0030	0.0000	-0.0027	-0.0019	0.0003	-0.0008	-0.0019	-0.0006	-0.0074	0.0017	-0.0060
t(alpha)	2.2535	-1.9112	2.6512	1.5684	-2.4267	0.0256	-2.2004	-1.8311	0.2319	-0.5076	-1.6164	-0.4493	-4.3605	1.5587	-3.5094

Regressed the excess monthly return on 49 industry portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment) over the period July 1963-Dec 2020. 30 industry portfolios as obtained from Fama-French database, include 49 portfolios formed based on classification of stocks into 49 industrial groups based on their four digit SIC codes. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 24: Regression results of 49 industry portfolios on Fama-French 5 factors plus innovation factor (Independent)

	Agric	Food	Soda	Beer	Smoke	Toys	Fun	Books	Hshld	Clths	Hlth	MedEq	Drugs	Chems	Rubbr	Txtls	BldMt
MR	0.8238	0.8323	0.9288	0.8684	0.8570	1.1295	1.2527	1.1036	0.8796	1.1051	1.4408	0.8674	0.8683	1.1482	1.0274	1.1641	1.2556
t(MR)	15.4610	22.0825	11.9943	17.8115	16.6928	25.1565	21.5143	24.8969	22.4994	20.6476	5.5319	24.1695	20.4353	38.4540	25.4596	17.8896	36.6759
SMB	0.4594	-0.0343	-0.0134	0.0266	-0.0976	0.6787	0.5099	0.3761	-0.0158	0.5538	0.0422	0.1481	-0.2262	0.0392	0.7055	0.7829	0.3799
t(SMB)	5.4138	-0.6917	-0.1562	0.3650	-0.9507	9.4299	5.9409	7.0931	-0.2561	5.9397	0.0719	2.5064	-3.4104	0.9037	12.2565	10.2374	7.6218
HML	-0.0259	-0.0649	0.0528	-0.1344	-0.1588	0.0498	0.1457	0.2069	-0.1685	0.3015	-1.0542	-0.2964	-0.4368	0.2106	0.0964	0.5734	0.2976
t(HML)	-0.2290	-0.9501	0.3675	-1.4609	-1.6993	0.4819	1.2353	3.2236	-2.0240	2.2642	-2.2098	-3.2166	-4.7645	3.4722	0.9907	3.1767	5.2210
RMW	0.1056	0.4572	0.6045	0.5675	0.6571	0.7173	0.2386	0.4082	0.5924	0.5864	1.4636	0.3117	0.2954	0.3186	0.3918	0.5370	0.4444
t(RMW)	1.0501	5.5322	3.6072	5.8074	4.9900	6.6179	1.6498	5.6259	7.2548	4.2429	2.5298	2.5724	2.5395	4.4911	5.0484	4.0773	5.4913
CMA	0.0515	0.4556	0.2637	0.3976	0.7915	0.0621	-0.2634	0.0145	0.2783	-0.1302	1.9205	0.0233	0.3446	0.2457	0.1225	0.0879	0.2063
t(CMA)	0.3494	5.2002	1.2712	3.2367	5.4425	0.4323	-1.8996	0.1530	2.3594	-0.8799	2.1560	0.1506	2.1873	2.5427	1.1120	0.4743	2.3643
INN	-0.1899	-0.2748	-0.0055	-0.1798	-0.0373	0.1477	0.0141	-0.1285	0.0285	-0.2155	-0.2093	0.0622	0.0135	0.0132	-0.1196	-0.0729	-0.1051
t(INN)	-1.7641	-4.3270	-0.0383	-1.7822	-0.3491	1.2758	0.1162	-1.5882	0.4296	-2.4636	-0.3430	0.8631	0.1461	0.2177	-1.4433	-0.4566	-1.6224
alpha	0.0007	0.0005	0.0003	0.0010	0.0016	-0.0049	0.0016	-0.0027	-0.0013	-0.0011	-0.1122	0.0026	0.0023	-0.0029	-0.0013	-0.0050	-0.0035
t(alpha)	0.3500	0.4022	0.1597	0.6716	0.7575	-2.4222	0.8385	-2.0263	-1.2026	-0.7155	-3.5476	1.8244	1.8096	-2.3265	-1.0472	-2.8211	-3.2637

	Cnstr	Steel	FabPr	Mach	ElcEq	Autos	Aero	Ships	Guns	Gold	Mines	Coal	Oil	Util	Telcm	PerSv	BusSv
MR	1.2505	1.2554	1.0232	1.1683	1.2194	1.2856	1.1792	1.2339	0.9137	0.5759	1.1235	1.1599	1.0156	0.6565	0.8441	1.0941	1.0704
t(MR)	27.6074	24.3889	20.2090	31.7991	34.4236	15.5813	22.8155	21.5715	14.3169	4.8407	17.8600	12.5197	17.0442	18.2066	22.3328	18.9407	52.8432
SMB	0.5912	0.3126	0.7038	0.2982	0.1385	0.2054	0.3631	0.3253	0.3684	0.3934	0.3834	0.4629	-0.0696	-0.1534	-0.2583	0.6640	0.4509
t(SMB)	6.8663	4.3453	6.3278	5.4256	2.1077	2.4395	4.7697	3.3743	3.8387	2.8228	4.1371	2.5848	-0.8854	-3.1155	-4.9887	7.8459	11.6074
HML	0.2172	0.3082	0.2756	0.0463	0.0347	0.4332	0.2949	0.2360	0.2275	-0.3002	0.2286	0.1552	0.2288	0.2007	0.0932	0.0037	-0.1115
t(HML)	2.0739	3.2359	2.2807	0.7096	0.4491	3.7596	2.8249	2.2364	1.9684	-1.4259	1.9111	0.6520	1.4933	2.3383	1.5039	0.0280	-2.2211
RMW	0.3697	-0.4476	0.2118	-0.0166	0.2119	0.2632	0.5766	0.4276	0.6726	-0.0599	0.1127	0.0823	0.1947	0.0459	-0.2614	0.5503	0.1696
t(RMW)	2.7371	-3.6211	1.8268	-0.2249	2.1604	1.5368	4.5564	2.6168	5.1898	-0.2430	0.8720	0.2341	1.7323	0.4879	-3.1753	4.8414	2.0838
CMA	-0.0598	0.1045	-0.2231	0.0572	0.0024	0.2745	-0.0231	0.4064	0.1657	0.4686	0.1970	0.2976	0.3741	0.3004	0.1181	0.0489	-0.0669
t(CMA)	-0.4249	0.7179	-1.5174	0.6157	0.0210	1.5195	-0.1455	2.6214	0.9601	1.2138	1.1424	0.8571	2.4236	2.2410	1.0002	0.3140	-0.9232
INN	-0.0675	0.0461	-0.0947	0.0968	0.0410	0.1510	0.0797	-0.2717	-0.1882	-0.3239	0.0065	-0.0444	-0.1473	-0.2464	-0.0364	-0.3088	-0.0772
t(INN)	-0.6978	0.4922	-0.8690	1.6646	0.5809	1.2242	0.7536	-2.5447	-1.4681	-1.5651	0.0610	-0.1877	-1.4548	-3.5050	-0.6568	-3.9682	-1.4698
alpha	-0.0029	-0.0044	-0.0036	-0.0012	0.0001	-0.0042	-0.0018	-0.0030	0.0000	0.0027	-0.0011	-0.0032	-0.0017	0.0005	0.0011	-0.0052	0.0001
t(alpha)	-1.5993	-2.4240	-1.6622	-0.9239	0.1004	-2.3802	-1.0408	-1.4344	0.0046	0.7657	-0.4368	-0.7203	-0.9206	0.4291	0.9129	-2.8112	0.1783

	Hardw	Softw	Chips	LabEq	Paper	Boxes	Trans	Whlsl	Rtail	Meals	Banks	Insur	RlEst	Fin	Other
MR	0.9489	1.1426	1.1448	1.0866	1.0846	0.9985	1.1107	1.0331	1.0159	1.0704	1.2025	1.0843	1.1661	1.1935	1.1641
t(MR)	21.1753	7.5264	26.1664	24.9632	29.3084	23.2020	31.3339	35.2081	26.9050	22.0094	30.0410	24.4459	23.5583	38.1753	24.0876
SMB	0.0098	1.0958	0.2254	0.4420	0.0690	0.0101	0.3049	0.5964	0.1612	0.4481	-0.1119	-0.0900	0.9816	0.0090	0.3370
t(SMB)	0.1471	3.8186	3.3837	7.8214	1.4899	0.1555	5.5741	10.8589	2.6626	6.1433	-2.3669	-1.2194	12.2822	0.2164	3.7556

Table 24 Continued

	Hardw	Softw	Chips	LabEq	Paper	Boxes	Trans	Whlsl	Rtail	Meals	Banks	Insur	RlEst	Fin	Other
HML	-0.2413	-0.6836	-0.3071	-0.4536	0.1414	0.1056	0.2531	-0.0248	-0.0618	0.0258	0.7679	0.3576	0.6043	0.4147	0.0810
t(HML)	-3.0209	-2.3014	-3.5775	-7.7280	2.2123	1.3001	3.5264	-0.4166	-0.5944	0.2967	9.4491	3.5711	5.6664	6.8550	0.7634
RMW	-0.2588	0.4598	-0.2956	0.0480	0.3532	0.2313	0.3695	0.3463	0.3791	0.7706	-0.0770	-0.0258	0.4141	-0.4955	0.1696
t(RMW)	-1.8959	1.4388	-2.2962	0.5965	3.4153	2.6110	3.8253	5.9674	5.3447	6.5271	-0.9900	-0.1784	4.1331	-9.1641	1.6766
CMA	-0.5513	-0.5633	-0.2903	0.0139	0.4063	-0.0875	0.0190	0.0850	0.0358	0.0350	-0.3162	0.0613	-0.1253	-0.3928	0.0610
t(CMA)	-3.7499	-1.2608	-2.0523	0.1213	4.3421	-0.7774	0.2216	0.8871	0.2906	0.2747	-2.8535	0.4309	-1.1010	-4.7344	0.3895
INN	0.7834	0.2798	0.6151	0.3224	-0.0367	-0.1637	-0.1451	-0.2152	-0.1486	-0.1208	-0.4360	-0.4583	-0.1235	-0.1750	-0.1340
t(INN)	7.9567	1.1525	6.2291	3.8986	-0.4620	-1.9707	-1.9118	-3.5692	-2.4743	-1.2710	-6.7595	-5.1273	-1.2010	-2.7679	-1.1516
alpha	0.0013	-0.0363	0.0014	0.0009	-0.0029	0.0006	-0.0022	-0.0012	0.0008	-0.0004	-0.0005	0.0009	-0.0070	0.0023	-0.0056
t(alpha)	0.8571	-1.9238	1.1577	0.7444	-2.2587	0.4007	-1.8569	-1.1502	0.6450	-0.2716	-0.4184	0.6368	-4.1301	2.0895	-3.2181

Regressed the excess monthly return on 49 industry portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) plus newly created innovation factor (INN) over the period July 1963-Dec 2020. 49 industry portfolios as obtained from Fama-French database, include 49 portfolios formed based on classification of stocks into 49 industrial groups based on their four digit SIC codes. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). To create innovation factor, in June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are also sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1. 6 size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 25:Regression results of 49 industry portfolios on Fama-French 5 factors plus innovation factor (conditional on size)

	Agric	Food	Soda	Beer	Smoke	Toys	Fun	Books	Hshld	Clths	Hlth	MedEq	Drugs	Chems	Rubbr	Txtls	BldMt
MR	0.8213	0.8326	0.9313	0.8708	0.8621	1.1302	1.2548	1.1063	0.8815	1.1012	1.4514	0.8696	0.8674	1.1493	1.0292	1.1663	1.2574
t(MR)	15.4149	21.9798	12.0633	17.8757	16.6600	25.3189	21.3282	25.2433	22.5218	20.5513	5.6055	24.2051	20.5547	38.4753	25.1809	17.3004	36.6630
SMB	0.4574	-0.0374	-0.0137	0.0243	-0.0984	0.6803	0.5099	0.3744	-0.0157	0.5516	0.0391	0.1486	-0.2260	0.0393	0.7040	0.7819	0.3786
t(SMB)	5.3711	-0.7490	-0.1576	0.3345	-0.9444	9.4082	5.9381	6.9991	-0.2521	5.8369	0.0665	2.4948	-3.4147	0.9081	12.1740	10.2015	7.5448
HML	-0.0250	-0.0666	0.0508	-0.1374	-0.1632	0.0501	0.1441	0.2040	-0.1699	0.3034	-1.0641	-0.2978	-0.4360	0.2098	0.0943	0.5711	0.2955
t(HML)	-0.2189	-0.9752	0.3547	-1.5074	-1.7547	0.4882	1.2276	3.2148	-2.0294	2.2612	-2.2357	-3.2275	-4.7612	3.4718	0.9768	3.2015	5.2354
RMW	0.1132	0.4497	0.5924	0.5514	0.6315	0.7175	0.2289	0.3922	0.5838	0.6003	1.4074	0.3024	0.3000	0.3137	0.3806	0.5246	0.4330
t(RMW)	1.0994	5.3168	3.5236	5.6937	4.6814	6.6977	1.6286	5.5893	7.0808	4.2331	2.4484	2.4522	2.6153	4.3416	5.1228	4.2110	5.4014
CMA	0.0500	0.4524	0.2631	0.3950	0.7899	0.0636	-0.2637	0.0124	0.2782	-0.1317	1.9156	0.0235	0.3449	0.2456	0.1208	0.0866	0.2047
t(CMA)	0.3383	5.1247	1.2685	3.2508	5.4285	0.4433	-1.9061	0.1323	2.3544	-0.8894	2.1589	0.1510	2.1946	2.5368	1.1083	0.4676	2.3300
INN	-0.1853	-0.3265	-0.0443	-0.2489	-0.1215	0.1634	-0.0148	-0.1922	0.0041	-0.1937	-0.4075	0.0392	0.0293	-0.0010	-0.1670	-0.1195	-0.1517
t(INN)	-1.5816	-4.4873	-0.2943	-2.4418	-1.0624	1.2892	-0.1144	-2.3616	0.0589	-2.0532	-0.6531	0.4896	0.3016	-0.0148	-2.0227	-0.8238	-2.2150
alpha	0.0006	0.0005	0.0004	0.0011	0.0018	-0.0049	0.0017	-0.0025	-0.0012	-0.0013	-0.1117	0.0027	0.0022	-0.0028	-0.0012	-0.0048	-0.0034
t(alpha)	0.3155	0.4701	0.2185	0.7884	0.8894	-2.4373	0.8954	-1.9268	-1.1238	-0.7867	-3.5391	1.8722	1.7733	-2.2933	-0.9708	-2.8141	-3.2177

	Cnstr	Steel	FabPr	Mach	ElcEq	Autos	Aero	Ships	Guns	Gold	Mines	Coal	Oil	Util	Telcm	PerSv	BusSv
MR	1.2482	1.2584	1.0248	1.1685	1.2203	1.2891	1.1787	1.2335	0.9170	0.5801	1.1231	1.1517	1.0132	0.6564	0.8422	1.0912	1.0715
t(MR)	27.2443	24.1784	20.3562	31.4148	34.2412	15.5494	22.8705	21.3121	14.6143	4.9147	17.8102	12.4700	17.0216	18.4537	22.6278	18.3979	53.2205
SMB	0.5906	0.3129	0.7026	0.2993	0.1389	0.2069	0.3640	0.3222	0.3660	0.3894	0.3835	0.4630	-0.0711	-0.1561	-0.2586	0.6607	0.4499
t(SMB)	6.8093	4.3864	6.3474	5.4437	2.1199	2.4609	4.7646	3.3546	3.8374	2.7848	4.1258	2.5742	-0.9030	-3.2044	-5.0345	7.7086	11.4610
HML	0.2187	0.3060	0.2737	0.0466	0.0341	0.4312	0.2958	0.2348	0.2236	-0.3055	0.2290	0.1616	0.2299	0.1994	0.0945	0.0043	-0.1128
t(HML)	2.0708	3.2044	2.2673	0.7160	0.4428	3.7362	2.8239	2.2304	1.9707	-1.4566	1.9017	0.6789	1.5018	2.3300	1.5357	0.0321	-2.2470
RMW	0.3792	-0.4612	0.2015	-0.0155	0.2082	0.2497	0.5808	0.4236	0.6519	-0.0879	0.1150	0.1211	0.2029	0.0408	-0.2531	0.5572	0.1626
t(RMW)	2.7739	-3.7681	1.7123	-0.2161	2.1610	1.5040	4.6877	2.6054	5.2541	-0.3589	0.8810	0.3454	1.8265	0.4270	-3.0817	4.7835	1.9804
CMA	-0.0600	0.1043	-0.2246	0.0582	0.0027	0.2753	-0.0221	0.4035	0.1628	0.4640	0.1971	0.2990	0.3730	0.2976	0.1182	0.0461	-0.0680
t(CMA)	-0.4270	0.7170	-1.5360	0.6265	0.0230	1.5256	-0.1396	2.6247	0.9655	1.2097	1.1435	0.8618	2.4125	2.2138	0.9988	0.2968	-0.9246
INN	-0.0445	0.0078	-0.1366	0.1099	0.0335	0.1237	0.1009	-0.3120	-0.2724	-0.4450	0.0142	0.0732	-0.1363	-0.2875	-0.0139	-0.3185	-0.1069
t(INN)	-0.3904	0.0734	-1.2771	1.7212	0.4202	1.0352	0.9182	-2.7409	-1.9711	-1.9010	0.1258	0.2663	-1.2550	-3.6996	-0.2147	-3.8814	-1.8871
alpha	-0.0030	-0.0043	-0.0035	-0.0012	0.0001	-0.0041	-0.0019	-0.0030	0.0002	0.0030	-0.0011	-0.0036	-0.0018	0.0005	0.0010	-0.0052	0.0002
t(alpha)	-1.6476	-2.3573	-1.6041	-0.9427	0.1309	-2.3337	-1.0607	-1.4010	0.1066	0.8449	-0.4485	-0.7980	-0.9756	0.4790	0.8411	-2.8511	0.2646

	Hardw	Softw	Chips	LabEq	Paper	Boxes	Trans	Whlsl	Rtail	Meals	Banks	Insur	RlEst	Fin	Other
MR	0.9524	1.1422	1.1461	1.0877	1.0890	0.9960	1.1088	1.0331	1.0150	1.0714	1.2007	1.0848	1.1707	1.1917	1.1648
t(MR)	21.6192	7.4848	26.6576	24.9104	29.5222	23.1593	30.8309	35.5428	26.7744	22.0078	29.4792	24.5849	23.1029	38.0660	24.0602
SMB	0.0185	1.0990	0.2323	0.4456	0.0683	0.0084	0.3034	0.5939	0.1596	0.4466	-0.1167	-0.0952	0.9799	0.0071	0.3354
t(SMB)	0.2695	3.8352	3.4488	7.7476	1.4760	0.1282	5.4638	10.7760	2.6157	6.0796	-2.3802	-1.2672	12.2053	0.1689	3.7309

Table 25 Continued

	Hardw	Softw	Chips	LabEq	Paper	Boxes	Trans	Whlsl	Rtail	Meals	Banks	Insur	RlEst	Fin	Other
HML	-0.2396	-0.6817	-0.3047	-0.4526	0.1376	0.1067	0.2538	-0.0261	-0.0619	0.0242	0.7669	0.3546	0.5998	0.4152	0.0796
t(HML)	-3.0290	-2.3070	-3.6389	-7.8430	2.1629	1.2907	3.4982	-0.4362	-0.5948	0.2786	9.4936	3.5404	5.7276	6.7340	0.7527
RMW	-0.2579	0.4682	-0.2881	0.0503	0.3311	0.2401	0.3753	0.3410	0.3802	0.7627	-0.0785	-0.0388	0.3889	-0.4907	0.1627
t(RMW)	-1.8443	1.4447	-2.2118	0.6288	3.0636	2.6797	3.8624	5.8118	5.3342	6.3879	-1.0070	-0.2615	4.2834	-9.1973	1.6242
CMA	-0.5433	-0.5600	-0.2837	0.0173	0.4049	-0.0888	0.0178	0.0825	0.0344	0.0334	-0.3207	0.0561	-0.1278	-0.3944	0.0593
t(CMA)	-3.7464	-1.2532	-2.0207	0.1512	4.2627	-0.7846	0.2081	0.8671	0.2783	0.2597	-2.9018	0.3947	-1.1333	-4.7236	0.3781
INN	0.8660	0.3346	0.7012	0.3623	-0.1101	-0.1529	-0.1417	-0.2537	-0.1602	-0.1579	-0.4850	-0.5458	-0.2156	-0.1776	-0.1693
t(INN)	7.3416	1.1582	6.3713	3.8257	-1.2606	-1.7922	-1.7195	-3.8890	-2.3313	-1.6098	-6.3598	-5.4860	-2.5458	-2.4918	-1.3465
alpha	0.0013	-0.0364	0.0014	0.0008	-0.0027	0.0005	-0.0022	-0.0011	0.0008	-0.0004	-0.0005	0.0010	-0.0067	0.0023	-0.0055
t(alpha)	0.8419	-1.9277	1.0891	0.7104	-2.0579	0.3472	-1.9013	-1.0938	0.6439	-0.2263	-0.3940	0.7382	-4.0493	2.0768	-3.1645

Regressed the excess monthly return on 49 industry portfolios using Fama-French 5 factors: MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability), CMA (conservative minus aggressive investment) plus newly created innovation factor (INN) over the period July 1963-Dec 2020. 49 industry portfolios as obtained from Fama-French database, include 49 portfolios formed based on classification of stocks into 49 industrial groups based on their four digit SIC codes. Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. The data on innovation is obtained from Kogan et al. (2016). To create innovation factor, in June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. Within each size group, the stocks are sorted into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1. This results in 6 size-innovation portfolios. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. The t values are based on heteroskedasticity and autocorrelation consistent standard errors.

Table 26: GRS Statistic and Equal Weight Metrics

	GRS	$A\,\lvert\alpha\rvert$	$A\,\lvert t(\alpha)\rvert$	$\frac{A\,\alpha^2}{V\bar{r}}$	$\frac{A\lambda^2}{V\bar{r}}$
6 Size_Inn Portfolios (Ind)	4.30	0.00192	1.85870	0.85670	0.75855
10 Inn portfolios (5 factors)	1.7146	0.00079	1.0376	1.1876	0.3550
10 Inn portfolios (5 + INN-Ind)	1.0928	0.00076	0.9384	0.8994	0.0698
10 Inn portfolios (5 + INN-Cond)	1.1029	0.00076	0.9355	0.9483	0.1126
Size-BM (5 factors)	2.9509	0.00082	1.2510	0.3844	0.2537
Size-BM (5 + INN-Ind)	2.6791	0.00076	1.2038	0.3420	0.2197
Size-BM (5 + INN-Cond)	2.7100	0.00077	1.2163	0.3532	0.2298
Size-OP (5 factors)	2.0401	0.00062	0.9871	0.2730	0.1007
Size-OP (5 + INN-Ind)	1.9720	0.00054	0.8477	0.2534	0.0943
Size-OP (5 + INN-Cond)	1.9800	0.00056	0.8649	0.2615	0.1010
Size-Inv (5 factors)	3.2826	0.00082	1.4202	0.4297	0.3021
Size-Inv (5 + INN-Ind)	3.0300	0.00082	1.4668	0.3996	0.2825
Size-Inv (5 + INN-Cond)	3.0500	0.00083	1.4760	0.4115	0.2932
30 industry (5 factors)	2.6742	0.00214	1.5686	3.4050	2.0988
30 industry (5 + INN-Ind)	2.1800	0.00200	1.4024	2.8953	1.5641
30 industry (5 + INN-Cond)	2.1400	0.00195	1.3976	2.8488	1.5253
49 industry (5 factors)	4.1290	0.00522	1.4990	1.1780	1.0574
49 industry (5 + INN-Ind)	3.7900	0.00503	1.3610	1.1657	1.0429
49 industry (5 + INN-Cond)	3.7700	0.00503	1.3609	1.1560	1.0336

The table provides GRS statistic and equal weights metrics to compare the Fama-French 5 factors model with 6 factors model (Fama-French 5 factors plus innovation factor) using different test assets. All the metrics in the table are based on regression of the test assets on 5 factors and 6 factors model. Fama-French 5 factors model includes MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment). The 6 factors model includes the above mentioned five factors plus innovation factor (INN). Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMNO in a year to the market capitalization against the PERMNO in December of respective year. In June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are also sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1. 6 size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios. For INN-Cond, same process is applied but the for the 6 size-innovation portfolios, three innovation portfolios are formed conditional on size.
The test assets include:
10 Innovation Portfolios: 10 innovation portfolios are formed in June of each year t, whereby securities are sorted into deciles using innovation value for t-1
25 Size-BM, 25 Size-OP and 25 Size-Inv portfolios as obtained from Fama-French database and formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on the ratio of book equity to market equity (BE/ME), 5 portfolios formed based on the operating profitability and 5 portfolios formed based on investment respectively.
30 industry and 49 industry portfolios as obtained from Fama-French database formed based on classification of stocks into 30 and 49 industrial groups based on their four digit SIC codes.
GRS statistic is calculated following Gibbon, Ross & Shanken (1989) and evaluates if the alphas are jointly equal to zero. A lower value of GRS statistic is better for a model. $A\,\lvert\alpha\rvert$ measures the average absolute alphas from regression, $\mathrm{A}\,\lvert\mathrm{t}(\alpha)\rvert$ measures average absolute t value of the alphas, $\frac{\mathrm{A}\,\alpha^2}{\mathrm{V}\bar{\mathrm{r}}}$ measure the average of the squared alphas of the test assets as ratio of the cross section variance of the average returns of the test assets and $\frac{A\lambda^2}{V\bar{r}}$ is calculated as A($\alpha^2 - s^2(\alpha)$) divided by variance of average return of test assets. A lower value of these metrics is better for a model.

Table 27: GRS Statistic and Equal Weight Metrics (Robustness Check)

	GRS	$A\,\lvert\alpha\rvert$	$A\,\lvert t(\alpha)\rvert$	$\frac{A\,\alpha^2}{V\bar{r}}$	$\frac{A\lambda^2}{V\bar{r}}$
10 Inn portfolios (5 factors)	1.7240	0.00091	1.1386	1.3036	0.4380
10 Inn portfolios (5 + INN-Ind)	1.0552	0.00070	0.8504	0.9187	0.0753
Size-BM (5 factors)	2.9509	0.00082	1.2510	0.3844	0.2537
Size-BM (5 + INN-Ind)	2.6392	0.00076	1.2012	0.3416	0.2199
Size-OP (5 factors)	2.0401	0.00062	0.9871	0.2730	0.1007
Size-OP (5 + INN-Ind)	1.9684	0.00055	0.8601	0.2539	0.0945
Size-Inv (5 factors)	3.2826	0.00082	1.4202	0.4297	0.3021
Size-Inv (5 + INN-Ind)	3.0606	0.00082	1.4757	0.4059	0.2884
30 industry (5 factors)	2.6742	0.00214	1.5686	3.4050	2.0988
30 industry (5 + INN-Ind)	2.1397	0.00200	1.4075	2.9246	1.5793
49 industry (5 factors)	4.1290	0.00522	1.4990	1.1780	1.0574
49 industry (5 + INN-Ind)	3.7894	0.00500	1.3582	1.1688	1.0451

The table provides GRS statistic and equal weights metrics to compare the Fama-French 5 factors model with 6 factors model (Fama-French 5 factors plus innovation factor) using different test assets. All the metrics in the table are based on regression of the test assets on 5 factors and 6 factors model. Fama-French 5 factors model includes MR (excess market return), SMB (small minus big), HML (high book to market ratio minus low book to market ratio), RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment). The 6 factors model includes the above mentioned five factors plus innovation factor (INN). Innovation is calculated as the ratio of nominal economic value of all patents issued against a PERMCO in a year to the market capitalization against the PERMCO in December of respective year. In June of each year t, stocks are sorted into two portfolios based on size as calculated by market equity in June of year t. The stocks are also sorted independently into three groups (bottom 30%, middle 40%, top 30%) based on innovation in year t-1. 6 size-innovation portfolios are formed at the intersection of two size and three innovation sorts. Based on this, innovation factor is calculated as average return on small-high innovation and big-high innovation portfolios minus the average return on small-low innovation and big-high innovation portfolios.
The test assets include:
10 Innovation Portfolios: 10 innovation portfolios are formed in June of each year t, whereby securities are sorted into deciles using innovation value for t-1
25 Size-BM, 25 Size-OP and 25 Size-Inv portfolios as obtained from Fama-French database and formed at the intersections of 5 portfolios created on size that is represented by market equity and 5 portfolios formed based on the ratio of book equity to market equity (BE/ME), 5 portfolios formed based on the operating profitability and 5 portfolios formed based on investment respectively.
30 industry and 49 industry portfolios as obtained from Fama-French database formed based on classification of stocks into 30 and 49 industrial groups based on their four digit SIC codes.
GRS statistic is calculated following Gibbon, Ross & Shanken (1989) and evaluates if the alphas are jointly equal to zero. A lower value of GRS statistic is better for a model. $A\,\lvert\alpha\rvert$ measures the average absolute alphas from regression, $A\,\lvert t(\alpha)\rvert$ measures average absolute t value of the alphas, $\frac{A\,\alpha^2}{V\bar{r}}$ measure the average of the squared alphas of the test assets as ratio of the cross section variance of the average returns of the test assets and $\frac{A\lambda^2}{V\bar{r}}$ is calculated as A($\alpha^2 - s^2(\alpha)$) divided by variance of average return of test assets. A lower value of these metrics is better for a model.

Appendix A

Fama-French 30 Industry Portfolios

	Industry	Full Name
1	Food	Food Products
2	Beer	Beer & Liquor
3	Smoke	Tobacco Products
4	Games	Recreation
5	Books	Printing and Publishing
6	Hshld	Consumer Goods
7	Clths	Apparel
8	Hlth	Healthcare, Medical Equipment, Pharmaceutical Products
9	Chems	Chemicals
10	Txtls	Textiles
11	Cnstr	Construction and Construction Materials
12	Steel	Steel Works etc
13	FabrPr	Fabricated Products and Machinery
14	ElcEq	Electrical Equipment
15	Autos	Automobiles and Trucks
16	Carry	Aircrafts, Ships and Railroad Equipment
17	Mines	Precious Metals, Nonmetallic and Industrial Metal Mining
18	Coal	Coal
19	Oil	Petroleum and Natural Gas
20	Util	Utilities
21	Telcm	Communication
22	Servs	Personal and Business Services
23	BusEq	Business Equipment
24	Paper	Business Supplies and Shipping Containers
25	Trans	Transportation
26	Whlsl	Wholesale
27	Rtail	Retail
28	Meals	Restaurants, Hotels, Motels
29	Fin	Banking, Insurance, Real Estate, Trading
30	Other	Everything Else

Fama-French 49 Industry Portfolios

	Industry	Full Name
1	Agric	Agriculture
2	Food	Food Products
3	Soda	Candy and Soda
4	Beer	Beer & Liquor
5	Smoke	Tobacco Products
6	Toys	Recreation
7	Fun	Entertainment
8	Books	Printing and Publishing
9	Hshld	Consumer Goods
10	Clths	Apparel
11	Hlth	Healthcare
12	MedEq	Medical Equipment
13	Drugs	Pharmaceutical Products
14	Chems	Chemicals
15	Rubbr	Rubber and Plastic Products
16	Txtls	Textiles
17	BldMt	Construction Materials
18	Cnstr	Construction and Construction Materials
19	Steel	Steel Works etc
20	FabrPr	Fabricated Products
21	Mach	Machinery
22	ElcEq	Electrical Equipment
23	Autos	Automobiles and Trucks
24	Aero	Aircraft
25	Ships	Shipbuilding, Railroad Equipment
26	Guns	Defense
27	Gold	Precious Metals
28	Mines	Nonmetallic and industrial metal mining
29	Coal	Coal
30	Oil	Petroleum and Natural Gas
31	Util	Utilities
32	Telcm	Communication
33	PerSv	Personal Services
34	BusSv	Business Services
35	Hardw	Computers
36	Softw	Computer Software
37	Chips	Electronic Equipment
38	LabEq	Measuring and Control Equipment
39	Paper	Business Supplies
40	Boxes	Shipping Containers
41	Trans	Transportation
42	Whlsl	Wholesale
43	Rtail	Retail
44	Meals	Restaurants, Hotels, Motels
45	Banks	Banking
46	Insur	Insurance
47	RlEst	Real Estate

	Industry	Full Name
48	Fin	Trading
49	Other	Everything Else