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Innovation Search Strategy and Predictable Returns

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Abstract: Because of the intangible and highly uncertain nature of innovation, investors may have difficulty processing information associated with a firm's innovation search strategy. Due to cognitive and strategic biases, investors are likely to pay more attention to unfamiliar explorative patents rather than incremental exploitative patents. We find that innovative firms focusing on exploitation rather than exploration tend to generate superior subsequent short-term operating performance. Analysts do not seem to detect this, as firms currently focused on exploitation tend to outperform the market's near-term earnings expectations. The stock market also seems unable to accurately incorporate information about a firm's innovation search strategy. We find that firms with exploitation strategies are undervalued relative to firms with exploration strategies and that this return differential is incremental to standard risk and innovation-based pricing factors examined in the prior literature. This result suggests a more nuanced view on whether stock market pressure hampers innovation, and may have implications for optimal firm financing choices and corporate disclosure policy.

Keywords: Exploration, Exploitation, Patents, Innovation, Market Efficiency, Limited Attention

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1. Introduction

A firm's innovative output contains information that is useful in the evaluation of its future cash flows. However, because of the intangible and highly uncertain nature of the innovation process (Atanassov & Liu, 2019), investors may have difficulty processing this information when assessing the value of the firm (Jensen 1993; Cohen, Diether & Malloy, 2013; Hirshleifer, Hsu & Li, 2013). This occurs even if a firm patents its inventions, thereby disclosing its technology and innovation strategy to the world.

Here we ask whether investors can accurately value the innovation search strategy of a firm, characterizing this strategy as a choice between the exploration of new capabilities and the exploitation of a firm's extant competencies (March, 1991; Manso, 2011). Firms following an exploration strategy seek novel technologies and approaches that are new to the firm while those following an exploitation strategy, in contrast, "stick to their knitting" and refine currently successful and previously patented approaches. Exploration requires search that is distant from the firm's current knowledge and capabilities while exploitation relies on local search of a firm's existing competencies.

Many studies show that, due to limited investor attention, prices do not fully incorporate all available information (e.g. Klibanof, Lamont & Wizman, 1998; Huberman & Regev, 2001; Barber & Odean, 2008; Cohen & Frazzini, 2008; Dellavigna & Pollet, 2009; Hirshleifer, Lin, & Teoh, 2009; Hou, Peng & Xiong, 2009; Da, Engelberg & Gao, 2011; Da, Gurun & Warachka, 2011; Da & Warachka, 2011; Cohen & Lou, 2012; Li & Yu, 2012). Recent work has illustrated this challenge for predicting the impact of innovation information in the form of patent grants (Hirshleifer et al., 2013; Cohen et al., 2013); here we propose two specific mechanisms that could lead investors to under value exploitation strategies. The first mechanism is cognitive; investors could display an inherent psychological bias towards interpreting salient information. The second mechanism is strategic; firms could direct investor attention towards significant technological advances, particularly if those advances occur outside of a firm's previously known research trajectory.

The psychology literature has historically suggested that people focus on salient and vivid information, especially when facing complex problems (Fiske & Taylor, 1991; Song & Schwartz, 2010). More recent neuroscience research has established a consistent preference for novelty when processing information and shown that the neurological structures of novelty recognition and reward are linked (Bunzeck, Guitart-Masip, Dolan & Duzel, 2011). Expected novelty is also remembered more strongly (Wittmann, Bunzeck, Dolan & Duzel, 2007). In contrast, investors may devote insufficient time to understanding the incremental economic significance of additional patents granted in technological areas that the firm and its investors are already familiar with. By definition, breakthroughs and new trajectories are rare, making it easier to focus on them, particularly in a complex and uncertain environment. As a result, investors may overlook the potentially significant value generated by typically more process-oriented and incremental patents in order to focus on different and more exciting inventions (Banbury & Mitchell, 1995; Hult, 2014). In other words, investors may ignore patents which fill in and solidify a previously known research trajectory in favor of patents which open up new trajectories.[1]

Independent of investors' cognitive processes, innovative firms and their managers are also more likely to publicize the granting of patents that are considerably different from the firm's current patent portfolio (Kogan, Papanikolaou, Seru & Stoffman, 2017). Assuming that firms are not trying to hide their innovative successes, firm executives may have multiple incentives to prefer the reporting of patenting in a new technology area, relative to additional patents in a previously patented area.

First, it is plausible that company executives will place greater emphasis on highlighting a firm's exploratory innovative activities in order to establish their reputation in the popular press as a 'pioneer' or 'radical innovator.' In the likely event that exploratory innovation activities will attract greater media coverage of both the firm and its key executives (Raimondo, 2019; Ahern & Sosyura, 2015), studies such as Nyugen (2015) and Kuhnen & Niessen (2012) suggest that corporate executives are likely to derive both monetary and other private benefits from this increased media attention. Therefore, consistent with the reporting obligations of publicly traded firms to disclose significant changes in their technological focus and/or operations in their regulatory filings, it is probable that firm managers will be more inclined to emphasize major changes in the technological focus of a firm's innovative activities in their press/10-K releases so as to educate investors on the success of the management team's long-term growth strategy.[2] In addition to fulfilling legal requirements, such announcements are usually intended to buoy investor confidence and stock prices (relative, for example, to the second, third, or fourth patent in a developing area).

[1] This mechanism is analogous to behavioral explanations of the value premium (see e.g. Lakonishok, Shleifer & Vishny, 1994), according to which "growth/glamour" stocks are overvalued because investors focus too much attention on these firms and become over-excited about their future earnings growth (Hong & Stein, 2007).

[2] The firm is even more likely to publicize such grants if it has an explicit diversification strategy, as patent grants in fields not previously patented in are credible initial evidence that the firm's diversification strategy is working.

Relatedly, it is also possible that a company's current managers (particularly more recent appointees) may believe that investors will give the current management team insufficient credit for their individual skill and efforts if they are perceived to be simply following the firm's preordained innovation trajectory (Warren & Sorescu, 2017). As a result, corporate managers may use a firm's exploratory innovative activities as an opportunity to emphasize the specific contribution of the current management team to overall firm value.[3]

Thus, the relatively lower amount of information provided by firms about the future implications of their exploitative activities may further compound the effect of investors' existing bias towards understanding a firm's relatively different or unusual inventions.

These two consistent mechanisms imply that investors will pay more attention to explorative patents than exploitative patents. Therefore, we expect that information about firms engaged in exploration will be quickly incorporated into prices, while information about firms engaged in exploitation takes time to be incorporated into prices. We are thus more likely to find return predictability among stocks that focus on exploitation.

In order to test our conjectures, we first develop two alternative measures that distinguish whether a firm in any given year is relatively more focused on exploitation of the firm's existing known technologies versus exploration of newer technologies. First, we introduce a new measure called *Internal Search Proximity* which examines the degree of overlap in terms of technology classes between patents granted to the firm in year t and the existing patent portfolio held by the *same* firm up to year $t-1$. A firm that focuses on exploitation will have substantial overlap in technology classes, while a firm that focuses on exploration will have relatively little overlap in technology classes. Second, we adapt the "explorative" patent definition developed by the recent innovation literature that classifies patents as being exploratory in nature if the majority of the patents it cites as prior art represent new knowledge to the firm. We use this to develop a firm's *Exploitative Patent Ratio* which classifies firms as being focused on exploration/(exploitation) if a relatively greater/(lesser) proportion of their newly granted patents utilize new knowledge sources. As a result, both *Internal Search Proximity* and *Exploitative Patent Ratio* will be our measures of exploitation search focus. Firms pursuing an exploitation-focused innovation strategy are associated with high exploitation search focus measures.

[3] This is analogous to the phenomenon of new CEOs seeking to "place their stamp" on the business by divesting poorly performing acquisitions made by the prior management team (Weisbach, 1995).

We then examine whether differences in firm innovative search focus contains predictive information about a firm's future profitability and operating cash flows. We conduct annual Fama & Macbeth (1973) cross-sectional regressions of an individual firm's future profitability, defined as either one year-ahead return on assets (*ROA*) or one year-ahead operating cash flow (*OCF*), on a firm's exploitation search focus score as well as a vector of other control variables. We find a significantly positive relationship between a firm's exploitation search focus and future ROA and OCF in all specifications. Specifically, we find that high exploitation firms tend to generate superior subsequent operating performance (at least in the near to intermediate term) relative to high exploration firms.

We next investigate the extent to which the market accurately incorporates any such predictability into its earnings expectations, using consensus analyst forecasts as proxies for market expectations. If the market fails to fully understand the positive impact of exploitative patents on future firm profitability, then we might observe more positive "earnings surprises" for exploitation-focused firms which may in turn result in these firms generating abnormally high future stock returns. We conduct quarterly Fama & Macbeth (1973) cross-sectional regressions of realized earnings surprise in each of the four quarters in year t+1 on the level of exploitation search focus in year t and other firm-specific control variables. Interestingly, we find that firms currently focused on exploitation tend to significantly outperform the market's near-term earnings expectations. This implies that high exploitation firms not only tend to generate superior subsequent operating performance relative to high exploration firms but that the market does not seem to fully factor the positive economic value generated by exploitative patents into its earnings expectations for these firms. As such, we identify a potential channel through which certain innovative firms may be systematically undervalued by the market.

We then examine whether the direction of a firm's innovative search efforts systematically predicts future stock returns. Using a portfolio sort methodology, we find that firms with high exploitation search focus scores (high exploitation firms) are undervalued relative to high exploration firms and that this return differential is incremental to standard risk and innovation-based pricing factors examined in the prior literature. Using Fama & Macbeth (1973) cross-sectional regressions, we confirm that the return predictive ability of our exploitation search focus measures is distinct from and robust to the inclusion of industry fixed effects as well as other commonly used firm-level return predictors and innovation-based variables.

Finally, in support of our conjecture that investor inattention drives our return predictability results, we find that the positive exploitation-future stock return relationship is stronger amongst groups of firms with a relatively higher proportion of inattentive investors (using both advertising intensity and transient institutional investors as proxies). Furthermore, we also find that the addition of *future* earnings surprises to our list of stock return predictors significantly attenuates the relationship between exploitation search focus and future stock returns. This implies that a large amount of the observed return predictability appears to be driven by investors and equity analysts failing to fully incorporate the beneficial impact of exploitative innovation into their initial earnings forecasts and subsequently observing exploitative firms exceed these initial earnings projections, resulting in abnormally high stock returns for exploitation-focused innovative firms.

To exemplify the theory and mechanisms underlying our hypothesis development and empirical results, we present the case study of Andrx Corporation in Appendix 1. The Andrx Corporation case illustrates in detail how limited investor attention resulted in the market failing to fully appreciate the positive impact of the firm's exploitative drug delivery patents on future firm profitability, leading to many years of positive "earnings surprises" and abnormally high future stock returns for this exploitation-focused firm.

It is a widely held view that stock market pressure hampers innovation (Stein, 1989; Ferreira, Manso & Silva, 2013), for example, through the impact of short-term earnings pressures. Our results provide a more nuanced view, as the stock market effect on innovation depends on the type of innovation. If as we show markets underestimate the significant value generated by exploitative innovation, then exploratory innovation rather than exploitative innovation becomes more attractive to firms, conditional on the amount of resources allocated to research and development. The lower cost of capital associated with exploration makes it more attractive for firms to pursue this type of innovation when compared to exploitation (see generally Levinthal & March, 1981; Levinthal & March, 1993).

Our earnings surprise and return predictability results also have implications for optimal firm financing policy and corporate disclosure policy in relation to a firm's innovative activities. With respect to firm financing policy, the undervaluation of high exploitation firms relative to high exploration firms by public equity markets will likely drive managers of exploitation-focused firms to strongly prefer the use of cash and debt to fund the firm's innovative investments. With respect to corporate disclosure policy, our results emphasize the need for firms pursuing an exploitative innovation search strategy to provide greater investor guidance as to the beneficial earnings impact, particularly in the short-term, of exploitative patents.

Our study contributes to the growing literature on the relationship between corporate innovative activities and financial markets. In particular, we introduce two new patent-based measures to capture the theoretical distinction between 'exploration' and 'exploitation' in corporate innovation search strategy (March, 1991; Manso, 2011). Our results expand on the recent findings that investors tend to undervalue firms that: (a) invest heavily in R&D and have exhibited historical success in converting R&D investment into sales (Cohen et al., 2013); (b) are efficient in translating R&D expenditure into future patents (Hirshleifer et al., 2013) and (c) produce patents that are relatively more "original" compared to all other patented innovation, proxied by the diversity of technology classes cited (Hirshleifer, Hsu & Li, 2018). While these papers illustrate investors' difficulty in comparing *distinct* firms across various innovation metrics, such as historical capacity or the originality of their patents, our findings highlight the added difficulty that investors face when interpreting the incremental economic significance of a firm's current innovative output relative to the past innovative output of the *same firm*.

Building on recent literature, we argue that the trade-off between exploration and exploitation that firms face is theoretically and empirically distinct from whether firms patent a relatively original or unoriginal innovation. Firms may patent a highly original/(unoriginal) innovation while following existing/(new) research trajectories and vice versa, which is probably why we observe very low correlations between our *Exploitation Search Focus* measures and previously studied innovation-related measures such as innovative efficiency (Hirshleifer et al., 2013) and innovative originality (Hirshleifer et al., 2018). We find that investors tend to overlook the potentially significant value generated by exploitative patents that build on the firm's existing knowledge base. This is not inconsistent with an undervaluation of original patents, as it is might well be those original technological advances that are exploited to appropriate the full value of an invention. Our findings suggest that exploration and originality are distinct concepts of a more nuanced view on innovation, and that an individual firm's *internal* focus on exploitative versus exploratory innovation contains independent value-relevant information that are more effective than the market would expect.

2. Data and sample description

We discuss this study's data sources in Section 2.1 while in Section 2.2 we outline the construction of our two empirical measures used to classify firms as having a relatively greater focus on exploitative or explorative innovation. We present key summary statistics and variable correlations in Section 2.3.

2.1 Data sources

Our empirical analysis is based on the joint availability of firm level data for publicly traded U.S. firms in the Compustat, CRSP (Center for Research in Security Prices) and NBER patent databases. We use stock return data from CRSP and obtain accounting data from Compustat. Our initial sample consists of all domestic common shares trading on the NYSE, AMEX or NASDAQ with sufficient accounting and returns data, excluding firms with negative book value of equity and financial firms with four-digit Standard Industrial Classification (SIC) codes between 6000 and 6999. Following Fama & French (1993), we exclude closed-end funds, trusts, American Depositary Receipts (ADRs), real estate investment trusts and units of beneficial interest. Following Hirshleifer et al. (2013), we require firms to be listed in Compustat for two years before including them in our sample in order to mitigate backfilling bias.

Patent-related data is sourced from both the NBER patent database, originally developed by Hall, Jaffe & Trajtenberg (2001), as well as the Fung Institute's public patent database at the University of California, Berkeley (Balsmeier, Fleming & Manso, 2017; Balsmeier et al., 2018). The NBER patent database contains various details on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO) between January 1976 and December 2006, including patent assignee identifiers that facilitate the matching of USPTO patent information with firm level data contained in the Compustat and CRSP databases. The information in the NBER database is then supplemented with technology class data from the Fung Institute's database. As discussed more extensively below, since many of the patent-based variables employed by this study require the examination of at least five years of historical patent information for each sample year, our sample period begins in 1981 and ends in 2006. For some of our tests, we also obtain institutional ownership data from the Thomson Reuters Institutional (13F) Holdings database and analyst estimates data from the Institutional Brokers' Estimate System (I/B/E/S).

2.2 Patent-based measures of exploitation search focus

In order to distinguish firms in any given year based on their relative focus on exploitation of existing known technologies versus exploration of newer technologies (otherwise referred to as a firm's level of *exploitation search focus*), we use two alternative empirical measures that draw on two distinct sources of patent-level information.

First, we develop a novel measure *Internal Search Proximity* which examines the degree of overlap between patents granted to the firm in year t and the existing patent portfolio held by the same firm up to year $t-1$. In particular, we employ the following variant of the Jaffe (1989) technological proximity measure to estimate the "closeness" in technological space of firm i's new patents in year t (patent flow f) and its depreciation-adjusted[4] pre-existing patent stock g at year $t-1$ using patent counts in different USPTO three-digit technology classes k:

$$Internal\ Search\ Proximity_{i,t} = \frac{\sum_{k=1}^{K} f_{i,k,t} g_{i,k,t-1}}{(\sum_{k=1}^{K} f_{i,k,t}^2)^{\frac{1}{2}} (\sum_{k=1}^{K} g_{i,k,t-1}^2)^{\frac{1}{2}}} \tag{1}$$

where $f_{i,k,t}$ is the fraction of patents granted to firm i in year t that are in technology class k such that the vector $f_{i,t} = (f_{i,1,t} \dots f_{i,K,t})$ locates the firm's year t patenting activity in K-dimensional technology space and $g_{i,k,t-1}$ is the fraction of all patents granted to firm i up to (and including) year $t-1$ that are in technology class k such that vector $g_{i,t-1} = (g_{i,1,t-1} \dots g_{i,K,t-1})$ locates the firm's patent stock in K-dimensional technology space.[5] *Internal Search Proximity* will be zero for a given firm year when there is no overlap in a firm's innovative output in year t with the firm's patent stock at time $t-1$ while *Internal Search Proximity* will equal one when the technology class distribution of firm i's patents granted this year is identical to that of patents accumulated in previous years. Therefore, we classify firms as being relatively more focused on exploration/(exploitation) when they have low/(high) values of *Internal Search Proximity*.

Second, to further enhance and validate the robustness of our identification of firms pursuing exploitative versus explorative innovative search strategies, we adopt an alternative measure used in many recent innovation-related studies such as Ma (2018), Brav, Jiang, Ma & Tian (2018), Gao, Hsu & Li (2018) and Lin, Liu & Manso (2017). Specifically, we define the "new cite ratio" and "explorativeness" as measures of the percentage of new knowledge used in a firm's current innovative output. New knowledge is identified by patent citations to patents that have not been previously developed or cited by the firm. In particular, we first define firm i's existing knowledge in year t as all patents either produced by firm i or that were cited by firm i's patents up to year $t-1$. The "new cite ratio" of a patent is calculated as the total number of citations made to new knowledge divided by the total number of citations made by the patent. Following Benner & Tushman (2002), a patent is flagged as "explorative" if at least

[4] Following studies such as Hall, Jaffe & Trajtenberg (2005), we apply a 15% depreciation rate to a firm's past patent stock when calculating our *Internal Search Proximity* measure. Our results are almost identical if we use a 0% or 20% depreciation rate instead.
[5] When computing *Internal Search Proximity* measures for each firm, we only use patents initially granted to the firm itself (since these patents are internally generated based on the firm's R&D activities). In robustness tests, we also include patents acquired by the firm in our calculations and find qualitatively similar results.

80% of its citations are based on new knowledge (new cite ratio $\geq$ 80%).[6] We can then transform these patent-level measures to the firm-year level by creating the "explorative patent ratio", defined as the total number of firm i's patents granted in year t that are classed as "explorative" divided by the total number of patents granted to firm i in year t. We can use the "explorative patent ratio" to create its corollary the *Exploitative Patent Ratio*, defined as one minus firm i's "explorative patent ratio" in year t. As a result, we classify firms as being relatively more focused on exploration/(exploitation) when they have a low/(high) value for their *Exploitative Patent Ratio*.

One particularly notable aspect of our exploitation search focus measures is that, in order to assess the *direction* of a firm's dynamic innovative search strategy over time, we need information about both the firm's current *and* past innovative activities. For example, for our *Internal Search Proximity* measure, we can only identify firms as being relatively more focused on exploration or exploitation by knowing about the technological classes in which the firm has previously been patenting. Similarly, we can only classify firms who are relatively more focused on exploiting existing knowledge as opposed to exploring new knowledge using the *Exploitative Patent Ratio* once we identify the focal firm's set of "existing knowledge." As a result, we only include firms that are granted at least one new patent in year t in our subsequent analysis.

Although this requirement results in a smaller overall sample compared to some other innovation-related studies,[7] our goal of identifying a firm's potentially dynamic innovation strategy means that we require access to objective patent-based information about a firm's current *and* past innovative activities. Furthermore, we believe that restricting research attention to the sample of more actively patenting firms who are more focused on conducting innovative activities as part of their core business operations is beneficial for interpreting our results and understanding the nature of the relationship between innovation search strategies and public equity markets. For example, we avoid imposing strong assumptions about whether firms with no current patents are engaged in explorative or exploitative innovation search strategies in the pursuit of obtaining the maximum possible sample size. Combined with the fact that our focus on actively patenting firms still results in our study examining publicly traded U.S. companies who comprise over 50% of total U.S. market equity (comparable to the 55% of total U.S. market

[6] We also conduct robustness tests whereby we either sort firms on their average new cite ratio or use alternative thresholds for identifying a patent as being "explorative" and obtain similar empirical results.
[7] For example, Hirshleifer et al. (2018) calculate their firm-year innovative originality measure using an average of all patents granted to the firm over the previous five years.

equity covered by the innovative efficiency measures in Hirshleifer et al., 2013) and the fact that we use two alternative measures (*Internal Search Proximity* and *Exploitative Patent Ratio*) that rely on two distinct sources of patent-based information (patent technology class and patent back citations, respectively) to classify firms as being relatively more focused on exploitation or exploration, we believe that our results robustly identify the relationship between firm innovative search strategy and stock market valuations as well as demonstrate a high level of economic relevance.

2.3 Sample composition and summary statistics

Table 1 reports summary statistics of the three exploitation search focus portfolios (based on *Internal Search Proximity* or *Exploitative Patent Ratio*) and the correlation between a firm's exploitation search focus measure and other firm characteristics. In particular, we form three portfolios at the end of June of year t based on the 30th and 70th percentiles of firm exploitative search focus scores measured in year $t-1$.

Panel A reports the average annual number of firms in each portfolio and the median value of various firm characteristics within these portfolios, where all characteristics are for the year prior to the ranking year except for size, momentum, illiquidity, idiosyncratic volatility and total skewness (which are measured at the end of June of the ranking year). These characteristics include *Size* (measured as the natural log of market capitalization), the year-end book-to-market equity ratio (*BTM*), *Momentum* (calculated as the prior six month stock return with a one month gap between the holding period and the current month following Hou, Peng & Xiong, 2009), *Patents* (defined as patents granted in year $t-1$ divided by lagged total assets), *Capex* (calculated as capital expenditure divided by lagged total assets), *R&D* (measured as R&D expenditures scaled by lagged total assets), *Firm Age* (computed as the number of years that a firm is listed on Compustat), *Conglomerate* (defined as a dummy variable that is equal to one when a firm has segments with positive assets and sales in more than one 3-digit SIC code industry during the year following Gopalan & Xie (2011), *Total Patent Stock* (calculated as the number of all patents granted to the firm up to year $t-1$ scaled by lagged total assets), *Advertising* (computed as advertising expense scaled by lagged assets per Grullon, Kanatas & Weston, 2004; Lou, 2014), *SG&A* is selling, general and administrative expenses divided by lagged total assets following Eisfeldt & Papanikolaou, 2013), *Illiquidity* (defined as the absolute monthly stock return divided by monthly dollar trading volume in June of year t as in Amihud, 2002), *Leverage* (equal to total debt divided by total assets), net stock issues (*NS*, defined as the change in the natural log of split-adjusted shares outstanding in year $t-1$), institutional ownership (*Inst. Own*, calculated as the fraction of firm shares held by institutional investors), idiosyncratic volatility (*IV*, measured at the end of June of year t as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three factor returns over the previous 12 months following Hirshleifer et al., 2018), total skewness (*SKEW*, calculated at the end of June of year t using daily stock returns over the previous 12 months), innovative efficiency (*IE*, defined as adjusted patent citations scaled by R&D expenses per Hirshleifer et al., 2013) and innovative originality (*IO*, defined as the average score of a firm's patents' originality scores, where originality is the number of unique technological classes (both primary and secondary classes) assigned to the patents cited by the focal patent over the past five years following Hirshleifer et al., 2018).

For example, across the 306, 406 and 306 firms that are on average in the low, middle and high exploitation search focus portfolios each year (based on *Internal Search Proximity*) respectively, the median market capitalization of firms in each portfolio is $146 million, $411 million and $530 million respectively. As such, our sample is concentrated in relatively larger firms that comprise an economically meaningful 50% of total US market equity. Furthermore, there is significant variation in the exploitation search focus measures across the various portfolios. In particular, the median exploitation search focus measure in the low group based on *Internal Search Proximity* and *Exploitative Patent Ratio* is zero in both cases while the median value in the high group is 0.94 and 0.88 respectively (the standard deviation for our *Internal Search Proximity* and *Exploitative Patent Ratio* measures are 0.35 and 0.37 respectively). We also find that firms with higher exploitation search focus scores have higher R&D intensity, higher innovative efficiency and a higher patent-to-total assets ratio.

Interestingly, there is some evidence to suggest that there exists a positive univariate relationship between a firm's current focus on exploitation and future operating performance. In particular, the high exploitation search focus portfolio exhibits a higher return on assets (measured as income before extraordinary items plus interest expenses scaled by lagged total assets) and higher operating cash flow (calculated as income before extraordinary items plus depreciation and minus changes in working capital scaled by lagged total assets) in the year following portfolio formation. We examine this relationship in greater detail in Section 3.

In Panel B of Table 1 we report the pairwise Pearson correlation coefficients among our exploitation search focus measures and other firm characteristics. In general, our two exploitation search focus measures do not strongly correlate with the firm characteristics shown in Panel A, ranging from -0.13 with BTM to 0.13 with size. However, there is very strong positive correlation of 0.51 between *Internal Search Proximity* and *Exploitative Patent Ratio* despite the fact that the two measures are constructed using two quite distinct sources of patent-level information (a patent's designated primary technology class and the back citations made by a particular patent respectively). The fact that one can use two distinct sources of information about individual patents to construct firm-level patent portfolio measures that reach a similar conclusion about whether a firm is pursuing an exploitation or exploration innovative search strategy provides additional comfort as to the robustness of our approach to classifying firms based on their innovative search strategies.

The correlation of the two exploitation search focus measures with previously used measures IE and IO is relatively low with *Internal Search Proximity* having a correlation with IE and IO of 0.02 and -0.01, respectively; *Exploitative Patent Ratio* has a correlation with IE and IO of 0.03 and 0.10, respectively. This indicates that our measures for distinguishing firms' relative focus on exploitation versus exploration remain distinct from other previously examined innovation-based return predictors and thus have the potential to contain independent value-relevant information. For example, a firm's patent portfolio may have a high innovative originality score and still be following an exploitative innovation search strategy because the citations made by the firm's current patents are to its own existing stock of patents and/or prior knowledge. Similarly, a firm with a low originality score in a given year may well be pursuing an explorative search strategy through the acquisition of new knowledge contained in patents not previously worked on or utilized by the firm's inventors and by patenting in new technology classes. These exploration strategies could be orthogonal to the diversity of technology class assignment (as reflected in IO, which counts the number of USPTO classes that are assigned to a patent). In unreported analysis (available upon request), we find that the commonly used "innovative originality" measure developed by Hall et al. (2001) does *not* load on either the 'exploitation' or 'exploration' component in a principal components analysis, further indicating the distinctiveness of our exploitation search focus measures from innovation-related variables studied in the prior literature. Nevertheless, for robustness purposes, we include both IE and IO as controls in all subsequent analysis and we find that both of our exploitation search focus measures continue to contain meaningfully incremental value-relevant information.

3. Exploitation search focus and future operating performance

We first examine whether differences in firm innovative search focus contains predictive information about a firm's future profitability and cash flows. We then investigate the extent to which the market accurately incorporates any such predictability into its earnings forecasts.

3.1. Exploitation search focus and future operating performance

Following Fama & French (2000), we conduct the following annual Fama & Macbeth (1973) cross-sectional regressions of an individual firm's future profitability, defined as either one year-ahead return on assets (*ROA*) or one year-ahead operating cash flow (*OCF*), on a firm's exploitation search focus score as well as a vector of other control variables (X):

$$OP_{i,t+1} = \alpha + \beta Exploitation\ Search\ Focus_{i,t} + \gamma X_{i,t} + \sum_{j=1}^{48} \delta_j Industry_j + \varepsilon_{i,t} \qquad (2)$$

Following the prior literature, we include a variety of control variables that have been found to be significant predictors of future operating performance. We first control for current firm profitability to accommodate the documented persistence in operating performance (Gu, 2005) as well as the change in firm profitability in order to account for mean reversion in future operating performance (Fama & French, 2000). We also follow Pandit, Wasley & Zach (2011) and control for the current levels of R&D expenditure, patenting, capital expenditure and market-to-book assets. Our regressions also control for leverage, firm age, an indicator variable for whether the firm is a conglomerate and the total patent stock held by a firm, as well as the current level of advertising and selling, general and administrative expenditures. We also include innovative efficiency (Hirshleifer et al., 2013) and innovative originality (Hirshleifer et al., 2018) as controls to facilitate comparison with prior innovation-based return predictors. All regressions include Fama & French (1997) 48 industry fixed effects while all variables are winsorized at the 1% and 99% level to mitigate the effect of outliers (Beaver & Ryan, 2000). Following Hirshleifer et al. (2013), we also standardize all independent variables to zero mean and one standard deviation.

Table 2 reports the time series average slopes and intercepts as well as the corresponding *t*-statistics (which incorporate a Newey-West correction with 12 lags to account for possible autocorrelation in the coefficient estimates) from the annual cross-sectional regressions specified in equation (2). We first observe that there exists a significantly positive relationship between a firm's exploitative search focus and future ROA and OCF in all specifications. For example, a one standard deviation increase in a firm's *Internal Search Proximity* (where higher values are interpreted as exhibiting a greater focus on exploitation) results in 0.45% (0.49%) increase in subsequent year ROA (OCF). As expected, the significantly positive (negative) coefficient on prior year operating performance (change in operating performance) confirms the existence of both persistence and mean reversion in firm operating performance. We also find that capital expenditure (*CapEx*) and *Firm Age* is positively correlated with subsequent

ROA and OCF, indicating that greater accumulated tangible investment helps to drive future profitability. Consistent with the findings in Hirshleifer et al. (2013), we observe that innovative efficiency (*IE*) has a positive association with subsequent OCF while *R&D* has a significantly negative relationship with next year's operating performance measures, potentially reflecting the long-term and uncertain payoffs associated with R&D investments.

3.2. Earnings surprise and exploitation search focus

While the evidence in the preceding section suggests that innovative firms that are focused on the exploitation of their existing technologies (namely firms with high exploitation search focus scores) exhibit better subsequent operating performance, it is important to consider whether the market accurately incorporates this information into its earnings forecasts. On the one hand, it is possible that the operating outperformance of exploitation firms documented in the previous section simply reflects fundamental differences in the expected timing of returns for exploitative versus exploratory innovation that is efficiently incorporated into the market's future earnings projections (see generally Fitzgerald, Gray, Hall & Jeyaraj, 2013; Asquith, Mikhail & Au, 2005). Conversely, if the market fails to fully understand the positive impact of exploitative patents on future firm profitability, then we might observe more positive "earnings surprises" for exploitation-focused firms which may in turn result in these firms generating abnormally high future stock returns.

Consider the case of U.S. drug delivery firm Andrx Corporation discussed in Appendix 1. In this case study, we directly quote the research reports of equity analysts covering Andrx who admit that they initially underestimated the potential profits that Andrx could generate from its strategy of exploiting its existing innovative capabilities to improve the release profile of legacy drugs. As a result, Andrx's actual earnings per share (EPS) substantially exceeded consensus EPS estimates for over two years, leading to a fivefold increase in Andrx's share price as the market updated its valuation of Andrx's exploitation strategy.

To formally test this earnings surprise channel, we follow So (2013) and define realized quarterly earnings surprises as the difference between actual EPS and the prevailing consensus EPS forecast, scaled by total assets per share. We proxy for the earnings expectations of all investors using the consensus analyst forecast from I/B/E/S. The consensus forecast is defined as the mean EPS forecast amongst all equity analysts that make a forecast in the last month prior to the earnings announcement (Dellavigna & Pollet, 2009).[8] The sample period for this particular empirical test only spans 1983 to 2006 because the I/B/E/S database only started systematically recording quarterly EPS forecasts from the beginning of fiscal year 1983.

To examine the multivariate relationship between a firm's exploitation search focus and future earnings surprises, we conduct quarterly Fama-Macbeth cross-sectional regressions of realized earnings surprises in each of the four quarters in year t+1 on exploitation search focus in year t and other firm-specific control variables. We initially control for the following firm-specific characteristics: last quarter's realized earnings surprise for firm i (*Lagged ES*) and the change in earnings surprise between the prior two quarters (ΔES) to account for the persistence and mean reversion in future firm profitability (So, 2013), *Accruals* (defined as total accruals in year t scaled by lagged total assets following Sloan, 1996), return on assets (*ROA*) and an indicator for whether the consensus analyst EPS forecast for that quarter is negative (*negative EPS*) per Fama & French (2006). In subsequent specifications we also control for *BTM*, *Momentum* (defined as the prior six month returns prior to the relevant earnings announcement), *R&D*, *CapEx*, *Patents*, *Leverage*, *Firm Age*, *Conglomerate*, *Total Patent Stock*, *Advertising* and *SG&A*. We also include innovative efficiency (Hirshleifer et al., 2013) and innovative originality (Hirshleifer et al., 2018) as further controls. All regressions include Fama-French 48 industry fixed effects while all variables are winsorized at the 1% and 99% level and standardized to have zero mean and standard deviation of one.

Table 3 presents the results of these regressions. Most notably, the significantly positive coefficient on exploitation search focus using either *Internal Search Proximity* or *Exploitative Patent Ratio* indicates that firms currently focused on exploitation tend to outperform the market's near-term earnings expectations. In particular, high exploitation firms on average generate "unexpected" positive income in year t+1 equal to approximately 12 basis points of total firm assets. Alternatively stated, this implies that the average firm in our sample generates profits that are 3% higher than market expectations in year t+1 for each one standard deviation increase in its exploitation search focus score.

In sum, the evidence in this section implies that high exploitation firms not only tend to generate superior near-term operating performance relative to high exploration firms but that

[8] If an individual analyst makes multiple forecasts prior to a firm's earnings release, we only use the most recent forecast. Our results are qualitatively similar if we use the median forecast as the consensus forecast measure.

the market does not seem to fully factor the economic value generated by exploitative patents into its near-term earnings expectations for these innovative companies.

4. Predictability of returns based on innovative search focus

Given the documented positive relationship between a firm's relatively greater focus on exploitation innovation and future operating performance as well as the evidence that sophisticated equity market analysts (and likely a significant fraction of institutional investors) appear to underestimate the near-term profit potential of exploitative patents, we next examine whether the direction of a firm's innovative search efforts systematically predicts stock returns using both portfolio sort and regression methodologies.

4.1. Portfolio tests

In this subsection, we examine the ability of the estimated direction of a firm's innovative search activities to predict portfolio returns. At the end of June of year t, we sort firms independently into two size groups (small "S" or big "B") based on the NYSE median size breakpoint and three groups for each innovative search dimension (low "L", middle "M" and high "H") based on the 30^{th} and 70^{th} percentiles of firms' exploitation search focus scores. Following Hirshleifer et al. (2013), we perform our portfolio allocations using either a firm's *Internal Search Proximity* or *Exploitative Patent Ratio* score in the year $t-1$ while defining size as the market value of equity at the end of June of year t. This intersection forms 6 size-innovative search dimension portfolios (i.e. S/H, B/H, S/M, B/M, S/L and B/L). We hold these portfolios over the next 12 months (July of year t to June of year $t+1$) and compute the value-weighted monthly returns of these six portfolios. We then calculate monthly size-adjusted returns of the low, middle and high portfolios using the formulas (S/L+B/L)/2 through to (S/H+B/H)/2. The "spread portfolio" return is calculated as the difference in returns between the high and low exploitation search focus portfolios.

Table 4 shows that excess returns, calculated as the average monthly size-adjusted return less the one-month Treasury bill rate, increases monotonically with exploitation search focus. For example, using *Internal Search Proximity* (see Panel A.1), the excess returns for the low, middle and high portfolios are 0.58%, 0.76% and 0.86% respectively with the return spread of 0.28% per month between the high and the low portfolio significant at the 1% level.

We next examine whether the size-adjusted returns of the innovative search dimension portfolios can be captured by standard risk factor models. In particular, we perform time-series regressions of the portfolios' excess returns on the Fama-French three factors (the market factor *MKT*, the size factor *SMB* and the value factor *HML*) as well as Carhart's (1997) momentum *MOM* factor. We also report the alphas (in percentage terms) estimated from other commonly used risk factor models as a robustness check. For example, we augment the Fama-French three-factor model with the robust-minus-weak (*RMW*) profitability factor and the conservative-minus-aggressive (*CMA*) investment factor in Fama & French (2015), the innovative efficient-minus-inefficient (*EMI*) factor (Hirshleifer et al., 2013), as well as the liquidity (*LIQ*) factor in Pastor & Stambaugh (2003). Lastly, we consider existing mispricing-based factor models, augmenting the Fama-French three-factor model with the undervalued-minus-overvalued (*UMO*) factor of Hirshleifer & Jiang (2010) as well as reporting the alphas from the *Mispricing* factor model of Stambaugh & Yuan (2017).

Table 4 shows that the risk-adjusted returns of the exploitation search focus portfolios increase monotonically with a firm's greater focus on exploitation relative to exploration. For example, the risk-adjusted monthly returns of the high-minus-low portfolio formed using *Internal Search Proximity* typically ranges from 0.28% to 0.40% and are usually significant at the 1% level. Importantly, since these portfolios are only rebalanced once a year and do not comprise small illiquid firms as shown in Table 1, these abnormal returns are unlikely to be nullified by typical trading costs.

In terms of noteworthy spread portfolio risk factor loadings (not reported in Table 4 for brevity), the significantly negative SMB loading and significantly positive CMA loading are consistent with the results in Table 1 that illustrate that high exploitation firms are generally bigger and undertake higher levels of investment. The significantly negative loading on the market factor indicates that high exploitation firms have lower market risk than high exploration firms while the significantly positive loading on the EMI factor suggests that high exploitation firms are more efficient in their R&D endeavors. This is consistent with an exploitation search strategy, which prefers refinement of opportunities already identified by the firm, relative to the exploration of enticing but less understood possibilities. While exploration may increase the chances of a breakthrough change in a firm's innovation trajectory, an explorative search strategy also fails more often and seems to result in a less R&D efficient search strategy on average. Finally, the significant positive loading of high exploitation firms on the UMO factor of Hirshleifer & Jiang (2010) provides further support for the conjecture that the return spread between high and low exploitation-focused firms is driven more by mispricing (arising from the undervaluation of exploitative innovation by the market) as opposed to systemic risk.

Nevertheless, our patent-based measures of firms' innovative search focus appear to provide statistically and economically significant incremental explanatory power for observed stock returns above and beyond previously studied risk and mispricing factors.

We also consider the time-series variation in spread portfolio returns over our 1982 to 2008 sample period. Figure 1 shows the return on the spread portfolio of high exploitation minus low exploitation focused firms (using *Internal Search Proximity* and *Exploitative Patent Ratio* respectively) as well as the market factor returns (*MKT*) from 1982 to 2008 (where we annualize the six month returns for 1982 and 2008). There are three noteworthy observations. First, the annual returns on both high-minus-low portfolios are positive in at least two-thirds of the sample years, have less than half the return volatility of the market factor and appear to offer a hedge against market downturns (for example, the correlation of annual returns between the *Exploitative Patent Ratio* spread portfolio and the market factor is -0.35). Second, the ex post annual Sharpe ratio for the high-minus-low exploitation search focus portfolio compares favorably to commonly used risk factors. For example, based on the *Exploitative Patent Ratio*, the spread portfolio's Sharpe ratio of 0.45 is above that of SMB (0.08), CMA (0.33) and HML (0.34) and is comparable to the Sharpe ratio of the market factor (0.47) and RMW (0.57). Finally, our aggregate abnormal return patterns appear to persist across our entire sample period. In particular, when we split our sample in half and compare portfolio performance, we find that spread portfolio returns are abnormally high and statistically significant in both halves of our sample (untabulated).

To further understand our return predictability results, Figure 2 plots the alphas of the high-minus-low exploitation search focus spread portfolio over the three years post portfolio formation for the Cahart and Fama & French five-factor models. Interestingly, the market appears to fully correct the undervaluation of high exploitation firms in the first year after portfolio formation. This is consistent with the earnings surprise evidence in Section 3.2 whereby investors initially under-estimate the beneficial impact of exploitative patents on future firm profitability and then quickly incorporate this unexpected positive news into its future earnings projections. While we do not conclusively rule out the possibility of risk-based explanations for our portfolio sort results, the observed pattern of stock price correction over relatively short time periods appears to be more indicative of mispricing-based return predictability rather than risk-based return predictability, consistent with the arguments in Chamber, Jennings & Thompson (2002) and Hirshleifer et al. (2018).

As a final robustness check, we use finer portfolio sorts to examine the monotonicity of our previously documented results. In particular, we independently sort firms into quintiles based on their exploitation search focus scores as well as two size groups based on the NYSE median size breakpoint. The spread portfolio return is calculated as the difference in returns between the size-adjusted returns of Quintile 5 (high exploitation search focus portfolios) and Quintile 1 (low exploitation search focus portfolios). The results in Appendix 2 indicate that our prior portfolio sort results do not appear to be solely driven by extreme portfolios since the risk-adjusted returns of the exploitation search focus portfolios increase in a reasonably monotonic manner across the five quintile portfolios, irrespective of whether *Internal Search Proximity* or *Exploitative Patent Ratio* is used as the sorting variable.

Overall, these portfolio results imply that high exploitation firms are undervalued relative to high exploration firms and that this return differential is incremental to risk, mispricing and innovation-based pricing factors examined in the prior literature.

4.2. Fama-Macbeth regressions

Using monthly Fama-Macbeth (1973) cross-sectional regressions, we examine the ability of a firm's innovation search strategy (characterized as the choice between exploitation vis-a-vis exploration) to predict cross-sectional stock returns. The advantage of this method is that it permits the inclusion of a comprehensive set of firm-level controls to ensure that the positive exploitation-return relation in the portfolio sorts analysis is not driven by other known return predictors or industry effects.

Following Fama & French (1992), for each month from July of year t to June of year t+1 we regress monthly returns of individual stocks (net of the one-month Treasury bill rate) on a firm's exploitation search focus score and other control variables at year $t-1$.[9] The control variables that we include in our regression specifications, namely *Size*, *BTM*, *Momentum*, short-term reversal (*ST reversal*, defined as the previous month's stock return), *CapEx*, *R&D*, *Patents*, Innovative Efficiency (*IE*), Innovative Originality (*IO*), *Firm Age*, *Conglomerate*, *Total Patent Stock*, *Advertising*, *SG&A*, *Illiquidity*, *Leverage*, *ROE*, *Inst. Own*, *NS*, *IV* and *SKEW*, are defined in Table 1. As in section 4.1, we winsorize all independent variables at the 1% and 99% levels and we standardize all independent variables to have a mean of zero and a standard deviation of one.

[9] Using the lagged values of the independent variables ensures that all accounting and patent-based measures are fully observable to the public prior to the return estimation period (Fama & French, 1992).

We report the time series average slopes (in percentage terms) and the corresponding heteroscedasticity-robust *t*-statistics from the monthly cross-sectional regressions in Table 5. In all specifications, the coefficient on exploitation search focus is significantly positive, ranging from 6 to 9 basis points per month. At least in terms of short-term stock returns, this implies that firms focused on the exploitation of their existing known competencies tend to significantly outperform firms pursuing innovations in fields that are more distant from the firm's existing knowledge set. The economic magnitude of this effect is noteworthy since a one standard deviation increase in a firm's *Internal Search Proximity* score increases the firm's annual stock returns by approximately 1.0%.

The coefficients on the control variables are in general consistent with the prior literature, whereby firms with a higher book-to-market ratio, higher ROE, lower net stock issuance and higher institutional ownership provide significantly higher future stock returns. Furthermore, the importance of the persistence and mean reversion in stock returns is evident in the positive coefficient on momentum and the negative coefficient on short-term reversal.

Overall, consistent with the notion that higher than expected profitability drives higher near-term stock returns, the return predictive ability of our exploitation search focus measures is distinct from and robust to the inclusion of other commonly researched return predictors and innovation-based variables as well as general industry effects.

4.3. Innovative search focus, limited attention and future earnings surprises

In this sub-section, we seek to directly test whether our results with respect to the undervaluation of exploitative innovation strategies is stronger in situations where cognitive biases, such as limited investor attention, may be more severe. To perform these tests, we use subsample Fama-Macbeth regressions whereby we run separate Fama-Macbeth regressions within sub-samples split by alternative proxies for investor attention, following the method in Hsu, Li, Teoh & Tseng (2018) and Hirshleifer et al. (2013). We also include all previously discussed controls for other well-known return predictors. For brevity, we only report the time series average slopes on *Exploitation Search Focus* (using either *Internal Search Proximity* or *Exploitative Patent Ratio*) and corresponding *t*-statistics from these subsample regressions.

We use two commonly used proxies for the level of investor attention given to a particular stock or firm. First, firms with lower advertising expenditures are less likely to be as visible or familiar to both individual and institutional investors (Grullon et al., 2004; Lou, 2014), resulting in investors tending to pay less attention to these firms' new patents and innovative search strategies (Hsu et al., 2018). Thus, we split our sample into those firms that spend relatively more or less on advertising (using the median scaled advertising expense ratio as the break point), where we expect greater return predictability among less well known firms with lower advertising expenditures. Second, we use the classification scheme developed by Bushee (1998, 2001) to categorize all institutional investors into transient investors, dedicated investors or quasi indexers. As argued in Bushee (1998) and Hirshleifer et al. (2018), transient institutional investors trade stocks based on strong-term strategies (e.g. momentum) and are thus less likely to pay as much attention to firms' fundamentals as long-term-orientated dedicated institutional investors. Thus, we partition our sample into those firms that have a relatively higher proportion of shares held by less attentive transient institutional investors (as a percentage of total shares outstanding) compared to those firms with relatively lower levels of ownership by transient institutional investors, based on the median of transient institutional investors' ownership.

Table 6 presents the results of the Fama-Macbeth regressions within subsamples split by our two measures of investor attention, namely advertising intensity and the proportion of a firm's equity held by transient institutional investors. Even after controlling for well-known return predictors and industry effects, it is clear from this analysis that how accurately the market values a firm's innovation search strategy differs depending on the level of investor attention dedicated to that firm. For example, in Panel A, the slope on *Exploitative Patent Ratio* for low advertising firms is 0.07% (*t*-stat = 2.37) while, in contrast, the corresponding slope for high advertising firms is statistically indistinguishable from zero at 0.03% (*t*-stat = 0.61). Similarly, in Panel B, the slope on *Exploitative Patent Ratio* for firms with higher levels of transient institutional investor ownership (and thus subject to less institutional investor attention) is 0.09% (*t*-stat = 1.98) while the corresponding slope for firms with lower levels of transient institutional investor ownership is insignificantly different from zero at 0.02% (*t*-stat = 0.67). The magnitude of the difference between the 'low' versus 'high' investor attention sub-sample coefficients in Panels A and B are economically substantial and usually statistically significant across various specifications (unreported results). Therefore, the contrasting results in this sub-sample analysis tend to support the hypothesis that limited investor attention explains the ability of exploitation search focus to predict future abnormal stock returns.

Another possible and related behavioral explanation for our return predictability results is that the significant underpricing of exploitative innovation is driven by "investor distraction" (see Hirshleifer et al., 2009, in the context of earnings announcements). Under this theory, investor efforts to discern a firm's innovative search strategy from its patenting activities and to understand its implications for future profitability can be hampered by "extraneous news events" (for example, too many patents granted to other firms) that draw attention toward other firms. To evaluate this potential channel, we identify groups of firms that are more likely to be subject to "attention crowding-out" by computing the total number of new patents granted in year t to all publicly listed companies in the same Fama-French 48 industry classification as the focal firm and then dividing this figure by the average number of patents granted each year to firms in the same industry as the focal firm over the past 5 years. The intuition behind this "industry patenting intensity ratio" is that in years where the focal firm's industry group has an 'abnormally' high number of patent grants, it is more likely that the attention paid by investors to the nuances and value implications of the focal firm's innovative search strategy will be diminished (due to greater competition for finite investor attention). Using this ratio, we split our sample of firms each year into 'high' and 'low' groups based on the median value of this industry-level patenting intensity ratio. Interestingly, we do not observe a significant difference in the coefficients on our exploitation search focus measures in the High versus the Low Industry Patenting Intensity Ratio sub-groups (see Table 6, Panel C). Therefore, the combined evidence in this sub-section suggests that the observed positive exploitation-stock return relationship is primarily driven by investors and equity analysts in general devoting insufficient time and effort to understanding the earnings implications of a firm's chosen innovative search strategy rather than equity investors only undervaluing exploitative search strategies when they are "overwhelmed" or "distracted" by abnormally high volumes of patenting activity by other firms.

In order to further examine the mechanism driving our empirical results, we consider the extent to which the return predictability generated by a firm's relative focus on exploitative rather than explorative innovation is driven by the under-reaction of stock market investors to future cash flows news. Specifically, we re-run the Fama-Macbeth regressions discussed in Section 4.2 but add both lagged earnings surprises as well as *futur*e earnings surprises to our list of right hand side return predictors. *Lagged earnings surprise* is defined as the cumulative annual earnings surprise in the year *prior* to portfolio formation (see Table 3 for further details on the computation of quarterly earnings surprise) while *future earnings surprise* represents the cumulative annual earnings surprise in the year *after* portfolio formation (we note that this is obviously information that is not observable by investors at time t).

Appendix 3 reports the regression results. Unsurprisingly, one-period ahead stock returns are substantially higher for firms who have positive future earnings surprises. Furthermore, it is interesting to note that the addition of *future* earnings surprise to our list of return predictors significantly attenuates the relationship between exploitation search focus and future stock returns. This implies that a large amount of the observed return predictability in this paper appears to be driven by investors and equity analysts failing to fully incorporate the beneficial impact of exploitative innovation into their initial short-term cash flow forecasts and then subsequently observing exploitative firms exceed these earnings projections, resulting in abnormally high subsequent stock returns for exploitation-focused innovative firms.

4.4. Potential alternative explanations

While the evidence in Section 4.3 suggests that limited investor attention is the key driver of our return predictability results, we nevertheless consider whether there are alternative risk-based explanations for our findings beyond those risk factors explicitly controlled for in the portfolio sort and Fama-Macbeth regression analyses.

One possible risk-based explanation for our results is that our exploitative search focus measures capture information asymmetry and/or valuation uncertainty (Hsu et al., 2018). However, both *Internal Search Proximity* and *Exploitative Patent Ratio* have low correlations with standard proxies for information asymmetry such as analyst earnings forecast dispersion and financial statement opacity, indicating that informational uncertainties are unlikely to be the primary cause of our return predictability results.

Another potential explanation for our results is that companies pursuing an exploitative innovation search strategy are more reliant on the application of existing knowledge and are thus more exposed to systematic risk. For example, Pastor & Veronesi (2009) argue that during "technological revolutions" (e.g. the Internet Revolution and the 1830-1861 American Railroads Revolution), the nature of the uncertainty regarding the average productivity of a new technology may change from an idiosyncratic risk to a systematic risk. Relatedly, firms pursuing an exploitative innovation search strategy may be viewed as repeating old protection technologies and are thus subject to priced obsolescence risk.

However, it is important to note that our sample covers firms operating in many different industries (43 out of the 48 Fama-French industries are represented in our sample) that span multiple decades and economic cycles (1982 to 2008). In contrast to the rare "technological revolutions" considered in Pastor & Veronesi (2009), it would seem more appropriate to classify the risk borne by individual firms in our sample that focus on the exploitation of known technologies as idiosyncratic and diversifiable risk. Notably, as shown in Table 5, the inclusion of idiosyncratic firm volatility as an additional return predictor in our Fama-Macbeth regressions has virtually no impact on the positive relationship between *Exploitation Search Focus* and future stock returns.

Furthermore, if firms' differing reliance on known knowledge is the risk-based driver of the observed exploitation search focus-return predictability relationship, one would expect that firms that more frequently use older, more widely known technologies as the basis for their current inventions would be at much greater risk of their technology/knowledge base becoming obsolete sooner (Ma, 2018; Machlup, 1962). As such, we construct two proxies for the potential risk of obsolescence: (1) *average age of prior art* and (2) the *average number of scientific references*/citations made per newly granted patent.[10] Average age of prior art is calculated as the average age of patents cited by the firm's newly granted patents (where age is defined as the difference between the year that the cited patent was granted and the year that the citing patent was granted) (Fleming & Sorenson, 2004; Sorensen & Stuart, 2000). Average number of scientific references is computed as the mean number of citations made by a firm's patents to prior scientific publications.[11] Importantly, when we include average age of prior art and/or average number of scientific references as additional return predictors in our Fama-Macbeth stock return regressions (untabulated), we find that the significantly positive coefficients on our two measures of *Exploitation Search Focus* are virtually identical to the coefficient estimates reported in Table 5. This is consistent with the fact that the correlation between our measures of exploitative search focus and both proxies for obsolescence risk is relatively low. This evidence suggests that the risk of overreliance on known knowledge and/or obsolescence risk cannot explain the strong positive relationship between exploitative innovative search strategies and future stock returns.

Finally, if exploitative firms were exposed to a persistent "technological revolutions" or "obsolescence" risk factor, it is difficult to reconcile this conjecture with the fact that: (a) the market seems to frequently underestimate the future near-term *cash flows* of exploitative firms (see the results in Table 3), (b) the market appears to fully correct the undervaluation of high exploitation firms in the first year after portfolio formation once the positive earnings surprises

[10] The rationale behind this second measure is that since peer-reviewed scientific journal publications are widely available and relied upon by both academic researchers and industry professionals (Fleming & Sorenson, 2004), it is plausible that a greater reliance on this codified and published knowledge may increase the risk that a firm's knowledge base becomes obsolete faster due to more intensive (and possibly competing) research in that field.
[11] Following the prior literature (e.g. Trajtenberg, Henderson & Jaffe, 1997), we use the number of non-patent citations as our measure of 'scientific' references. We thank the Berkeley Fung Institute of Engineering Leadership for providing the scientific citation data.

are observed (see Figure 2) and (c) the exploitation-return predictability relationship is much stronger in sub-samples of firms with greater investor inattention (see Table 6).

Nevertheless, while we believe that the totality of the evidence presented in this paper suggests that our return predictability results are primarily attributable to behavioral biases whereby investors pay insufficient attention to the significant value generated by exploitative innovation, we acknowledge that it is impossible to completely rule out all potential risk-based explanations for our findings.

Before continuing, it is important to consider the limits to arbitrage that result in high exploitation search focus stocks being (at least initially) significantly undervalued. There are several factors that may drive this phenomenon. First, numerous studies such as ours have demonstrated that the equity market tends to undervalue information contained in patent-based measures about future firm fundamentals (e.g. Hirshleifer et al, 2013; Hirshleifer et al., 2018). Given that the analysis and evaluation of patent value is a complex task that often requires specialist product market expertise, it seems reasonable to believe that investors may devote insufficient attention to understanding less salient exploitative innovations in favor of focusing on more noticeable explorative innovations (see, for example, the Andrx Corporation case study discussed in Appendix 1). Second, it is well documented that even institutional investors appear to have limited information processing capacity (e.g. Hirshleifer et al., 2009; Cohen & Frazzini, 2008) and exhibit bounded rationality in their trading decisions (Coval & Shumway, 2005; Frazzini, 2006). Given that we show in Table 3 and Appendix 1 that equity analysts who are dedicated to covering only a small number of companies and enjoy greater access to firm management consistently struggle to accurately forecast the near-term cash flows generated by exploitation-focused firms, it seems plausible that even more sophisticated institutional investors (particularly more transient ones) will also fail to immediately impound the valuable information contained in a firm's innovation search strategy into traded stock prices.

5. Conclusion

How innovation impacts a firm's future earnings is difficult to predict, particularly for investors with limited attention and bounded cognition. We focus on how accurately investors can assess the impact of a firm's internal innovation search strategy on its stock market valuation. We find that firms that exploit extant technologies close to the firm's existing technological specialties ('exploitation' focused firms) tend to generate superior subsequent operating performance, relative to those firms that explore for new opportunities outside of the firm's existing knowledge base ('exploration' focused firms). Equity analysts do not appear to detect this phenomenon, as firms currently focused on exploitation tend to significantly outperform the market's near-term earnings expectations. The stock market similarly fails to immediately incorporate all information about a firm's innovative search strategy. We find that exploitation focused firms are undervalued relative to exploration focused firms and that this return differential is incremental to standard risk and innovation-based pricing factors examined in the prior literature. Furthermore, we find that our return predictability results are much stronger amongst groups of firms that are likely to receive less investor attention.

We interpret our work as building on the growing literature examining the relationship between firm innovation and public equity markets (Lerner & Seru, 2017; Hirshleifer et al., 2013; Cohen et al., 2013). One would expect exploitation strategies to correlate with R&D productivity and past success. If the argument for the riskiness of exploration holds, it would be surprising if an exploration search strategy proved more productive in patenting, as one would expect an increase in unsuccessful research efforts. Similarly, if one assumes that search requires learning and adjustment of organizational routines and development processes, one would also be surprised if search resulted in immediately greater R&D productivity (it might well subsequently result in greater labor productivity or higher overall productivity although those are topics beyond the scope of this paper). Similarly, one should not automatically expect firms that follow exploration search strategies to be more successful, on average, than those that follow exploitation strategies. Indeed, the hope of exploration is that the strategy finds a new vein of rich payoff and that the firm can then mine those payoffs in the future with an exploitation strategy. At some point, however, exploitation veins run out and a firm must search for new opportunities (Levinthal & March, 1981; Levinthal & March, 1993). Therefore, while we present evidence consistent with the hypothesis that the market (at least in the short-term) undervalues firms that are engaged in the exploitation of their existing technologies, it would be incorrect to characterize our results as demonstrating that exploration-focused search strategies are not beneficial for corporations to pursue.

Our return predictability results have significant implications for optimal firm financing policy and corporate disclosure policy in relation to a firm's innovative activities.

With respect to firm financing policy, the relatively short-term undervaluation of high exploitation firms relative to high exploration firms by public equity markets (see discussion in Section 4.1) implies that corporate executives may need to adjust their mix of project financing choices depending on the type of innovation search strategy being pursued. In particular, if a firm is following an innovation exploitation search strategy, then value-maximizing firm managers will prefer to use cash and/or issue debt rather than issue underpriced equity securities to fund R&D operations. Thus, as advocated in He & Tian (2018), our results speak to the broad and relatively unexplored question of how corporate innovation affects a firm's financial performance and policies.

With respect to corporate disclosure policy, our results highlight the need for companies focusing on innovative exploitation to provide greater investor guidance as to the beneficial earnings impact, particularly in the short-term, of exploitative patents. Indeed, as shown in Section 3.2, even relatively sophisticated equity analysts seem to struggle to quantify the significant short-term earnings potential and thus overall value inherent in exploitative patents. Given studies such as Haggard, Martin & Pereira (2008) who find that increased corporate disclosure leads to an increase in a firm's stock price informativeness, exploitation-focused firms would appear to have the most to gain from detailing the incremental value of new patents granted within the firm's pre-existing areas of technological expertise.

Finally, our empirical findings have important implications for the market valuation of exploitative and explorative innovation search strategies.

First, our results point to a more nuanced view of the belief that firms respond to short-term earnings pressures by underinvesting in fundamental research, possibly decreasing the number of patents, breakthroughs, and overall innovative output (Dechow & Sloan 1991; Bushee 1998; Arora, Belenzon & Patacconi, 2018). The argument is that stock market pressure hampers innovation, due to short term pressures for performance (Stein 1989; Ferreira, Manso, & Silva 2014). Our paper suggests that the market's feedback effects on innovation might depend on the type of innovation. If exploitative efforts are given overly low attention and value, firms might surprisingly be biased towards exploratory innovation rather than exploitation. This would be consistent with increased private investment in fundamental research and development (Mervis, 2017). Relatedly, if explorative efforts were positively related to socially beneficial knowledge spillovers (the social value of innovations) and negatively related to business stealing effects (Bloom, Schankerman & Van Reenen, 2013), then the relative lack of attention given to exploitative innovations by investors might well turn out to be economically beneficial.

Second, our results have implications for the interpretation of research findings that rely on firms' patent counts as an outcome measure or explanatory variable (Lerner & Seru, 2017). Since patent portfolios that are of exploitative nature seem to be systematically undervalued, the relation between patent counts and market value based measures like Tobins' Q will be biased as well and vary according to whether the underlying portfolio reflects an exploitative or explorative strategy. In unreported regressions of patent portfolio values (based on Kogan et al., 2017 data) on our innovation search measures, for instance, we find that the average value of a patent increases with increased focus on exploitation and declines with increased focus on exploration.

Third, our proposed mechanisms rely heavily on the assumption that an investor has limited attention and that s/he focuses on the impact of explorative rather than exploitative patents. One of our proposed mechanisms assumes that firms (with or without a conscious understanding of the mechanism) manipulate the focus of investor attention, for example, by highlighting certain types of innovation. This assumption could be tested empirically, by comparing the measure of a published patent portfolio with respect to innovation strategy, relative to a firm's media strategy (for example, how often, to what extent, and for which types of patents, is the publication of a grant announced or commented upon by the firm). While our comparison of the extent of mispricing observed for low advertising firms versus high advertising firms in Table 6 strongly suggests that investor inattention is an important channel through which the stock market fails to properly value firms' different innovative search strategies, it would nevertheless be interesting to use more granular data to assess how corporate disclosures with respect to exploitative versus explorative innovation affect investor perception of their respective value. For example, the effectiveness of a firm's media strategy could be gauged, along with the technology and inventor communities' reactions, through an analysis of social media. The differences across types of innovation and how they are publicized and perceived might reveal additional mismatches in valuation and performance. This line of reasoning could be extended to a more granular level and build on recent work that predicts the value of a particular patent based on stock market reaction (Kogan et al., 2017). We leave these and many other related questions to future research.

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Table 1: Summary statistics

At the end of June of year *t*, we sort firms into three groups (low, middle and high) based on the 30th and 70th percentile of our exploitation focus measures, *Internal search proximity* and *Exploitative patent ratio*, in year *t*-1 (where low and high values are classified as firms focused more on exploration and exploitation respectively) (see Section 2.2 for further details on the construction of these two measures). The portfolios are formed every year from 1982 to 2007. Panel A reports the average annual number of firms and pooled median characteristics of each of the three groups. *Size* is the Center for Research in Security Prices (CRSP) price per share times the number of shares outstanding at the end of June of year *t*. The book-to-market equity ratio (*BTM*) is the ratio of book equity of fiscal year ending in year *t*-1 to market equity at the end of year *t*-1. *CapEx* is capital expenditure in fiscal year *t*-1 divided by lagged total assets. *R&D* is R&D expenditure in fiscal year *t*-1 divided by lagged total assets. *Patents* is the number of patents granted to the firm in year *t*-1 divided by lagged total assets. *Firm Age* is defined as the number of years that a firm is listed on Compustat. *Conglomerate* is a dummy variable equaling one when a firm has segments with positive assets and sales in more than one 3-digit SIC code industry during the year. *Total Patent Stock* is the number of all patents granted to the firm up to year *t* scaled by lagged total assets. *Advertising* is advertising expense scaled by lagged total assets. *SG&A* is selling, general & administrative expense divided by lagged total assets. *Momentum* is the prior 6 month returns (with one month gap between the holding period and the current month). *Return on assets* (ROA) is defined as income before extraordinary items plus interest expenses scaled by lagged total assets. *Return on equity* (ROE) is defined as income before extraordinary items divided by lagged shareholder's equity. *Operating Cash Flow* (OCF) is calculated as income before extraordinary items plus depreciation less changes in working capital (defined as changes in current assets minus changes in current liabilities plus changes in short term debt and minus changes in cash) scaled by lagged total assets. *Net stock issues* (NS) is the change in the natural log of the split-adjusted shares outstanding. Split-adjusted shares outstanding is Compustat shares outstanding times the Compustat adjustment factor. *Institutional ownership* (Inst. Own) denotes the fraction of firm shares outstanding owned by institutional investors. *Illiquidity* is the absolute monthly stock return divided by monthly dollar trading volume in June of year *t* as in Amihud (2002) (the raw value has been multiplied by 1,000,000 for presentation purposes). *Leverage* is defined as total debt divided by total assets. *Idiosyncratic volatility* (IV) is measured at the end of June of year *t* as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three factor returns over the previous 12 months with a minimum of 31 trading days following Hirshleifer et al. (2018). *Total Skewness* (SKEW) is calculated at the end of June of year *t* using daily returns over the prior 12 months with a minimum of 31 trading days. *Innovative efficiency* (IE) is the patent citations-based measure developed in Hirshleifer et al. (2013). *Innovative Originality* (IO) is defined as the average patent citation diversity across all patents granted to the firm over the past five years following Hirshleifer et al. (2018). Panel B reports the Pearson correlation coefficients between selected variables with *p*-values reported in parentheses.

Panel A: Firm characteristics

	Internal search proximity			Exploitative patent ratio		
Variable	Low	Middle	High	Low	Middle	High
Number of firms	306	406	306	383	322	314
Internal search proximity	0.00	0.62	0.94	0.00	0.71	0.83
Exploitative patent ratio	0.00	0.40	0.61	0.00	0.40	0.88
Size (millions of dollars)	146.3	411.3	530.0	143.8	769.4	336.0
BTM	0.49	0.49	0.42	0.52	0.46	0.42
Capex	0.05	0.05	0.05	0.05	0.05	0.05
R&D	0.03	0.04	0.06	0.03	0.05	0.05
Patents	0.01	0.02	0.03	0.01	0.02	0.02
Firm Age	11.0	14.0	13.0	11.0	15.0	13.0
Conglomerate	0.30	0.41	0.33	0.31	0.41	0.35
Total Patent Stock	0.04	0.07	0.10	0.04	0.07	0.11
Advertising	0.02	0.02	0.02	0.02	0.02	0.02
SG&A	0.33	0.29	0.31	0.33	0.28	0.31
Momentum	0.07	0.09	0.09	0.08	0.08	0.09
ROA	0.06	0.07	0.07	0.06	0.07	0.07
ROE	0.08	0.10	0.11	0.09	0.11	0.10
OCF	0.06	0.08	0.08	0.06	0.08	0.08
NS	0.01	0.01	0.01	0.01	0.01	0.01
Inst. Own	0.31	0.41	0.36	0.31	0.44	0.38
Illiquidity	0.47	0.15	0.10	0.49	0.16	0.17
Leverage	0.16	0.18	0.16	0.16	0.18	0.16
IV	0.03	0.02	0.03	0.03	0.02	0.03
IE	0.03	0.18	0.24	0.04	0.17	0.29
IO	5.75	5.67	5.17	5.20	5.61	5.86

Panel B: Correlation matrix

Variable	Internal search prox.	Exploitative patent ratio	Size	BTM	Patents	R&D	ROA	IE	IO
Internal search prox.	1.00								
Exploitative patent ratio	0.51	1.00							
	(0.00)								
Size	0.13	0.10	1.00						
	(0.00)	(0.00)							
BTM	-0.10	-0.13	-0.08	1.00					
	(0.00)	(0.00)	(0.00)						
Patents	0.06	0.08	-0.01	-0.10	1.00				
	(0.00)	(0.00)	(0.00)	(0.00)					
R&D	0.04	0.09	-0.01	-0.21	0.32	1.00			
	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)				
ROA	0.04	-0.06	0.06	0.04	-0.18	-0.53	1.00		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
IE	0.02	0.03	-0.00	-0.01	0.04	-0.01	-0.00	1.00	
	(0.01)	(0.00)	(0.41)	(0.14)	(0.00)	(0.01)	(0.81)		
IO	-0.01	0.10	0.09	-0.08	0.26	0.00	0.01	0.20	1.00
	(0.28)	(0.00)	(0.00)	(0.00)	(0.00)	(0.38)	(0.00)	(0.00)	

Table 2: Innovative search focus and future operating performance

This table reports average slopes (in %) and *t*-statistics (corrected for heteroscedasticity & serial correlation using the Newey-West correction, 12 lags) from annual Fama-MacBeth (1973) cross-sectional regressions of profitability in year *t*+1 on exploitation search focus and other controls in year *t* from 1981 to 2006. Profitability equals either return on assets (*ROA*), computed as income before extraordinary items plus interest expenses scaled by lagged total assets, or Operating Cash Flow (*OCF*), defined as income before extraordinary items plus depreciation less changes in working capital (defined as changes in current assets minus changes in current liabilities plus changes in short term debt and minus changes in cash) scaled by lagged assets. The measure of a firm's focus on exploitative innovation in columns (1) and (2) is *internal search proximity* while in columns (3) and (4) it is *exploitative patent ratio*. Δ*ROA* and Δ*OCF* is the change in ROA and OCF between year *t* and year *t*–1 respectively. *BTM*, *CapEx*, *R&D*, *Patents*, Leverage, IE, *IO*, *Firm Age*, *Conglomerate*, *Total Patent Stock*, *Advertising* and *SG&A* are defined in Table 1. All regressions include industry dummies based on Fama-French (1997) 48 industries. We winsorize all variables at the 1% and 99% levels and standardize independent variables to have zero mean and one standard deviation. Average R^2 is the time-series average of R^2 from the annual cross-sectional regressions.

	Internal search proximity		Exploitative patent ratio	
Profitability	ROA (Next year)	OCF (Next year)	ROA (Next year)	OCF (Next year)
Exploitation search focus	0.45	0.49	0.16	0.15
	(5.14)	(7.90)	(2.79)	(2.18)
BTM	0.14	0.14	0.14	0.13
	(0.34)	(0.38)	(0.34)	(0.34)
CapEx	0.52	0.76	0.55	0.78
	(1.13)	(3.75)	(1.20)	(3.66)
R&D	-0.22	-1.34	-0.16	-1.28
	(-0.53)	(-7.88)	(-0.38)	(-7.57)
Patents	-0.59	-0.79	-0.58	-0.78
	(-4.26)	(-9.31)	(-4.61)	(-9.98)
Leverage	0.07	0.67	0.08	0.69
	(0.32)	(2.48)	(0.36)	(2.59)
IE	0.23	0.17	0.25	0.21
	(1.33)	(2.51)	(1.41)	(2.80)
IO	-0.26	-0.23	-0.32	-0.18
	(-1.36)	(-1.57)	(-1.64)	(-1.45)
Firm Age	1.06	0.71	1.13	0.78
	(5.19)	(8.50)	(5.46)	(9.99)
Conglomerate	-0.17	0.01	-0.16	0.01
	(-1.68)	(0.06)	(-1.69)	(0.11)
Total Patent Stock	-0.43	-0.20	-0.40	-0.17
	(-1.13)	(-1.05)	(-1.04)	(-0.82)
Advertising	0.18	0.07	0.22	0.10
	(3.82)	(0.86)	(4.51)	(1.25)
SG&A	1.28	1.30	1.18	1.24
	(2.43)	(3.19)	(2.32)	(3.02)
ROA	16.20		16.26	
	(7.37)		(7.33)	
ΔROA	-2.57		-2.56	
	(-6.18)		(-6.08)	
OCF		13.54		13.61
		(6.01)		(5.88)
ΔOCF		-4.32		-4.34
		(-12.09)		(-11.87)
Constant	1.36	2.41	1.25	2.22
	(0.50)	(0.83)	(0.46)	(0.77)
Average R^2	0.59	0.51	0.58	0.50

Table 3: Innovative search focus and earnings surprise

This table presents quarterly Fama-Macbeth (1973) cross-sectional regressions of earnings surprise in each of the four quarters in year t+1 on a firm's exploitation search focus in year t and other controls from 1983 to 2006. Following So (2013), quarterly earnings surprise equals the realized difference between actual earnings per share (EPS) and the consensus EPS forecast in I/B/E/S scaled by total assets per share. *Exploitation search focus*, *BTM*, *R&D*, *Patents*, *CapEx*, *Leverage*, *IE*, *IO*, *Firm Age*, *Conglomerate*, *Total Patent Stock*, *Advertising*, *SG&A* and *ROA* are defined in Table 1. *Momentum* is the prior 6 month stock return leading up to the earnings announcement (with one month gap between the holding period and announcement month). *Accruals* equal total accruals scaled by lagged assets (Sloan, 1996). *Negative EPS* is an indicator for whether the consensus EPS forecast for that quarter is negative (Fama & French, 2006). We include last quarter's realized earnings surprise for firm i (*Lagged ES*) and the change in earnings surprise between the prior two quarters (Δ*ES*). We include industry dummies based on the Fama-French 48 industry classification scheme, winsorize all variables at the 1% and 99% levels and standardize independent variables to have zero mean and one standard deviation. Average R^2 is the time-series average of the R^2 from quarterly cross-sectional regressions. Newey-West autocorrelation-adjusted heteroscedasticity-robust t-stats are reported in parentheses.

	Internal search proximity		Exploitative patent ratio	
Dependent variable	EPS surprise	EPS surprise	EPS surprise	EPS surprise
Exploitation search focus	0.04	0.04	0.02	0.02
	(2.84)	(3.91)	(3.73)	(3.04)
Lagged ES	0.39	0.39	0.38	0.40
	(11.02)	(11.68)	(8.81)	(12.30)
ΔES	-0.15	-0.13	-0.15	-0.14
	(-4.96)	(-3.31)	(-5.23)	(-4.62)
ROA	0.16	0.10	0.15	0.09
	(3.57)	(3.36)	(3.73)	(3.74)
Negative EPS	-0.11	-0.10	-0.11	-0.08
	(-1.92)	(-1.63)	(-1.95)	(-1.14)
Accruals	-0.06	-0.07	-0.05	-0.08
	(-3.97)	(-2.27)	(-4.16)	(-1.99)
BTM	-0.02	-0.06	-0.02	-0.06
	(-0.91)	(-1.27)	(-0.86)	(-1.28)
Momentum	0.07	0.08	0.07	0.09
	(6.42)	(3.61)	(5.29)	(2.98)
Firm Age	0.02	0.07	0.04	0.09
	(1.13)	(1.47)	(2.59)	(1.41)
Conglomerate	0.03	0.01	0.03	-0.01
	(1.53)	(0.81)	(1.48)	(-0.53)
Total Patent Stock	-0.01	-0.03	-0.01	-0.04
	(-2.10)	(-1.39)	(-0.62)	(-1.44)
Advertising	-0.01	0.01	-0.01	0.01
	(-0.85)	(0.45)	(-0.92)	(0.41)
SG&A	-0.01	0.04	-0.01	0.03
	(-0.40)	(1.13)	(-0.32)	(1.04)
R&D		-0.02		-0.02
		(-0.66)		(-0.52)
Patents		-0.03		-0.03
		(-2.04)		(-1.73)
CapEx		0.03		0.02
		(1.09)		(0.94)
Leverage		-0.09		-0.09
		(-1.70)		(-1.62)
IE		0.15		0.17
		(1.11)		(1.10)
IO		-0.04		-0.03
		(-0.99)		(-1.27)
Constant	-0.22	-0.10	-0.26	-0.08
	(-2.91)	(-0.82)	(-3.04)	(-0.49)
Average R^2	0.26	0.30	0.26	0.30

Table 4: Portfolio returns and risk factor models

At the end of June of year *t* from 1982 to 2007, we sort firms independently into three groups (low [L], middle [M] or high [H]) based on the 30th and 70th percentiles of either a firm's *internal search proximity* or *exploitative patent ratio* score in year *t-1* and two size groups (small [S] or big [B]) based on the NYSE median size breakpoint at the end of June of year *t*. We hold these portfolios over the next 12 months and compute value-weighted monthly returns for each portfolio. We then calculate monthly size-adjusted returns of the three exploitation search focus portfolios as (S/L+B/L)/2, (S/M+B/M)/2 and (S/H+B/H)/2 respectively. We measure exploitation search focus by *internal search proximity* and *exploitative patent ratio* (as defined in Section 2.2) in Panels A and B respectively. The first half of each Panel reports the monthly average size-adjusted excess returns to these portfolios in the first column (computed as the difference between size-adjusted portfolio returns and the one-month Treasury bill rate, expressed in percentage terms) while the remaining columns report the alphas (α, expressed in percentage terms) from regressing the time-series of portfolio excess returns on various factor returns. The second half of each Panel reports the associated adjusted R^2 for each time-series regression. All returns and alphas reported are value-weighted while heteroskedasticity-robust *t*-statistics are provided in parentheses. *MKT*, *SMB* and *HML* are the market, size and book-to-market ratio factors of the Fama & French (1993) three-factor model (*3F*) whilst *MOM* is the momentum factor developed by Carhart (1997). *RMW* and *CMA* are the robust-minus-weak factor and the conservative-minus-aggressive factors in Fama & French (2015). *EMI* is the innovative efficient-minus-inefficient factor in Hirshleifer et al., 2013). *LIQ* is the liquidity factor defined in Pastor & Stambaugh (2003). *UMO* is the undervalued-minus-overvalued factor of Hirshleifer & Jiang (2010). We also report the alpha from the *Mispricing* factor model of Stambaugh & Yuan (2017).

Panel A: Portfolio sorts based on internal search proximity

Panel A.1 – Excess returns and alphas from different factor models

			3F plus					
Portfolio	Exret	3F	MOM	RMW+CMA	EMI	LIQ	UMO	Mispricing
Low	0.58	-0.16	-0.03	-0.02	-0.12	-0.17	0.02	-0.00
t-stat	(1.79)	(-1.35)	(-0.33)	(-0.15)	(-1.01)	(-1.46)	(0.21)	(-0.20)
Middle	0.76	-0.02	0.08	0.02	-0.03	-0.02	0.07	0.08
t-stat	(2.57)	(-0.21)	(1.21)	(0.14)	(-0.38)	(-0.22)	(0.61)	(0.76)
High	0.86	0.22	0.26	0.26	0.17	0.22	0.22	0.22
t-stat	(2.86)	(2.43)	(2.58)	(2.82)	(1.93)	(2.45)	(2.51)	(2.43)
High-Low	0.28	0.38	0.29	0.28	0.30	0.40	0.20	0.22
t-stat	(2.81)	(3.58)	(2.66)	(2.46)	(3.03)	(3.69)	(1.71)	(2.01)

Panel A.2 – R^2 of different factor models

		3F plus					
Portfolio	3F	MOM	RMW+CMA	EMI	LIQ	UMO	Mispricing
Low	0.89	0.92	0.90	0.89	0.89	0.91	0.90
Middle	0.91	0.94	0.92	0.92	0.92	0.93	0.93
High	0.92	0.94	0.93	0.92	0.92	0.93	0.92
High-Low	0.17	0.17	0.18	0.20	0.17	0.21	0.15

Panel B: Portfolio sorts based on exploitative patent ratio

Panel B.1 – Excess returns and alphas from different factor models

			3F plus					
Portfolio	Exret	3F	MOM	RMW+CMA	EMI	LIQ	UMO	Mispricing
Low	0.58	-0.13	-0.02	0.00	-0.10	-0.16	0.00	-0.06
t-stat	(1.83)	(-1.15)	(-0.60)	(0.04)	(-0.78)	(-1.40)	(0.16)	(-0.70)
Middle	0.84	0.08	0.11	0.14	0.03	0.09	0.11	-0.04
t-stat	(2.69)	(0.90)	(1.13)	(1.38)	(0.32)	(0.98)	(1.36)	(-0.40)
High	0.85	0.21	0.19	0.21	0.18	0.22	0.18	0.15
t-stat	(3.10)	(2.54)	(1.99)	(2.50)	(2.20)	(2.68)	(2.03)	(1.68)
High-Low	0.27	0.34	0.21	0.20	0.28	0.39	0.18	0.21
t-stat	(2.63)	(3.39)	(2.08)	(1.96)	(2.83)	(3.89)	(1.67)	(2.16)

Panel B.2 – R^2 of different factor models

		3F plus					
Portfolio	3F	MOM	RMW+CMA	EMI	LIQ	UMO	Mispricing
Low	0.88	0.93	0.89	0.89	0.89	0.90	0.89
Middle	0.92	0.94	0.92	0.92	0.92	0.92	0.92
High	0.92	0.93	0.92	0.92	0.92	0.91	0.91
High-Low	0.15	0.24	0.26	0.23	0.17	0.22	0.23

Table 5: Innovative search focus and future stock returns

This table reports the average slopes (in %) and their associated Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics (with 12 lags) from Fama-MacBeth (1973) cross-sectional regressions of individual monthly stock returns from July of year *t* to June of year *t*+1 on exploitation search focus (defined as *internal search proximity* and *exploitative patent ratio* in year *t*-1 for columns (1)-(2) and (3)-(4) respectively) and other control variables. *Size*, *BTM*, *ROE*, *CapEx*, *R&D*, *Patents*, *NS*, *Inst. Own*, *Illiquidity*, *Leverage*, *IV*, *SKEW*, *IE*, *IO*, *Firm Age*, *Conglomerate*, *Total Patent Stock*, *Advertising* and *SG&A* are defined in Table 1. *Momentum* is the prior 6 month returns (with one month gap between the holding period and the current month). *ST reversal* is the previous month's stock return. All regressions include industry dummies based on the Fama & French (1997) 48 industry classification scheme. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and one standard deviation. Average R^2 is the time-series average of the R^2 from the monthly cross-sectional regressions. The stock return data are from July 1982 to June 2008.

	Internal search proximity		Exploitative patent ratio	
Dependent variable	Monthly stock return	Monthly stock return	Monthly stock return	Monthly stock return
Exploitation search focus	0.08	0.09	0.06	0.06
	(2.27)	(2.15)	(2.02)	(1.71)
Size	-0.08	-0.16	-0.06	-0.13
	(-0.69)	(-1.38)	(-0.48)	(-1.09)
BTM	0.30	0.28	0.31	0.30
	(3.87)	(3.36)	(3.98)	(3.47)
Momentum	0.19	0.18	0.19	0.19
	(2.34)	(2.30)	(2.39)	(2.29)
ST reversal	-0.82	-0.89	-0.84	-0.88
	(-8.69)	(-8.85)	(-8.68)	(-8.82)
R&D	0.06	0.12	0.06	0.12
	(0.48)	(1.02)	(0.48)	(1.05)
Patents	-0.13	-0.14	-0.12	-0.12
	(-3.15)	(-3.10)	(-2.91)	(-2.83)
CapEx	-0.08	-0.06	-0.08	-0.07
	(-1.01)	(-0.57)	(-1.05)	(-0.59)
ROE	0.18	0.13	0.17	0.12
	(2.84)	(1.87)	(2.98)	(1.82)
Firm Age	0.04	-0.00	0.05	0.00
	(0.61)	(-0.08)	(0.66)	(0.04)
Conglomerate	-0.00	0.02	-0.01	0.01
	(-0.02)	(0.22)	(-0.15)	(0.11)
Total Patent Stock	0.08	0.06	0.08	0.06
	(1.98)	(1.23)	(2.02)	(1.20)
Advertising	0.02	0.00	0.02	0.00
	(0.35)	(0.04)	(0.37)	(0.03)
SG&A	0.03	0.07	0.03	0.07
	(0.34)	(0.69)	(0.32)	(0.72)
IE		0.04		0.05
		(1.24)		(1.33)
IO		0.07		0.05
		(1.39)		(1.06)
Illiquidity		0.20		0.19
		(1.46)		(1.40)
Leverage		0.03		0.04
		(0.47)		(0.63)
NS		-0.24		-0.25
		(-3.07)		(-3.17)
Inst. Own		0.14		0.15
		(3.27)		(3.65)
IV		-0.05		-0.04
		(-0.28)		(-0.26)
SKEW		-0.09		-0.10
		(-1.85)		(-1.89)
Constant	1.01	0.73	0.98	0.71
	(2.36)	(1.53)	(2.31)	(1.49)
Average R^2	0.14	0.18	0.14	0.17

Table 6: Innovative search focus, investor attention & future stock returns: subsample analysis

This table reports the average slopes (in %) and their associated Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust t-statistics (with 12 lags) from Fama-MacBeth (1973) cross-sectional regressions of individual monthly stock returns from July of year t to June of year t+1 on exploitation search focus (defined as *internal search proximity* and *exploitative patent ratio* in year t-1 for columns (1)-(2) and (3)-(4) respectively) and other control variables. Panel A separates firms into two subsamples depending on whether they have below or above median scaled advertising expenditure (*Low Advertising* and *High Advertising*, respectively). Panel B separates firms into two subsamples depending on whether the ownership percentage of transient institutional investors, following the classification in Bushee (2001), is above or below the relevant median value (*High Transient Institutions* and *Low Transient Institutions*, respectively). Panel C splits firms into two subsamples depending on whether a firm is operating in an industry sector with above or below median industry patenting intensity ratio (*High Industry Patenting Intensity Ratio* and *Low Industry Patenting Intensity Ratio*). Industry patenting intensity ratio is defined as the total number of new patents granted in year t to all publicly listed firms in the same Fama-French (1997) 48 industry classification as the focal firm divided by the average number of patents granted each year to firms in the same industry as the focal firm over the past 5 years. *Low ATT* denotes groups of stocks with relatively lower investor attention (i.e. Low Advertising and High Transient Institutions) while *High ATT* denotes groups of stocks with relatively higher investor attention (i.e. High Advertising and Low Transient Institutions). *High DISTRACT* represents groups of firms that are more likely to be subject to the effects of "investor distraction" (i.e. firm years with a High Industry Patenting Intensity Ratio) while *Low DISTRACT* represents groups of firms that are less likely to be subject to the effects of "investor distraction" (i.e. firm years with a Low Industry Patenting Intensity Ratio). Other controls comprise *Size*, *BTM*, *ROE*, *CapEx*, *R&D*, *Patents*, *NS*, *Inst. Own*, *Illiquidity*, *Leverage*, *IV*, *SKEW*, *IE*, *IO*, *Firm Age*, *Conglomerate*, *Total Patent Stock*, *Advertising* and *SG&A* which are defined in Table 1 as well as *Momentum* (defined as the prior 6 month returns with one month gap between the holding period and the current month) and *ST reversal* (defined as the previous month's stock return). All regressions include industry dummies based on the Fama & French (1997) 48 industry classification scheme. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and one standard deviation. Average R^2 is the time-series average of the R^2 from the monthly cross-sectional regressions. The stock return data are from July 1982 to June 2008.

Panel A: Subsamples split by the intensity of advertising expenditure

Subsample	Internal search proximity: Low Advertising (*Low ATT*)	Internal search proximity: High Advertising (*High ATT*)	Exploitative patent ratio: Low Advertising (*Low ATT*)	Exploitative patent ratio: High Advertising (*High ATT*)
Exploitation search focus	0.07	0.04	0.07	0.03
	(2.07)	(0.87)	(2.37)	(0.61)
Other Controls	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Average R^2	0.23	0.29	0.23	0.28

Panel B: Subsamples split by the proportion of transient institutional investors

Subsample	Internal search proximity: High Transient Institutions (*Low ATT*)	Internal search proximity: Low Transient Institutions (*High ATT*)	Exploitative patent ratio: High Transient Institutions (*Low ATT*)	Exploitative patent ratio: Low Transient Institutions (*High ATT*)
Exploitation search focus	0.09	0.04	0.09	0.02
	(1.77)	(0.79)	(1.98)	(0.67)
Other Controls	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Average R^2	0.29	0.22	0.28	0.22

Panel C: Subsamples split by industry patenting intensity ratio

Subsample	Internal search proximity: High Industry Patenting Intensity Ratio (*High DISTRACT*)	Internal search proximity: Low Industry Patenting Intensity Ratio (*Low DISTRACT*)	Exploitative patent ratio: High Industry Patenting Intensity Ratio (*High DISTRACT*)	Exploitative patent ratio: Low Industry Patenting Intensity Ratio (*Low DISTRACT*)
Exploitation search focus	0.07	0.05	0.06	0.06
	(1.67)	(1.37)	(1.94)	(1.85)
Other Controls	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Average R^2	0.21	0.24	0.21	0.25

Figure 1: Innovative search focus and market factor returns (1982-2008)

This figure plots the return on the spread portfolio of high exploitation minus low exploitation focused firms (using *internal search proximity* and *exploitative patent ratio* respectively) and the market factor returns (*MKT*) from 1982 to 2008 (where we annualize the observed six month returns for 1982 and 2008).

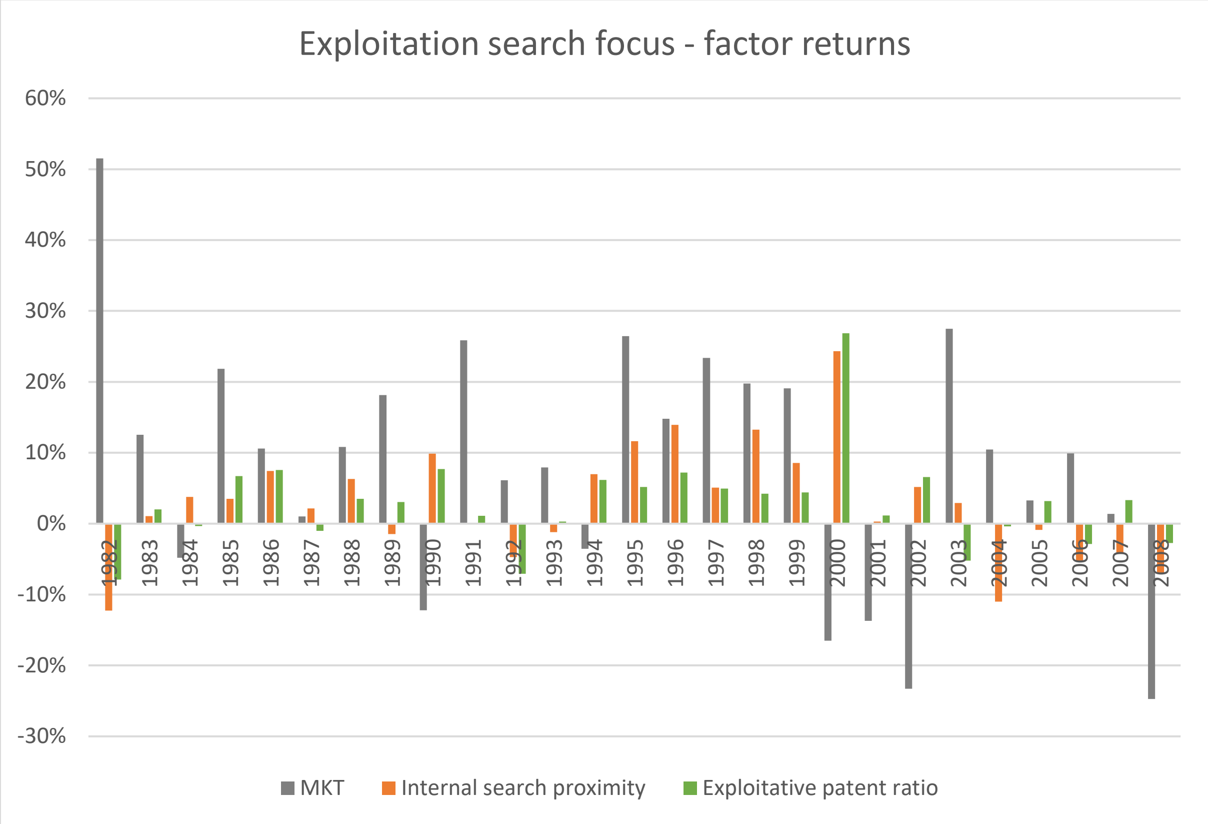
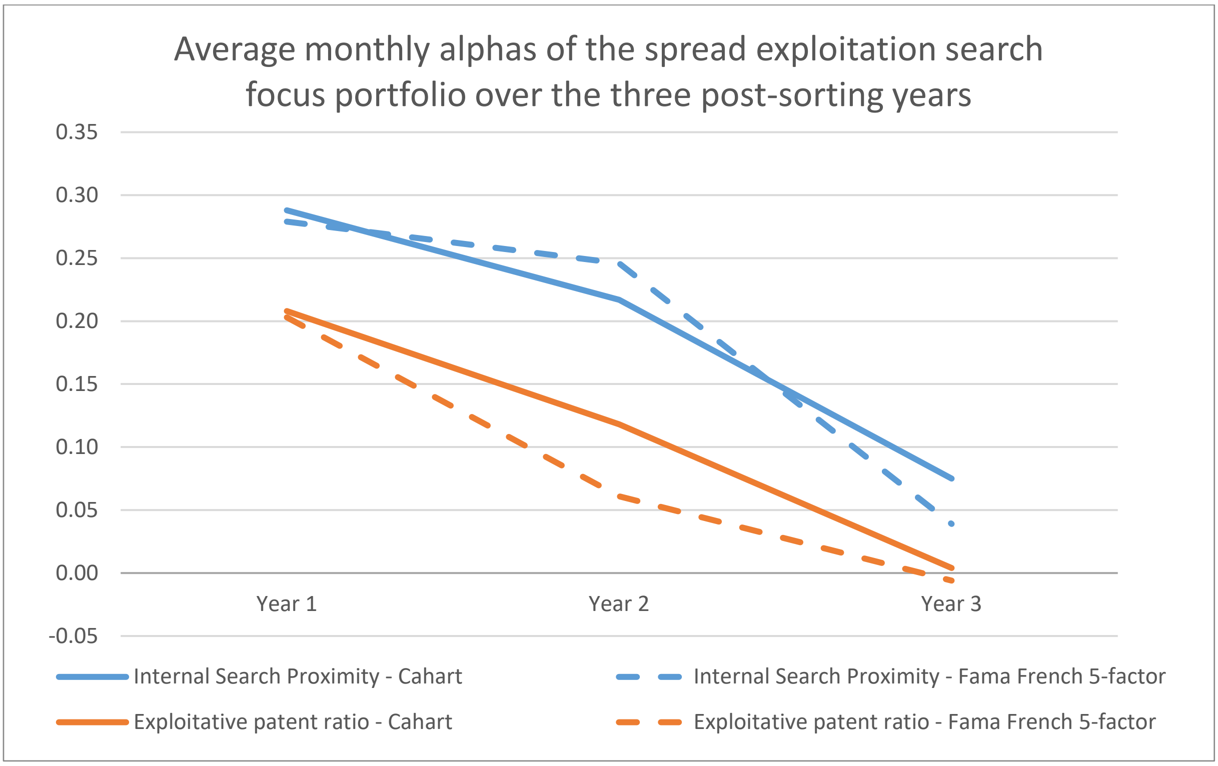


Figure 2: Monthly average alphas of High-minus-Low exploitation search focus spread portfolio over the 3 years post portfolio formation

This figure plots the monthly average alphas for the High-minus-Low exploitation search focus spread portfolio (formed using *internal search proximity* and *exploitative patent ratio* as described in Section 4.1) over the three post-sorting years. The portfolio alphas shown are calculated using either the Cahart four-factor model or the Fama & French five-factor model (see Section 4.1 for further details).



Appendix 1: Case study - Andrx Corporation

In this appendix, we provide the example case study of Andrx Corporation, a U.S. specialty drug delivery and distribution company, to: (a) outline the numerical calculation of our two measures of a firm's exploitation search focus (*Internal Search Proximity* and *Exploitative Patent Ratio*), (b) describe how these measures differ from previously studied innovation-related variables (in particular the innovative originality and innovative efficiency measures developed in Hirshleifer et al. (2018) and Hirshleifer et al. (2013) respectively) and (c) illustrate how limited investor attention can drive the observed positive relationship between exploitative innovative search strategies and future stock returns.

***Description of Andrx Corporation*:**

In 1992, pharmacist Alan P. Cohen founded Andrx Corporation with the goal of working with brand-name pharmaceutical companies to develop generic products using the company's proprietary oral timed-release drug delivery technologies. In particular, Andrx developed oral drug delivery technology that could be used to (a) improve the dosage release characteristics of existing drugs (e.g. instead of a patient taking several doses of medication each day, a patient could take a single timed-release dose that would automatically produce the desired effects throughout the day) and (b) develop bioequivalent formulations of products for which the pharmacokinetic profile is difficult to replicate. This sustained drug delivery transformation had the advantage of improving patience compliance, decreasing side effects, providing greater convenience to the patient and even enhancing drug efficacy. Furthermore, these costly and more difficult-to-duplicate single dose formulations had the ability to extend product life cycles and serve as barriers to entry by generic competitors. This in turn offered Andrx the opportunity to capture higher profit margins on its exploitative innovations:

> "These complex, controlled-release generics will hold some of the most lucrative profit margins for the generic drug industry and Andrx in particular, whom we believe can sustain gross margins in excess of 70%."
>
> - CIBC Oppenheimer Equity Research Report, 21 April 1998

In addition, many market analysts noted that Andrx Corporation could exploit its core complex generic formulation expertise to incrementally improve the delivery characteristics of many related drug products:

> "Andrx has developed and applied six drug delivery technologies in the area of oral solid-dose controlled-release drug products. Andrx's patents will likely serve the same function

as those of patents issued to [New Drug Application focused] companies. Although each technology was developed to address a particular drug problem, we believe the technology is flexible enough to be applied to any number of products."

- UBS Dillon Reed Equity Research Report, 17 March 1997

Andrx Corporation completed its initial public offering (IPO) in June 1996 at $12.00 per share with an implied market capitalization of approximately $200 million.

***Calculation of Exploitation Search Focus measures*:**

We now use the patenting history of Andrx Corporation to describe how our two measures of Exploitation Search Focus, namely *Internal Search Proximity* and *Exploitative Patent Ratio,* are computed from 1997 to 1999. Table A1 documents the raw values (which can take on values between zero and one) and percentile ranks of Andrx Corporation's *Internal Search Proximity* and *Exploitative Patent Ratio* scores for the years 1997 to 1999. We show the detailed calculations for 1999 as an example of the procedure that we follow.

Table A1.1 – Exploitation Search Focus measures for Andrx Corporation (1997–1999)

	Internal search proximity		Exploitative patent ratio	
	Raw value	Percentile rank	Raw value	Percentile rank
1997	0.99	93	1.00	99
1998	0.99	94	0.80	78
1999	1.00	98	1.00	99

Computation of Internal Search Proximity in 1999:

In 1999, Andrx Corporation was granted two new U.S. patents, 5916595 and 5922352, where both patents had a primary USPTO technology class of 424 (Drug, bio-affecting and body treating compositions). Table A1.2 provides a comparison of the technology class distribution of the current year (1999) patent portfolio with the technology class distribution of the firm's previously granted patents (pre-1999).

Table A1.2 – Breakdown of Andrx Corporation's patent portfolio by technology class

Period	Grant year	Total number of patents granted	Primary USPTO technology class (count of newly granted patents in a given class shown in brackets)
Current (1999)	1999	2	424 (2)
Past (Pre 1999)	1998	5	424 (5)
	1997	1	424 (1)
	1996	4	424 (3); 514 (1)
	1995	5	424 (5)

As can be seen in Table A1.2, there is a very high degree of similarity or overlap between the technology classes covered by Andrx's newly granted patent portfolio in 1999 (100% in technology class 424) and the technology classes spanned by Andrx's previously issued patents (over 93% of the firm's pre-1999 patents are also encompassed in technology class 424). Using the depreciation-adjusted Equation (1) in Section 2.2, we compute Andrx's 1999 *Internal Search Proximity* score as 0.998. This is consistent with Andrx Corporation pursuing an exploitation innovation search strategy whereby a company focuses its current innovative activities on technological areas that are familiar to the firm.

Computation of Exploitative Patent Ratio in 1999:

In order to calculate Andrx Corp's *Exploitative Patent Ratio* in 1999 (our alternative measure of a firm's exploitation search focus), we first compute the "new cite ratio" for each of the two patents granted to Andrx Corporation in 1999. This is defined as the total number of citations made to "new knowledge" (i.e. patents not previously developed or cited by Andrx) divided by the total number of 'back' citations made by the patent.

Table A1.3 – New knowledge cited by Andrx Corporation's 1999 granted patents

Patent number	Total back citations	Citations to 'new knowledge'	New cite ratio
5916595	12	7	58%
5922352	44	2	5%

Following Benner & Tushman (2002), a patent is flagged as "explorative" if at least 80% of its citations are based on new knowledge (new cite ratio ≥ 80%). Since the development of both of these new patents relied heavily on Andrx's existing knowledge base such that both patents' new cite ratios fell below the 80% threshold established by Benner & Tushman (2002) and followed in Ma (2018), Brav et al. (2018), Gao et al. (2018) and Lin et al. (2017), both of these patents are classified as 'exploitative' patents such that Andrx Corporation's *Exploitative Patent Ratio* for 1999 is set equal to one.[12]

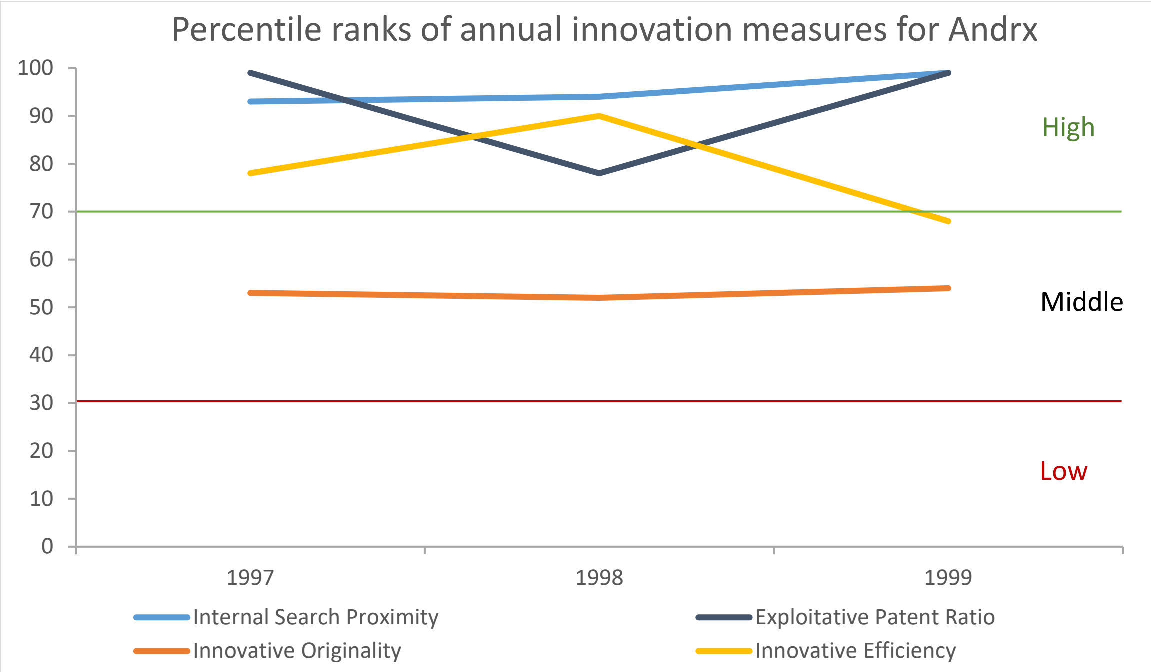
***Comparison with alternative innovation-related variables*:**

In this subsection we consider how our two measures of a firm's exploitation search focus (*Internal Search Proximity* and *Exploitative Patent Ratio*) compare to other innovation-related variables, namely innovative originality (Hirshleifer et al., 2018) and innovative efficiency (Hirshleifer et al., 2013). In order to facilitate the comparison of these four measures and to

[12] We note that our empirical results are robust to simply sorting firms on their average new cite ratio or using alternative thresholds for identifying a patent as being "explorative."

more directly compare the strength of the resulting trading signal, Figure A1.1 shows the percentile ranks of Andrx's *Internal Search Proximity*, *Exploitative Patent Ratio*, *Innovative Originality* and patents-based *Innovative Efficiency* scores for each year from 1997 to 1999.

Figure A1.1 – Percentile ranks of innovation-related measures for Andrx Corporation (1997-1999)



One of the key takeaways from Figure A1.1 is that a firm's internal innovative search strategy (characterized as the choice between exploitation versus exploration) can be quite distinct from the 'originality' of a firm's patents as measured in Hirshleifer et al. (2018). For example, while both the *Internal Search Proximity* and *Exploitative Patent Ratio* measures clearly identify Andrx Corporation as pursuing an exploitation innovation search strategy (and thus a candidate to be included in the 'long' portfolio), the innovative originality of Andrx's patents over this same time period is similar to the median publicly traded firm in the U.S. economy (and thus not offering a clear buy or sell signal for Andrx during this time period).

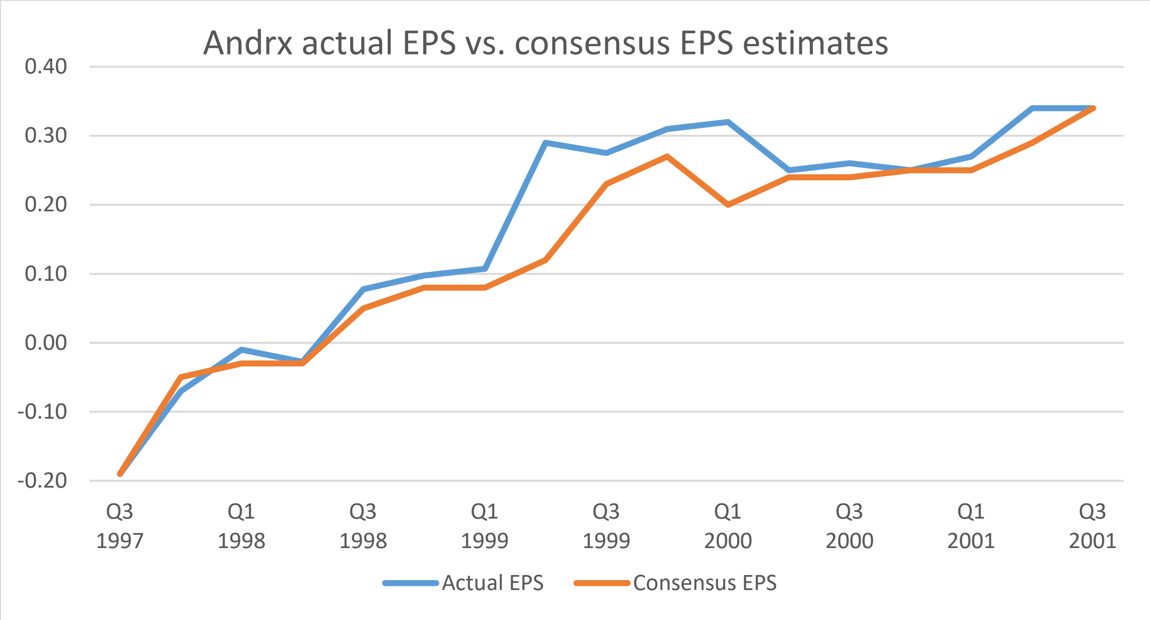
As argued earlier in the Introduction and Section 2.3, we view *Internal Search Proximity* and the *Exploitative Patent Ratio* as being both conceptually and empirically distinct from Innovative Originality (IO) and Innovative Efficiency (IE). As shown in the case of Andrx, our focus on understanding the value-relevant information contained in examining a firm's current innovative output relative to the past innovative output of the *same firm* (i.e. a firm's *internal* focus on exploitative versus explorative innovation) is quite distinct from the question of how original or different a firm's patents are relative to *other* firms. This is because a firm can create highly original/(unoriginal) patents while following existing/(new) research trajectories and vice versa. The limited relationship that we observe between our Exploitation Search Focus measures and other innovation-related measures for Andrx Corp is consistent with the low correlations (<0.10) between our two measures of Exploitation Search Focus and both IO and IE in our full sample as well as with the unreported principal component analysis (available upon request) which finds that the innovative originality measure in Hall et al. (2001) does *not* load on either the 'exploitation' or the 'exploration' component. In any case, even after we include both IO and IE as controls in all of our subsequent empirical analysis, we find that both of our exploitation search focus measures continue to contain meaningfully incremental value-relevant information.

***Limited investor attention and under-reaction to exploitative innovation strategy*:**

Given that Andrx Corporation was following an exploitative innovation search strategy, a natural question to ask is how did equity analysts and the stock market in general assess and value this innovation search strategy?

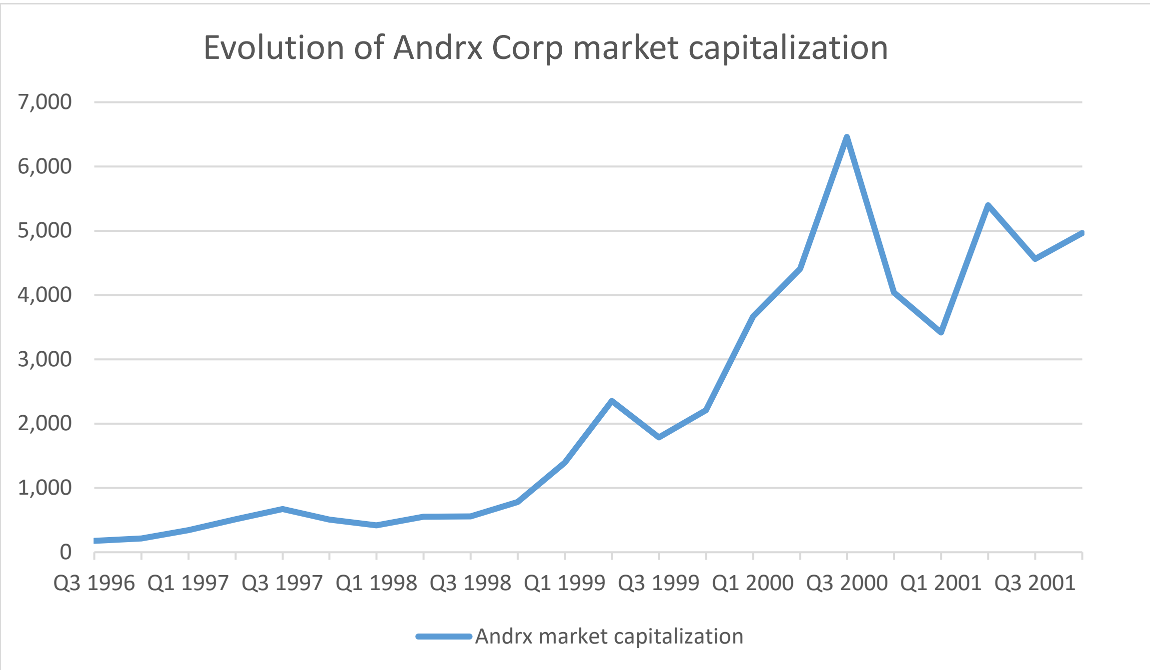
As discussed in Section 3.2, if the market fails to fully understand the positive impact of exploitative patents on future firm profitability due to limited investor attention, then we may observe more positive "earnings surprises" for exploitation-focused firms which may in turn result in these firms generating abnormally high future stock returns. In Figure A1.2 below, we plot the I/B/E/S consensus earnings per share (EPS) estimates as well as the realized EPS results (adjusted for stock splits) for Andrx Corp for each quarter between the third quarter (Q3) of 1997 and Q3 2001. Interestingly, we find that actual EPS exceeded consensus EPS estimates for nine consecutive quarters between Q3 1998 and Q3 2000.

Figure A1.2 – Actual EPS vs. consensus EPS estimates for Andrx Corporation (quarterly)



Over the multiple years that the realized profitability of Andrx Corporation exceeded the market's earnings expectations, the market capitalization of the firm's stock (shown in Figure A1.3) rose dramatically as the market incorporated higher earnings forecasts into its valuation of the company's operations.

Figure A1.3 – Market capitalization of Andrx Corporation (1996-2001)



In this time period of consecutive positive earnings surprises, equity analysts covering Andrx Corporation noted several reasons for the consistent outperformance of Andrx's exploitative innovative search strategy relative to their initial earnings expectations. As eluded to in a research note by Salomon Smith Barney on 23 June 1999, the overarching theme of this commentary was the failure of the market to fully recognize the commercial potential of Andrx's core proprietary technology. Specifically,

> "ADRX has an ongoing program geared toward improving the release profile of existing drugs. In our opinion, a significant portion of ADRX's value will be driven by the strength of the technology platform, *and realization of that commercial potential by the market should help drive the stock* [*emphasis added*]."

First, analysts noted that sales of Andrx's first manufactured controlled release generic product *Diltia XT/Dilacor XR* (a once-daily formulation of diltiazem, a calcium channel blocker indicated for the treatment of chest pain (angina) and moderate hypertension) were significantly higher than initial market expectations. For example, a CIBC Oppenheimer equity research report released on 26 April 1999 stated that:

> "As in the previous quarter, strong sales of the company's first manufactured controlled-release drug, a generic equivalent of Watson Pharmaceuticals' *Dilacor XR*, exceeded our [Q1 1999] estimate by nearly 50%, likely contributing at least $0.05 of the positive EPS surprise. [This was due to] *Dilacor XR*, the company's first marketed controlled-release generic, capturing additional market share as substitution rates for the product also increase (i.e. increased share in a growing market)."

Second, many analysts significantly underestimated the profitability of Andrx's second manufactured controlled release generic product *Cartia XT* (a once-daily diltiazem calcium channel blocker product indicated for the treatment of high blood pressure and angina) which had further improvements in terms of pharmacokinetic profile and competitive positioning as Andrx learned from its first product launch and further refined its core technology platform. In particular, the market did not appear to appreciate how profitable the continued application of this core technology to related drugs could be for Andrx Corporation. For example, CIBC Oppenheimer said the following in its 28 July 1999 research report:

> "We reiterate our Strong Buy on the shares of ADRX after the release of record operating results for Q2 1999 that confirm our thesis that *ADRX possesses some of the most substantial earnings leverage in the specialty pharmaceutical spectrum [emphasis added]*.
>
> *Andrx's Cartia XT generic launch redefines Andrx's pipeline potential*. Andrx's Cartia XT generic is off to the fastest start of any generic launch ever, we believe, currently capturing 34% unit market share. The extraordinary launch performance of the company's second

> generic controlled release diltiazem hydrochloride was the catalyst for Andrx's second-quarter record results that blew past even the most optimistic projections.
>
> We had been using the sales ramp of Dilacor XR, Andrx's first marketed product, as our baseline for estimating the potential of future Andrx pipeline launches. The impressive launch of Andrx's first potential blockbuster Cartia XT clearly redefined the launch trajectory for the sales potential of Andrx's controlled release pipeline."

Separately, Salomon Smith Barney in a research report dated 10 February 2000 stated that:

> "ADRX reported Q4 1999 EPS of $0.63, again beating consensus and our expectations [the company's sixth consecutive upside earnings surprise]. Andrx had another strong quarter…powered by Cartia XT sales which drove the upside surprise. In our opinion, the company's impressive drug delivery technology platform should provide the basis for sustainable long-term growth."

Overall, it is clear that both equity analysts and the stock market failed, at least initially, to recognize the potential profits that Andrx Corporation could generate from its strategy of exploiting its existing innovative capabilities to improve the release profile of existing drugs. However, as the commercial potential of the firm's core drug delivery technology platform manifested itself in continual positive earnings surprises, the market price of Andrx increased substantially, thus generating abnormally high stock returns.

Appendix 2: Quintile sorts - portfolio returns from selected risk factor models

At the end of June of year *t* from 1982 to 2007, we sort firms independently into five groups based on the 20th, 40th, 60th and 80th percentiles of either a firm's *internal search proximity* or *exploitative patent ratio* score in year *t-1* and two size groups (small [S] or big [B]) based on the NYSE median size breakpoint at the end of June of year *t*. We hold these portfolios over the next 12 months and compute value-weighted monthly returns for each portfolio. We then calculate monthly size-adjusted returns of the five exploitation search focus portfolios in the same manner as Table 4. We measure exploitation search focus by *internal search proximity* and *exploitative patent ratio* (as defined in Section 2.2) in Panels A and B respectively. This table reports the monthly average size-adjusted excess returns to these portfolios in the first column of each Panel (computed as the difference between size-adjusted portfolio returns and the one-month Treasury bill rate, expressed in percentage terms) while the remaining columns of each Panel report the alphas (α, expressed in percentage terms) from regressing the time-series of portfolio excess returns on various factor returns. Heteroskedasticity-robust *t*-statistics are reported in parentheses. *MKT*, *SMB* and *HML* are the market, size and book-to-market ratio factors of the Fama & French (1993) three-factor model (*3F*). *RMW* and *CMA* are the robust-minus-weak factor and the conservative-minus-aggressive factors in Fama & French (2015). *LIQ* is the liquidity factor developed in Pastor & Stambaugh (2003).

	Internal search proximity			Exploitative patent ratio		
Portfolio	3F	3F+RMW+CMA	3F+LIQ	3F	3F+RMW+CMA	3F+LIQ
1 (Lowest)	-0.10	-0.05	-0.12	-0.12	-0.08	-0.15
t-stat	(-0.79)	(-0.39)	(-0.92)	(-1.03)	(-0.61)	(-1.24)
2	-0.09	-0.10	-0.11	0.00	-0.03	0.00
t-stat	(-0.80)	(-0.83)	(-0.94)	(0.00)	(-0.40)	(0.03)
3	0.03	-0.02	0.03	0.02	0.00	0.03
t-stat	(0.30)	(-0.17)	(0.31)	(0.21)	(0.03)	(0.28)
4	0.05	0.02	0.06	0.21	0.07	0.24
t-stat	(0.54)	(0.22)	(0.55)	(1.93)	(0.93)	(1.96)
5 (Highest)	0.22	0.19	0.23	0.25	0.33	0.25
t-stat	(2.07)	(1.76)	(2.14)	(2.30)	(3.12)	(2.48)
5 minus 1	0.32	0.25	0.35	0.37	0.41	0.40
t-stat	(2.85)	(2.26)	(3.05)	(2.80)	(2.63)	(3.16)

Appendix 3: Innovative search focus, return predictability and future earnings surprises

This table reports the average slopes (in %) and their associated Newey-West (1987) autocorrelation-adjusted heteroscedasticity-robust *t*-statistics from Fama-MacBeth (1973) cross-sectional regressions of individual monthly stock returns from July of year *t* to June of year *t* + 1 on exploitation search focus (defined as *internal search proximity* and *exploitative patent ratio* in year *t*-1 for columns (1)-(2) and (3)-(4) respectively) and other control variables. *Lagged Earnings Surprise* is defined as cumulative annual earnings surprise in the year *prior* to portfolio formation (see Table 3 for further details on the computation of quarterly earnings surprise). *Future Earnings Surprise* is calculated as the cumulative annual earnings surprise in the year *after* portfolio formation. *Size*, *BTM*, *ROE*, *CapEx*, *R&D*, *Patents*, *NS*, *Inst. Own*, *Illiquidity*, *Leverage*, *IV*, *SKEW*, *IE*, *IO*, *Firm Age*, *Conglomerate*, *Total Patent Stock*, *Advertising* and *SG&A* are defined in Table 1. *Momentum* is the prior 6 month returns (with one month gap between the holding period and the current month). *ST reversal* is the previous month's stock return. All regressions include industry dummies based on the Fama & French (1997) 48 industry classification scheme. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and one standard deviation. Average R^2 is the time-series average of the R^2 from the monthly cross-sectional regressions. The stock return data are from July 1982 to June 2008.

Dependent variable	Internal search proximity		Exploitative patent ratio	
	Monthly stock return	Monthly stock return	Monthly stock return	Monthly stock return
Exploitation search focus	0.09	0.08	0.08	0.04
	(1.74)	(1.42)	(1.96)	(0.91)
Lagged Earnings Surprise	-0.04	-0.00	-0.04	-0.01
	(-0.54)	(-0.03)	(-0.58)	(-0.15)
Future Earnings Surprise	0.77	0.74	0.77	0.73
	(10.80)	(10.08)	(10.73)	(10.00)
Size	-0.27	-0.17	-0.24	-0.14
	(-1.83)	(-1.14)	(-1.63)	(-0.92)
BTM	0.15	0.15	0.17	0.16
	(1.19)	(1.15)	(1.30)	(1.19)
Momentum	-0.07	-0.09	-0.07	-0.09
	(-0.72)	(-0.90)	(-0.66)	(-0.83)
ST reversal	-0.93	-0.91	-0.92	-0.92
	(-6.80)	(-6.59)	(-6.79)	(-6.60)
R&D	0.18	0.15	0.19	0.16
	(1.08)	(1.11)	(1.14)	(1.18)
Patents	-0.11	-0.09	-0.09	-0.07
	(-1.72)	(-1.42)	(-1.37)	(-1.08)
CapEx	-0.10	-0.07	-0.11	-0.07
	(-1.05)	(-0.64)	(-1.14)	(-0.66)
ROE	0.03	0.05	0.02	0.05
	(0.26)	(0.43)	(0.17)	(0.43)
Firm Age	-0.05	-0.03	-0.05	-0.03
	(-0.63)	(-0.48)	(-0.59)	(-0.41)
Conglomerate	0.14	0.14	0.12	0.13
	(1.64)	(1.45)	(1.39)	(1.29)
Total Patent Stock	0.10	0.06	0.08	0.05
	(1.66)	(0.98)	(1.32)	(0.79)
Advertising	0.04	-0.02	0.05	-0.01
	(0.77)	(-0.27)	(0.80)	(-0.22)
SG&A	-0.09	-0.03	-0.10	-0.04
	(-0.49)	(-0.16)	(-0.51)	(-0.23)
IE		0.03		0.03
		(0.57)		(0.56)
IO		0.07		0.05
		(1.01)		(0.68)
Illiquidity		-0.50		-0.56
		(-1.05)		(-1.10)
Leverage		0.05		0.05
		(0.56)		(0.53)
NS		-0.25		-0.26
		(-2.41)		(-2.58)
Inst. Own		0.05		0.06
		(1.03)		(1.12)
IV		0.61		0.63
		(1.93)		(1.99)
SKEW		-0.18		-0.17
		(-3.48)		(-3.35)
Constant	1.09	1.20	1.11	1.21
	(1.79)	(1.80)	(1.87)	(1.75)
Average R^2	0.22	0.25	0.22	0.26