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By *Sapnoti K. Eswar*, *Michael F. Ferguson*, *Jayoung Yoon*

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Sapnoti K. Eswar†
University of St Andrews
United Kingdom

Michael F. Ferguson
University of Cincinnati
United States

Jayoung Yoon
Drake University
United States

Abstract

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Keywords: Research & Development, absorptive capacity, patents, returns predictability, market efficiency.

JEL Classification Numbers: G14, G32, G4, O32, O33, L22.

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†Correspondence: Sapnoti K. Eswar, Department of Finance, St Andrews Business School, Castlecliffe, The Scores, St Andrews KY16 9AZ, Scotland, U.K. Email: se58@st-andrews.ac.uk

1 Introduction

Research and development is, conventionally, regarded as an investment which leads to the creation of new information, such as new products, processes, or patents. Cohen and Levinthal (1989) argue that research and development (R&D) has a dual purpose within the firm. Not only does R&D generate new information, but it also enhances a firm's ability to assimilate and utilize *existing* information, such as that arising from other firms' R&D investments ('spillovers'). The industrial organization literature has documented a strong positive effect of R&D spillovers on firm value (Bloom, Schankerman, and Van Reenen (2013)). Spillovers create more value for firms which have a greater ability to "exploit" outside information. This can be interpreted as both an ability to imitate new innovations or research, and an ability to utilize external knowledge of an intermediate sort, such as findings in basic research. A firm's ability to learn from other firms' R&D is what we will call its 'absorptive capacity.' Absorptive capacity represents an important alternative to direct R&D investment for creating new information and knowledge.

Absorptive capacity need not arise through happenstance; it can be, and often is, a strategic choice made by the firm. Through targeted investments in R&D a firm can obtain insights into its competitors' research programs, which it can then translate into refinements and extensions of its own research. The firm, thus, learns from its rivals; in effect creating a second mover advantage for itself in research and development. In this way, investments in absorptive capacity serve as a substitute for direct R&D investment.

There are numerous examples of firms exploiting second-mover advantages to learn from and eventually surpass first-movers. A well-known example from the early days of the internet involving a specific product is the web browser. Microsoft's Internet Explorer succeeded as a new entrant in the market for web browsers by copying several features and adding features that Netscape, the incumbent pioneer, did not have. For example, Internet Explorer enabled users to look at web pages through familiar applications such as Word, and to hear compact disc (CD)-quality sound. Bill Gates has referred to this as an "embrace and extend" strategy, where one embraces existing standards and then extends them. Microsoft is often not the first to market a product, however, it is often a winner that succeeds by out-featuring and outlasting its competitors (Zhang and Markman (1998), Mossberg (1997)).[1]

[1] A related issue is the antitrust lawsuit brought against Microsoft by U.S. federal and state antitrust authorities in 1998. The government's case was rested on allegations that Microsoft compelled computer manufacturers to license and install Internet Explorer, entered into contracts that tended to exclude rivals, and engaged in various forms of predatory conduct primarily to eliminate the competitive threat posed by Netscape (Gilbert and Katz (2001)). While the success of Internet Explorer was clearly enhanced by the anti-competitive business *tactics* used by Microsoft, it is also clear that the "embrace and extend" *strategy* was a key element of its success.

The interpretation of absorptive capacity as an alternative (or substitute) form of R&D investment has several implications. First, this may be a more efficient form of R&D investment for many firms, especially smaller or financially constrained firms. The efficiency of a second mover's investment can be improved in two ways: reducing cost or creating a higher quality product. In a sequential game, the second mover can reduce R&D costs by learning from the first-mover's technology. Furthermore, second-movers can take advantage of being a follower by improving the existing technology. This can include enhancing and/or adding new features. Second, the critique that R&D is complex, opaque, option-like, and generally difficult to value will apply to absorptive capacity as well. Thus, to the extent that direct R&D investments are mis-valued by investors, absorptive capacity may be as well. Finally, as with traditional R&D investments, the effects of investments in absorptive capacity on productivity, and ultimately firm value should be seen over long horizons (i.e., years, not months).

In this paper, we employ a new measure of absorptive capacity based on total factor productivity. We proxy for absorptive capacity by the contribution of R&D spillover to total factor productivity after controlling for own R&D. R&D spillover for each firm constitutes the sum of other firms' R&D weighted by technological distance. The technological distance between each pair of firms is estimated by calculating the distance between each firm's technology profiles, identified as the composition of each firm's patent portfolio (Bloom et al. (2014)). Controlling for own R&D is an important feature of our model as it helps us establish the absorptive capacity channel of R&D.

An example of an industry in our sample which has high median values of absorptive capacity is Drugs. Cohen et al. (2000) argue that industries in which patent protection is more effective would be one where patentors obtain monopoly rents. We posit that if patents are not as effective in an industry, then learning from counterparts is likely to be lower cost than if patents are more effective barriers. Consequently, the incentive to develop AC will be high in such an industry. Therefore, we anticipate that our measure of AC will be higher in pharma due to the observed proliferation of "me-too" drug products.[2] The high median values of AC that we document in the pharma industry provides suggestive evidence that our measure is capturing firm-level AC.

A well-known non-pharmaceutical example of a firm that has demonstrated a high degree

[2]Anecdotal pharmaceutical industry examples include Eli Lilly and Merck. Eli Lilly (Mounjaro) is a second mover to Novo Nordisk (Ozempic) in the obesity space but is poised to overtake them with a more powerful drug. Likewise, Merck (Keytruda) has trailed Bristol-Myers Squibb (Opdivo) in the oncology space but has recently developed a more effective follow-up drug. For more systematic analyses of the phenomenon of 'small innovations' in pharma and 'me too' drugs, see Ganuza et. al. (2009) and Aronson and Green (2020).

of absorptive capacity is Apple. Several products reveal the ability of Apple Inc. to develop and improve upon its competitors' offerings. For example, in the early 2000s, Research in Motion's Blackberry was a popular smartphone among business and government users due to its inclusion of email capabilities alongwith a QWERTY keyboard. Apple improved on the idea of the Blackberry and transitioned to a touchscreen keypad for its iPhone, which launched in 2007. Tellingly, in 2006 Apple had one of the highest estimated values of absorptive capacity in our sample.

We find that absorptive capacity appears to forecast returns. However, the effect is almost exclusively driven by the smallest quintile of firms. Overall, stocks characterized by high absorptive capacity in the past and that are also small outperform bigger firms or small firms with low absorptive capacity. We obtain similar results using either a portfolio formation approach or a Fama-MacBeth (1973) regression approach. Our results are robust controlling for firm characteristics (e.g., size, book-to-market, momentum, illiquidity, lagged returns,and idiosyncratic volatility) and various measures of R&D expenditures (e.g., ratio of R&D to market equity, ratio of number of patents to market equity, and ratio of capital expenditures to market equity).

A potential concern is that absorptive capacity of small firms captures existing linkages between firms within the same or closely related industries. Under this alternative hypothesis, existing linkages between firms would be responsible for, and thus entirely account for, the absorptive capacity channel. We include a multitude of known predictors of firm returns in our specification to account for this concern. For example, we include each firm's industry returns (Moskowitz and Grinblatt (1999)). In a separate specification, we control for each firm's supplier and customer returns (Cohen and Frazzini (2008), Menzly and Ozbas (2010)). In addition, for firms that have more than one business line, we control for returns generated by a portfolio of its "pseudo-conglomerate" peer firms, i.e., a portfolio of single-line firms that collectively span the firm's lines of business (Cohen and Lou (2012)). In all these specifications, our main result remains statistically significant. This indicates that the information firms acquire through learning via the absorptive capacity channel is not explained by information transferred within the industry or through the supply chain.

The relation between innovation and stock returns has been widely-studied. We show that our main results are unchanged after controlling for other documented R&D effects. We control for technological leaders, i.e., firms in the same industry as the focal firm which have large investments in R&D, and peers, firms which are technological followers (Jiang et al. (2016)). We control for large increases in R&D that took place in the last year, and over the last five years (Eberhart and Maxwell (2004)).

We confirm the forecast stock return results using portfolio analysis. Specifically, forming portfolios by double sorting firms into absorptive capacity and size quintiles, we show that a portfolio of firms with high absorptive capacity and small size outperforms a portfolio of low absorptive capacity, large size as well as a portfolio with low absorptive capacity, small size. A portfolio of high absorptive capacity, and small size firms earns 190 basis points per month (t= 4.58) and 218 basis points per month (t = 4.45) in equal- and value-weighted excess returns, respectively. The Carhart four-factor equal-weighted alphas are 135 basis points (t= 5.77) and value-weighted alphas are 146 basis points (t = 5.02) for the high absorptive capacity, small size firms. In contrast, a portfolio of firms with low absorptive capacity, and small size earns 44 basis points per month (t = 1.86), and 9 basis points (t = 0.35) in four-factor equal- and value-weighted alpha, respectively .

If AC is a substitute form of R&D, then we should see real effects of AC consistent with own firm R&D investment. For example, we should see firms with high AC generating more and higher quality innovative outputs than firms less well positioned to learn from spillovers. In fact, we do find that small firms with high absorptive capacity produce a greater number of patents and they produce more highly cited patents. Strikingly, we find that small market cap, High AC firms generate an additional 1.59 patents per year. This is roughly equivalent to a 0.07 standard deviation increase in patent output. In addition, these firms are also more likely to make future R&D investments of their own. These results are consistent with the hypothesis that small firms with higher absorptive capacity invest in future R&D and convert potential spillovers into valuable innovations.

Although, we cannot entirely rule out risk based explanations, our results suggest that higher returns earned by small firms with high absorptive capacity cannot be explained by risk factors alone. We conduct two further tests to explore a mispricing based explanation for our results. First we use the factors developed by Asness, Frazzini, and Pedersen (2019) (Quality minus Junk, QMJ, a long-horizon mispricing factor), Stambaugh and Yuan (2017) (PERF for transient mispricing and MGMT for long-horizon mispricing), and Daniel, Hirshleifer, and Sun (2020) (PEAD for short-horizon mispricing and FIN for long-horizon mispricing). Interestingly, we find that the higher returns earned by small firms with high absorptive capacity are not related to the short-horizon factors, but they are strongly associated with the long-horizon mispricing factors.

Second, we examine the stock price reaction around subsequent earnings announcements. This test is well established in the literature as a test to separate risk from mispricing explanations (La Porta et al. (1997), Gleason and Lee (2003), Engelberg et al. (2018) among others). Earnings announcements help correct investor expectation errors about future cash flows and, therefore, if an anomaly is associated with investor misperceptions about the firms' cash flows, then a disproportionate amount of its returns should be realized around subsequent earnings announcements. On the other hand, if an anomaly is driven by changes in underlying risk then future returns should accrue more evenly over subsequent periods. Our tests show that the high absorptive capacity effect for small firms is 550% higher during the 3-day earnings announcement window than on a non-announcement day. This result is evidence in favour of a mispricing hypothesis.

We evaluate the potential channels by which mispricing may be operating. We identify firms which are exposed to high costs of arbitrage (high idiosyncratic volatility, low firm age, and high Bid-Ask spread) and limited investor attention (low analyst coverage, high forecast dispersion, and low institutional ownership). We find that our main result is significantly stronger for firms subject to higher arbitrage costs and characterized by less investor attention.

In addition to the tests reported in the main text of this study, our Internet Appendix provides several robustness tests. First, we document the robustness of our specification to changes in the definition of small firms. We use an indicator for the smallest quintile of firms as a proxy for size. We also use the bottom 10 percentile of NYSE size deciles to define small firms. Second, we report the robustness of our return predictability result for two sub-periods. In both sub-periods, we find that the high absorptive capacity effect on small firms is robust. Third, we employ alternative definitions of absorptive capacity, varying the regression specification to accommodate alternative measures of absorptive capacity. Our results show that for these alternative proxies, the high absorptive capacity effect on small firms is positive and significant. In addition, we control for own R&D intensity, which has been used in earlier work as a proxy for absorptive capacity (Cohen and Levinthal (1989), Oh (2017)). Our main result is robust to this inclusion. Fourth, we use alternative industry classifications to control for industry fixed effects. In separate specifications, we use Fama-French 12 industry, Fama-French 30 industry classifications, and SIC 2-digit classifications. In all these ases, our main result continues to be robust and significant.

Our main result is most similar to Stoffman, Woeppel and Yavuz (2022). They focus on documented innovators (firms with recent patent grants) whereas we focus on firms that more generally are able to convert R&D spillovers into increased productivity. They find that small innovators earn higher future returns than small non-innovators. They argue that under-reaction cannot explain long-term returns and so their finding must be driven by a risk borne by small innovators. Our paper focuses on innovative firms, more generally, and we find evidence consistent with long-horizon mispricing in these firms.

In addition to our contribution to the literature on innovation, R&D spillovers, and returns, we create a novel measure of absorptive capacity. Our method is motivated by economic theory which models innovation as the driver of sustainable economic growth and is directly responsible for generating changes in total factor productivity (TFP). Theoretically, absorptive capacity contributes directly to TFP by increasing the output of the firms capital and labor outputs beyond that implied by traditional R&D investments alone (Yoon (2022)). Based on this theoretical linkage, we proxy for absorptive capacity using TFP as the channel through which spillovers contribute to firm value.

Our approach also has two key strengths over other empirical proxies. First, our measure does not impose the constraint that absorptive capacity always manifests itself as a patent. In other words, second movers do not necessarily have to register a patent for the firm to have increased the value of their productive assets. By contrast, Mancusi (2008), measures absorptive capacity based on the elasticity of an industry's patent outputs to domestic and foreign R&D spillovers at the country level. This measure obviously captures patent outputs, but understates the absorption (learning) actually taking place. We know the direction of this bias, but not its magnitude.

Second, our method controls for the contribution of a firm's own R&D to its TFP. This allows us to differentiate between direct R&D effects and R&D spillover effects. In other words, we focus on the incremental contribution of a firm's ability to utilize external knowledge. By contrast, proxies for absorptive capacity like R&D intensity (Cohen and Levinthal (1989), and Oh (2017)) that are based on own R&D, have confounding implications as the relationship between spillovers and own R&D investment is intermingled. Both the direction and the magnitude of the bias are unclear in this case. On one hand, a firm may be motivated to invest in R&D to exploit existing external knowledge, this would increase an absorptive capacity proxy such as R&D intensity. On the other hand, a firm that has high absorptive capacity may substitute absorptive capacity for its traditional R&D investments to focus on the existing pool of knowledge created by spillovers. This would decrease the R&D intensity measure. Because our measure differentiates between absorptive capacity and own R&D it can, therefore, be utilized to study such confounding effects of absorptive capacity. Yoon (2022), for example, shows using a firm-level measure, related to our AC measure, that high AC along with spillovers is positively related to R&D intensity in non-high-tech sectors while it is negatively related to R&D intensity in high-tech sectors.

In contrast to the conclusion that returns associated with innovation are compensation for risk, numerous authors find a positive relation between changes in R&D and future returns which they attribute to mispricing (early examples include Chambers et al., 2002; Eberhart et al., 2004). Gu (2005) shows that a change in patent citation impact scaled by total assets predicts future returns.[3] In a series of papers Cohen, Hirshleifer, and their co-authors argue

[3]However, Gu(2005) concludes that abnormal returns are very small and unlikely to survive trading costs.

that R&D investments are undervalued for several non-risk driven reasons including the difficulty of evaluating complex R&D, the low salience of R&D investment announcements, information processing costs, and limited investor attention.[4] We contribute to this literature by documenting that the mispricing in our results is more in line with long-horizon mispricing.

In summary, we identify a novel channel, absorptive capacity, as a source of market underreaction to the information contained in reported R&D investments. Our specific measure of absorptive capacity allows us to estimate the extent to which firms are able to exploit the information environment created by R&D spillovers. This matters because, in short, it is not simply that R&D investment is opaque, option-like, or difficult to value. R&D appears to be mis-priced in part because the impact on firm value of a firm's own R&D investments is also a function of complex interactions of those investments with its technological rivals' R&D investments.

2 Literature Review

This paper is related to the literature relating R&D productivity and future returns. Cohen, Diether, and Malloy (2013) measure a firm's ability to innovate by relating a firm's R&D stock to its sales growth. They interpret this measure as capturing a firm's past track record, allowing investors to predict returns and future outcomes in patents and innovations. Hirshleifer, Hsu, and Li (2013) create measures of innovative efficiency that represent the output per input of R&D based on the ratio of patents or patent citations to R&D. They find that high innovative efficiency is related to high future returns and operating performance. Stoffman, Woeppel, and Yavuz (2019) focus on small innovators and document that they have higher returns in comparison to small non-innovators. The authors conclude that these returns are compensation for risks faced by small innovators.

We focus on a firm's ability to utilize external R&D. Cohen and Levinthal (1989) focus on the two roles of Research and Development (R&D): producing new knowledge and enhancing the ability to utilize external knowledge. They call this second aspect a firm's absorptive capacity. The traditional concern was that knowledge or R&D efforts can be appropriated by others and this could lead to underinvestment. However, the logic of absorptive capacity, implies there may be incentive to invest more (or atleast offset some of the negative spillover effects). The main contribution of Cohen and Levinthal (1989) is to document that contrary to the traditional fear that knowledge spillovers always have negative effects on own R&D

[4]Cohen et al.(2013) (firm's ability to transform R&D investments into future sales), Hirshleifer et al.(2013) (ratio of patents or citations to R&D assets), and Hirshleifer et al.(2018) (innovative originality) each develop R&D-related measures that forecast higher future returns which they attribute to mispricing rather than risk.

investment, the knowledge gain from spillovers may encourage R&D investment because the ability to capitalize on spillovers is dependent on prior R&D investment. In other words, spillovers can have positive effects.

Bloom, Schankerman and Van Reenen (2013) also recognize the externalities arising from rival's R&D spillovers. The paper relates the spillovers to market value, patents, productivity and R&D intensity. The R&D spillover from technologically close firms should have positive effects on a firm's market value, whereas R&D spillover from firms in closely related product markets, should have negative effects on a firm's market value. Their paper shows that firm-specific spillovers matter and that the effects can be different across product and technology spaces. Lychagin, Pinkse, Slade, and Van Reenen (2016) focus on the effects of R&D spillovers on productivity. They distinguish three sources of R&D spillovers: technological, product market, and geographic. Their main contribution is in identifying the importance of geographic distance in knowledge spillovers.

Our paper is broadly motivated by the economic implications of spillovers. Chalioti (2019) shows that when R&D between firms are strategic complements, there is a regenerative feedback effect that makes spillovers have positive effects on own R&D investment. Firms benefit from the cost reduction effects of R&D and spillovers even when they are producing homogenous goods. Smrkolj and Wagener (2019) utilize an infinite horizon dynamic model to show that spillovers have different implications on future market structure, depending on the original state of the market. Low initial spillovers may induce entry or creation of markets with high production cost, as the potential profits can be strong incentives for R&D efforts. High spillovers can induce competition in the market as firms take advantage of the spillovers, however, in the later stages of development when production costs are low, it reduces the innovative efforts of the frontier firms as the potential spill-outs are more costly then the benefits. In addition, high levels of spillover may be related to laggards free-riding; the overall effect being a lower level of technological development. Lopez and Vives (2019) model the effect of overlapping ownership agreement and its effect on R&D activity and production output. Their model shows that in industries that have large spillovers, overlapping ownership agreements are welfare enhancing and increase R&D.

Providing some insight to the empirical economic effects of spillovers, Konig, Liu, and Zenou (2019) model the economic effect of R&D alliance network in terms of spillovers and market effect of product rivalry. Empirically, they show that spillovers dominate, and the net effect is strictly positive. Lucking, Bloom, and Van Reenen (2019) investigate the nature of spillovers through time. Spillovers have been relatively stable in magnitude except around the period of the dot-com bubble, when there was an increase.

At the firm level, Li, Qui, and Wang (2019) show that conglomerate firms, firms with high technological proximity to other patenting firms, are more likely to form alliances. These alliances in turn lead to more patents, novel patents as well as patents with more impact, especially for these technology conglomerates. Glitz and Meyersson (2020) documents how industrial espionage helped reduce sector TFP gap between East and West Germany during the Cold War. This implies that spillover of knowledge has effects on productivity.

This paper is also related to the theoretical literature that investigates the dynamics of R&D leaders and followers. Bondarev and Greiner (2018) model the complex dynamics between R&D leaders and followers. Their model illustrates that the dynamics depend on the technological gap between the leader and follower as well as the number of competitors. Aldieri, Sena, and Vinci (2018) distinguishes between technological knowledge spillovers and rent spillovers to show that absorptive capacity is important for knowledge spillover. They focus on the nature of knowledge a firm requires.

Our paper is most closely related to the literature on spillovers and future returns. Nguyen and Keckes (2020) focus on the economic information inherent in technology spillovers that is relevant to innovative firms. They argue that the information gleaned from technologically related firms potentially reduces the overall cost of collecting information. However, this abundance of information can cause an increase in information processing costs if the valuation of firms become too complex and uncertain. The increased complexity decreases the motivation for outsiders to process information and as a result they are at a disadvantage relative to insiders. Lee, Sun, Wang, and Zhang (2019) note that firms' R&D investments interact and show that past technologically linked firms' returns predict (lead) the focal firm's return. They coin this, technology momentum, and they show that it is different from industry momentum as firms can be technologically related but be in different industries. The effect is attributed to mispricing due to slow incorporation of information for technology-intensive firms and firms with more industry specific technology. Oh (2017) shows that technology spillovers alone are not sufficient for future high returns; a complementary relationship between spillovers and absorptive capacity is necessary. The effect is greater for stocks with limited attention, implying mispricing as a source. Oh (2017) uses R&D intensity as a proxy for absorptive capacity. Our measure is based on firm productivity or value added. Moreover, as noted above, we view absorptive capacity as a substitute for some R&D investment.

Finally our paper is related to the growing literature on mis-pricing factors. Asness, Frazzini, and Pedersen (2019) define quality as a combination of various firm characteristics such as profitability, growth and safety. They document that quality is underpriced. High quality stocks tend to have (only moderately) high prices, which leads to these stocks having higher risk-adjusted returns. They create a factor portfolio, QMJ, and show that returns on QMJ are correlated with analyst errors. Stambaugh and Yuan (2017) aggregate 11 separate anomalies into two clusters by ranking stocks according to these anomalies. The clusters are identified by combining the stocks with the greatest return co-movement. The clusters correspond to a short- and a long-time horizon over which they operate. In a similar spirit, Daniel, Hirshliefer and Sun (2020) augment existing asset pricing models by adding two factors based on long- and short-horizon mispricing. The underlying intuition is that investors with limited attention underreact to public information which arrives at a high frequency. For example, stock prices underreact to earnings surprises, but these misperceptions are corrected at short-time horizons. An example of mispricing that would have longer-horizon consequences is investor overconfidence.

3 Data

We discuss data sources and construction of our absorptive capacity measure, and then present the summary statistics of the variables. Our sample includes firms in the intersection of Center for Research in Security Prices (CRSP), Compustat, and the National Bureau of Economic Research (NBER) patent database[5].

We obtain accounting data from Compustat, and firm returns from CRSP. All domestic common shares trading on NYSE, NASDAQ, and AMEX (with CRSP codes 10 or 11) with accounting and returns data are included except financial firms, which have four-digit standard industrial classification (SIC) codes between 6000 and 6999 (finance, insurance, and real estate sectors), and utilities, which have SIC codes between 4900 and 4949. To ensure that the relevant accounting information is publicly known to investors at the time of portfolio formation, we impose at least a six-month gap between fiscal year end month and the date of portfolio formation.

The NBER patent database spans patents applied for within the years 1970 to 2006. We first match the NBER patent data with Compustat accounting data for the most recent fiscal year, i.e., the fiscal year ended in calendar year t. We then match CRSP stock returns from July of year $t+1$ to June of year $t+2$. We restrict our sample to include firms which have at least one patent granted over the period 1976 to 2006. To reduce the impact of micro-cap stocks, we eliminate observations that have a price of less than one dollar at the time of portfolio formation.

[5]https://sites.google.com/site/patentdataproject/Home

3.1 Absorptive Capacity, Spillover, and Total Factor Productivity

Absorptive capacity is the ability of a firm to "learn" from the R&D expenditures of its competitors or "technologically-close" firms, to improve its performance. In this section, we define three main elements - absorptive capacity, R&D spillover, and firm performance. Bloom, Schankerman, and Van Reenen (2013) show that R&D spillover, or the R&D expenditures of technologically-close firms, can have a measurable impact on firm value. We define absorptive capacity (AC) as the ability of a firm to take advantage of the R&D expenditures of technologically-close firms and turn those R&D spillovers into higher *own* value. As we detail below, our measure of AC will be firm-year specific.

Following Bloom et al (2013) and Jaffe (1986), we define technological distance, $TECH_{ij}$, as the uncentered correlation of the patent distributions between all pairs of firms i and j.

$$TECH_{ij} = \frac{(T_i T_j')}{(T_i T_i')^{1/2}(T_j T_j')^{1/2}} \tag{1}$$

where $T_i = (T_{i1}, T_{i2}, ..., T_{i421})$ is a vector of firm i's proportional share of patents across the 421 USPTO technology classes over the time period 1970 to 2006. Technological closeness ranges between zero and one, depending on the degree of overlap in technology space, and is symmetric in firm ordering ($TECH_{ij} = TECH_{ji}$).

We then define R&D spillover ($Spilltech_{it}$) as the average R&D stock of technologically-close firms, weighted by pairwise technological distance (Jaffe (1986)). Formally, Spilltech for firm i in year t is defined as:

$$\begin{aligned} Spilltech_{it} &= \sum_{j \neq i} TECH_{ij} G_{jt} = \sum_{j \neq i} \frac{(T_i T_j')}{(T_i T_i')^{\frac{1}{2}}(T_j T_j')^{\frac{1}{2}}} G_{jt} \\ where\ G_{jt} &= RD_{jt} + (1-\delta)G_{jt-1} \end{aligned} \tag{2}$$

G_{jt} is the R&D stock of firm j in year t, calculated using the perpetual inventory method with a depreciation rate $\delta = 15\%$ (Bloom et al (2013), Hall, Jaffe, and Trajtenberg (2005)). RD_{jt} is the R&D expenditure of firm j in year t.

We then calculate total factor productivity of each firm for each year, which is our measure of firm performance. Total factor productivity (TFP) measures the overall effectiveness with which capital and labor are used in the production process. It is a broader gauge of firm performance than some of the more conventional measures, such as firm profitability (İmrohoroğlu and & Tüzel (2014)). We estimate the following production function :

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \tag{3}$$

where y_{it} is the log of value added (defined as sales minus material expense, where material expense is the difference between total expense and labor expense), for firm i in year t, l_{it}, and k_{it} are the logged values of labor and capital respectively, and ω_{it} is the productivity (or TFP) of the firm. η_{it} represents an idiosyncratic error term.

The parameters of the production function are estimated using a semi-parametric method (Olley and Pakes (1996)), explained in detail in the Appendix. A major advantage of this method, over other approaches such as the ordinary least squares (OLS) method, is that it controls for simultaneity and selection biases as well as within-firm serial correlation in productivity.

We use Compustat for the years 1963 to 2006 to estimate value added, and get firm-specific capital expenditure and employment data. Following İmrohoroğlu and & Tüzel (2014), National average wage index from the Social Security Administration is incorporated to compute labor expense. We include industry-year fixed effects, based on SIC three-digit industries, in the estimation. This inclusion ensures that our TFPs are free from the effect of aggregate, and industry level shocks in any given year.

The production function parameters are estimated each year using data up until that year to mitigate a potential look-ahead bias in our TFP estimates. We compute TFPs for each year between 1980 and 2006 using that year's data and the corresponding production function estimates for the year.

$$Ln(TFP_{it}) = y_{it} - \hat{\beta}_{0t} - \hat{\beta}_{kt}k_{it} - \hat{\beta}_{lt}l_{it} \tag{4}$$

We proxy for absorptive capacity by the contribution of R&D spillover to firm productivity.[6] We run firm-by-firm rolling regressions of firm performance ($Ln(TFP_{it})$) on lagged R&D spillover ($Ln(Spilltech_{it-j})$), where j = 1, 2, 3, 4, and 5. We run separate regressions for each of the five, R&D spillover lags; we then take the average of these five coefficients as our measure of absorptive capacity (AC_{it}) (Cohen, Diether, Malloy (2013))[7]. We also include the firm's own R&D stock ($Ln(G_{it-j}$), and an indicator for zero value of own R&D stock, to account for the effect of own R&D on firm productivity.

[6] Productivity is actually a more direct measure of the firms ability to convert externally created knowledge into real output than patent output. Patent output is a noisy measure of absorptive capacity because only a small fraction of innovations are patented.

[7] We conduct several robustness tests for the regression specification which include (1) using the average of past 5 years' Spilltech as the independent variable and the average of five years' TFP as the dependent variable, and (2) Including all five lags of Spilltech in the same regression specification

$$
\begin{aligned}
Ln(TFP_{it}) = {} & a_{it-j} + b_{it-j} Ln(G_{it-j}) + c_{it-j} \mathbb{1}(G_{it-j} = 0) \\
& + d_{it-j} Ln(Spilltech_{it-j}) + e_{it-j} && (5)
\end{aligned}
$$

$$
AC_{it} = \frac{1}{5} \sum_{j=1}^{5} d_{it-j} \qquad (6)
$$

where, G_{it-j} is the R&D stock of firm i in year $t-j$, $\mathbb{1}(G_{it-j} = 0)$ is an indicator for zero R&D stock. We calculate AC_{it} at the end of each fiscal year, and then map it to the return data from July of year $t+1$ to June of year $t+2$.

The final sample consists of 219,839 firm-month observations spanning July 1986 to Dec 2006, i.e., 246 months.

3.2 Summary Statistics

Table 1 Panel A reports descriptive statistics for our sample firms. Given our focus on cross-sectional variation in AC, we sort the sample by lagged absorptive capacity. At the end of June of year t, we divide firms into five AC groups based on the absorptive capacity twelve months ago by the 20th, 40th, 60th, and 80th percentiles of AC. The average number of firms in each of the quintiles is around 184. The average monthly excess return, i.e., monthly firm return minus the one-month Treasury bill rate, is around 0.96%. The average AC is -4.45 in the lowest quintile, monotonically increasing to 4.09 in the highest quintile. The total factor productivity (Ln(TFP)) is -0.24 in the lowest AC quintile, and -0.05 in the highest AC quintile.

The mean value of Spilltech is \$ 0.59 billion in the lowest AC quintile and \$ 0.61 billion in the highest AC quintile. The values of Spilltech across the AC quintiles are not statistically different. This fact is noteworthy as it implies that firms across AC quintiles are, on average, exposed to similar levels of spillover from their counterparts. The mean value of Size is also similar across the AC quintiles, which suggests that firms of similar sizes are present in all quintiles. We report the means of all remaining control variables across the AC quintiles in the following rows. For nearly all of these variables, the means are not significantly different across the lowest and the highest AC quintile. Finally, note that excess returns, return on assets (ROA), and asset growth (AG), are increasing across AC quintiles. This is consistent with the hypothesis that firms with higher AC have a greater ability to transform R&D spillovers into its *own* value (i.e., into productive assets).

In Panel B, we focus on some diagnostics of our AC measure. If we are truly capturing a meaningful measure of a firm's ability to learn from its counterparts, we might expect to see some level of persistence in this firm characteristic. We report the annual persistence in a firm's AC quintile for yearly lags of one to five years. If our measure of AC was completely random we would expect to see firms remain in the same quintile about 20% of the time from one year to the next. Instead we find that firms stay in the same quintile about half the time from one year to the next. This persistence is most pronounced at the extremes. Firms in the highest AC quintile remain in this same top quintile in the following year 56% of the time. Similarly, firms in the lowest AC quintile remain in this same bottom quintile in the following year 54% of the time.

In Table 2, we provide some summary statistics for AC across industries. These industry statistics are meant to serve as examples to illustrate that AC is likely measuring firm-level learning or absorptive capacity.

Our AC measure will be higher if R&D spillovers (*Spilltech*) from "technologically close" firms is high and if the correlation between these R&D spillovers and the TFP of the firm is high. Therefore, for each industry we provide summary statistics for AC and Spilltech. It is also noteworthy that in our calculation for TFP, we have included industry-year fixed effects. As a result, our TFP and AC measures do not incorporate aggregate, industry-level shocks but firm-level changes in these measures.

The industries with some of the highest median values for AC are Drugs and Food. The industries with some of the lowest median values of AC are Textiles, Oil & Petroleum and Mining and Minerals. Cohen et al. (2000) posit that industries in which patents are strong and effective would be one where patentors obtain monopoly rents. This relates closely to our channel of absorptive capacity. Our hypothesis that firms are able to learn from technologically close counterparts depends on industry level intellectual property protection or patent effectiveness. If patents are strong and effective then we argue that AC will be low, on average, in such an industry.

Ganuza et al. (2009), and Aronson and Green (2020) have highlighted the existence of "me-too" products in the Drugs industry. These are follow-on products which are small modifications to existing competitor products. The ease of creating me-too products suggests that the patent effectiveness is likely to be relatively low in drugs and pharmaceuticals. Consequently, we would expect firms to invest in AC to exploit this weak protection. This hypothesis aligns with the high estimated values of AC for this industry in our sample. The ability to create small changes based on existing products is an example of firm-level learning.

KamranBilir (2014) documents that the length of the product lifecycle in any industry can have a knock-on effect on patent effectiveness. If product lifecycle length is long, then this greater length can further increase the "effectiveness" of patents. On the flip side, if product lifecycle length is short, then this has a dampening effect on patent effectiveness. Drugs or pharmaceutical products are categorized as low to medium lifecycle length. This fact also aligns with the high AC for the Drugs industry documented in our sample.[8]

To further develop our intuition about the AC measure, we focus on two industries, one which has some of the highest AC firms and one which includes some of the lowest AC firms, Drugs and Textiles respectively. Figure 1 plots the median AC for all firms across the two industries over time. The higher line shows the median AC for Drugs and the lower line for Textiles. Over the entire sample period, except for the first year, the median AC for firms in the Drugs industry is equal to or higher than that for firms in the Textiles industry. This figure illustrates that the median AC is not driven by outliers over time. It also reveals that, to some extent, our measure of AC is relatively stable within an industry.

To provide concrete examples of AC, we focus on two firms in our sample with high estimated values of absorptive capacity: the first example is Apple. In 1983, Apple introduced its personal computer, Lisa, using several innovations such as the graphical user interface (GUI) from the Alto computer at Xerox PARC[9]. In 2001, Apple introduced the iPod. There were over 50 other mp3 players in the market at the time of release, however, the iPod quickly took over the market. In the early 2000s, Blackberry was a popular smartphone among business and government users due to its inclusion of email capabilities into a phone. Apple improved on Research in Motion's Blackberry and transitioned from a full physical keypad to a touch screen keypad. In the early 2000s, the estimated value of AC for Apple was at least in the second highest quintile each year.

Another example of a firm with a high AC is Spectranetics Inc. This example illustrates the phenomenon of high AC in a small firm, which is the group of firms which contribute directly to our main result of higher returns. Spectranetics was a second mover as a medical laser manufacturer, following Advanced Interventional Systems Inc., its major competitor. Advanced Interventional System Inc. was started by a team of cardiovascular specialists in California, who wanted to apply lasers to arteries in surgery. The team brought in laser physicists and fiber optics scientists to make it a reality.[10] The follower, Spectranetics, was founded by an electrical engineering instructor in Colorado, Robert Golobic, who had research experience in lasers but no medical knowledge.[11] Both companies worked on excimer laser coronary atherectomy (ELCA) devices used for coronary surgeries. Advanced

[8]KamranBilir (2014) also document that one of the industries with long product lifecycle length is Fabricated Products. In our sample, this industry has medium AC. This fact aligns well with the hypothesis that longer product lifecycles can lead to higher effectiveness of patents, and thereby to lower AC.

[9]Source: https://www.forbes.com/sites/gilpress/2017/01/15/steve-jobs-steals-from-xerox-to-battle-big-brother-ibm/?sh=42f8064312e0

[10]Norman Bauman.Corporate Profile: Advanced Interventional Systems: Powerful Excimers, Flexible Fibers.Laser Medicine and Surgery News and Advances. Aug 1989.21-24. http://doi.org/10.1089/lms.1989.7.4.21

[11] https://gazette.com/business/spectranetics-survives-challenges-to-become-company-worth-nearly-1b/article_8bf6e5a8-6a9a-5ff9-9fa1-c9a3a1f629be.html

Interventional Systems' medical device received approval from the U.S. Food and Drug Administration before Spectranetics' device. Spectranetics' device was similar enough in design and outcomes that the competitor sued Spectranetics for infringement of four of its patents. Spectranetics later improved upon existing technology and medical research, published in 2004, accredited Spectanetics for these improvements.[12] The firm was succesfully acquired by Philips, which continues to manufacture modern ELCA equipment. Spectranetics has an AC which is in the highest quintile in the last several years of our sample period, 2004-2006.

In the next section, we conduct a formal analysis of the effect of the absorptive capacity channel on firm returns.

4 Methodology and Main Results

4.1 Portfolio Returns

In this subsection, we examine average returns on portfolios using information about a firm's absorptive capacity and size. As detailed above, AC is lagged (measured as of year $t-1$) while size is the market value of equity at the end of June of year t. The intersection of quintile sorts on these two characteristics forms 25 AC-size portfolios. We hold these portfolios over 12 months (July of year t to June of year $t+1$) and compute equal-weighted (and value-weighted) monthly returns for each of the 25 portfolios (Hirshleifer, Hsu, and Li (2013)).

Table 3 Panel A shows the average monthly portfolio return net of the one-month Treasury bill rate (excess returns) for these portfolios. The excess returns on the portfolios increase with AC, although this increase is not monotonic. Specifically, for the High AC-Small size portfolio (highest quintile on AC, and lowest quintile on size) the average monthly excess return is 190 basis points (t-state= 4.58) and the Low AC-Small size portfolio excess return is 118 basis points (t-stat= 2.73).[13] The spread between these two portfolios is 72 basis points (t-stat=3.96). Holding AC constant, we see that the spread between the largest and smallest quintiles is always significantly positive except for the firms with lowest AC.

Table 3 Panel B shows the average monthly excess return for value-weighted portfolios. The High AC-Small portfolio has an average of 218 basis points (t-stat=4.45), and the Low

[12]Bilodeau, L., Fretz, E. B., Taeymans, Y., Koolen, J., Taylor, K., and Hilton, D. J. (2004), 62(2), 155-161

[13]The greatest return by far is to the High AC-Small market capitalization portfolio. The natural short against this would be to sell the Low AC-Big portfolio represented by the opposite corner of each panel in Table 2. Panel A shows that the equal-weighted spread between these portfolios is 98 basis points (t-stat=2.70). The analogous 'diagonal' spread in Panel B is 148 basis points (t-stat=2.73). For the value-weighted portfolios this is comparable to the 140 basis points spread from High AC-Small portfolio minus High AC-Big portfolio.

AC-Big portfolio 70 basis points (t-stat=2.49). For the smallest firms,the spread between High AC and Low AC is 132 basis points (t-stat=4.88). Note that in both Panel A and Panel B the most attractive trade implied by the column or row spreads is long the High AC-Small portfolio and short the High AC-Big portfolio. These spreads are 115 basis points (t-stat=2.97) for the equal-weighted portfolios and 140 basis points (t-stat=2.40) for the value-weighted portfolios.

The major takeaway from Table 3, and our main result, is that AC appears to forecast returns. However, this effect is almost exclusively driven by the smallest quintile of firms. Stocks characterized by high absorptive capacity in the past and that are also small outperform in the future. This is intriguing, albeit not surprising in light of our discussion of returns to small innovators in the Introduction. Gaining a better understanding of these firms will be the focus of the rest of the paper. Consequently, we will focus our analysis on firms in the High AC, Small portfolio throughout the rest of the paper.

4.2 Fama-Macbeth Regressions

In this subsection, we examine the ability of AC to predict returns using monthly Fama-Macbeth (1973) cross-sectional regressions. This analysis allows us to control for other firm characteristics that can predict returns, to verify whether there is a positive relation between high AC and stock returns.

Following Fama and French (1992), we impose a minimum six-month lag between stock returns and the accounting variables to assure the full visibility of the accounting variables to investors. Specifically, for each month from July of year t to June of year $t+1$, we regress monthly returns for the firm minus the one-month Treasury bill rate on our main variable of interest *High AC * Small* in the year $t-1$, other control variables, and industry fixed effects using the Fama and French (1997) 17 industry classifications.

High AC takes the value one if the firm is in the highest quintile of AC, and *Small*, is an indicator variable which takes the value one if the firm is in the lowest size quintile. Other control variables include lagged size(*Size*), book-to-market(BM), ratio of R&D to market equity($RDME$), capital expenditure ($CAPXME$), patenting intensity ($PATME$), profitability (ROA), asset growth (AG) and industry indicator variables based on the Fama and French (1997) 17 industries. In separate specifications, we include *Size* in place of the variable *Small* because these are based on market capitalization. We use alternative measures for capital expenditure and patenting intensity, the ratio of capital expenditure to assets ($CAPXAT$), and the ratio of patents to total assets ($PATAT$) respectively.

We include a short-term return reversal variable, defined as the firm's stock return in the previous month (*Reversal*) (Jegadeesh and Titman (1993)), and a medium-term price momentum variable defined as the firm's stock return over the last twelve months excluding the previous month's return (*Momentum*) (Chan, Jegadeesh, and Lakonishok (1996)). We also include illiquidity defined as the absolute value of the monthly stock return divided by the monthly dollar trading volume (*Illiquidity*) (Amihud (2002)), and idiosyncratic volatility defined as the standard deviation of the residual from a regression of daily stock returns in excess of the risk-free rate on daily market returns in excess of the risk-free rate over the previous twelve months (*IVOL*) (Ang, Hodrick, Xing and Zhang (2006)).

All independent variables are winsorized at the 1% and 99% level to reduce the impact of outliers, and then they are all standardized (except indicator variables) to zero mean and one standard deviation to facilitate the comparison of economic effects of all variables. Cross-sectional regressions are run each calendar month and the standard errors, shown in parentheses, are Newey and West (1987) adjusted using twelve lags, for heteroskedasticity and auto-correlation.

Table 4, columns (1) to (3) report the main results. In all specifications, the slopes on *High AC * Small* are positive and significant, ranging from 0.58% to 0.74%. With industry fixed effects and including book-to-market as the only control variable, the coefficient on *High AC * Small* is 0.737 with a t-statistic of 4.10, indicating that the average monthly return spread of firms with High AC and small size is 73.7 basis points. In column (4) we include book-to-market, log of R&D to market equity, capital expenditure, patenting intensity, short-term reversal, and momentum. The coefficients on the control variables are consistent with prior literature: size, capital expenditure, and reversal are negatively correlated with future returns; book-to-market, R&D, patenting intensity, and momentum are positively correlated with future returns. With these additional controls, the coefficient on *High AC * Small* and the t-statistic decrease compared to column (3), but the coefficient continues to be positive and statistically significant. In columns (5) and (6), we further control for observables which are known to predict future returns. In column (5), we include *Illiquidity* and *IVOL*. The coefficient of interest continues to be positive and statistically significant. In column (6), we control for alternative measures of capital expenditure and patenting intensity, and profitability and asset growth.[14] We obtain similar results in this specification. Small firms, that have high AC in the past, have higher future returns. After controlling for known predictors of returns, we find that small firms with High AC have a higher monthly return spread between 52.3 and 73.7 basis points.

[14]Comparing column (4) with column (5) and, especially, column (6) it appears that the effect of size (without interaction with AC) on returns is driven by its negative correlation with IVOL. Once IVOL is added to the regressions, the size coefficient is not significant.

Existing literature has identified several linkages between firms within industry, and documented the effects of these linkages on firm returns. To distinguish our absorptive capacity effect from other industry-related effects, we consider several alternative measures of industry linkages. Table 5 reports the results of controlling for these alternative industry-linkage measures.

Moskowitz and Grinblatt (1999) document that industry returns can predict firm returns over the short term; this phenomenon is strongest in the month immediately after portfolio formation. In column (1), we control for lagged industry returns based on 2-digit SIC code industries, to make sure that we are not rediscovering the industry momentum effect. The coefficient on our variable of interest is 0.520%. Comparing these coefficients to the coefficients in columns (4) to (6) in Table 4, reveals that the magnitude of the effect is somewhat smaller, but its statistical significance is nearly unchanged when we include lagged industry returns. In addition, the coefficient on industry returns is not significant in our specification. In column (2), we control for supplier and customer returns (Menzly and Ozbas (2010)), and in column (3) we control for pseudo-conglomerate returns (Cohen and Lou (2012)). The coefficient on *High AC * Small* remains significant after controlling for return predictability across the supply chain and for pseudo-conglomerate firms. The significantly positive pseudo-conglomerate coefficient is consistent with the finding in Cohen and Lou (2012) that complex firms earn a premium. In addition, the significantly positive *High AC * Small* coefficient means that while High AC firms are complex, the High AC effect we document is incremental to the complexity effect. The magnitude and significance of the coefficients of *High AC * Small* are qualitatively the same as our main results (Table 4). This indicates that the information firms acquire through learning via the AC channel is not explained by information transferred within the industry or through the supply chain.

Finally, we show that our main results are unchanged after controlling for other documented effects of R&D. In column (4), we control for technological leaders, i.e., those firms which have large investments in R&D, and peers, those firms which are technological followers who do not have significant investments in R&D (Jiang et al. (2016)). We follow Eberhart, Maxwell, and Siddique (2004), who find that large increases in firm R&D predict positive future abnormal returns, to construct variables $\Delta RDlarge_{t-1}$, and $\Delta RDlarge_{t-5}$, which reflect large increases in own R&D that took place in the previous year, and over the previous five years, respectively. We control for large growth in R&D in the last year, and over the last five years in columns (5) and (6), respectively. We find that our results for absorptive capacity are unaffected by large changes in own-firm R&D. In each of these specifications, the coefficient of interest is similar in both magnitude and significance compared to our main results. These results suggest that our measure of absorptive capacity provides information incremental to existing measures of R&D that have been used to predict stock returns.

4.3 Other Robustness Tests

Our key specification relies on the interaction between size of the firm and its absorptive capacity. We carry out a series of robustness tests varying the specification for size, AC and other parameters in our main specification. In a first robustness test, we replace the variable, *Size* with the indicator variable, *Small*. The results are reported in the Internet Appendix Table IA.1. Our main result is qualitatively similar in magnitude and significance.

On a similar note, we investigate whether our result is robust to identifying small firms using NYSE-based size break-points. We re-define small firms as those which lie in the bottom market capitalization decile of the NYSE. We create an indicator variable, *Small NYSE* which takes the value one if the firm is in the bottom decile in the June of year t and hold this value for each month from July of year t to June of year $t+1$. Results are presented in the Internet Appendix Table IA.2, columns (1) and (2). Our main result is robust to this change of definition for small firm size.

Also in the Internet Appendix Table IA.2, we examine whether the return predictability of small, high absorptive capacity firms varies across time. We divide our full sample into two sub-periods, 1986 - 1995 and 1996 - 2006. We then repeat our baseline analysis from Table 4 for each sub-period. Columns (3) and (4) report the results for the period 1986-1995, and columns (5) and(6) report the results for the period 1996-2006. Our results hold up well to this time disaggregation. The coefficients for *High AC * Small* are all positive and statistically significant after controlling for various return determinants. The effect of High AC on small firms is robust in both time periods.

We examine the sensitivity of our measure to variations in the specification used to estimate AC. Results are presented in Table IA.3. In the first instance, we use an alternative definition of *Ln(Spilltech)* as in equation 6. We use the average of the one to five year lags of *Ln(Spilltech)* as the main independent variable. We estimate *AC avg* as the coefficient for this average value. Columns (1) and (2) of Table IA.3 report the results. Our main result is robust to this alternative definition of AC. In a second specification, we include all five lags of *Ln(Spilltech)* in place of only one lag in equation 6. We estimate *AC all* as the average of all five coefficients. Columns (3) and (4) of Table IA.3 report the results. In this case as well, our main result is robust to this alternative specification.

The literature has documented a couple of alternative definitions of absorptive capacity. Oh (2017) uses the ratio of own R&D stock to sales as a firm-level measure. Mancusi (2008) calculates self-citations to patents at the industry-country level as a measure of absorptive capacity. We provide a firm-level measure of absorptive capacity, and, therefore, we are able to directly compare our measure with Oh (2017) to determine whether our measure provides incremental information. As noted before, we include own R&D as a control variable in our regression specification for calculation of AC. This inclusion addresses the concern that we may be rediscovering the own R&D effect with our AC measure. To further refine this analysis, we calculate *RDC/Sale* as the ratio of R&D stock, calculated using the perpetual inventory method with a depreciation rate, $\delta = 20\%$, to sales (Oh (2017)). We include this variable as a control in our main specification. Our main result is robust to this inclusion. Moreover, the coefficient to the variable, *RDC/Sale*, is not significant in this specification, which implies that our measure of absorptive capacity subsumes the alternative measure of absorptive capacity.

Our results are sensitive to the inclusion of fixed effects, so we use several industry classifications to create the industry fixed effects as alternatives to the Fama-French 17 industry classification presented in our main results. Table IA.4 reports the results. In separate specifications, we use the Fama-French 12 industry, 30 industry, and the SIC 2-digit industry classifications. In all these specifications, our main result continues to be robust.

4.4 Real Outcomes: Patents and Citations

We have established that small market cap firms with high AC earn higher returns than large firms or even small firms with low AC. Before turning to the question of whether these returns are compensation for risk, we will briefly focus on the real outcomes associated with the firms in the high AC, small size portfolio. Our objective is to assess the validity of our AC estimates. The AC-return relation is robust, as shown above, but we have not yet empirically established that AC is plausibly a substitute for a firm's own R&D investment. In particular, we want to see if the firms which we classify into the high AC and small size portfolio produce the kinds of tangible results we would expect if they are in fact learning via the AC channel.

There are two specific questions we will ask. First, does high AC eventually transform into own R&D? Once a firm has successfully utilized its AC, and obtained higher returns, it may be more likely to supplement its AC with its own in-house R&D program to protect the market position it has acquired via AC. This may be especially true for smaller firms and those in highly competitive industries. So, our first hypothesis is that i) high AC firms should exhibit greater likelihood of own firm R&D investment in future periods. Second, does high AC manifest itself through more and better innovation? Successful R&D programs should lead to measurably better outcomes. Thus, our second and third hypotheses are that ii) high AC firms should generate more patents and iii) high AC firms should generate higher quality patents (i.e., patents that generate more citations).

To examine the real effects, we explore patents and patent citations from the NBER US Patent Citations Data File. Patents enable firms to build their intangible capital, and increase or maintain their competitive advantage. Using patent citations, we are able to create indicators of the importance of individual patents (Hall, Jaffe, and Trajtenberg (2001)), in particular, citations are a proxy for patent quality. Our approach is based on a large, and growing body of literature showing that patents, and patent citations are viable measures of R&D "success" (Griliches (1981 and 1984), Pakes (1985), Jaffe (1986), Griliches, Pakes, Hall (1987 and 1991), Connolly and Hirschey (1988), Hall (1993a and 1993b), Hall, Jaffe, and Trajtenberg (2005), Cohen, Diether, and Malloy (2013), and Kogan, Papanikolaou, Seru, and Stoffman (2017) among others).

Table 6 reports the results of annual Fama-Macbeth (1973) cross-sectional regressions to test our three hypotheses. First, we evaluate whether firms with high AC and small size are more likely to conduct R&D in the future. In columns (1) and (2), the dependent variable is an indicator variable for positive R&D in the next year. We include indicator variables, High AC * Small and High AC, as independent variables. We also include lagged size, book-to-market ratio, and leverage as control ariables. We include industry fixed effects, based on the Fama and French 17 industry classifications, where indicated. Note that High AC is positive and significant in both specifications. Thus, our measure of AC is associated with a greater likelihood of investing in R&D in the next year. In addition, High AC * Small, is positive and significant in both specifications indicating that this likelihood is even greater for small market capitalization firms.

We now turn to measurable innovative outcomes associated with AC, total patents and total citations to those patents. In columns (3) and (4), the dependent variable is the natural logarithm of (1+ patents). For each firm-year observation, we count the number of patents applied for (and eventually granted) in the year. We use the application year, instead of the grant year of the patent, as the relevant year because we are trying to estimate the effect of learning on firm-level actions. By using the year of application, we are closer to the actual year of firm action which is potentially related to firm-level learning. In both specifications, columns (3) and (4), the coefficient of Size is positive. This result implies that small firms patent less than large firms. More importantly, the coefficient of High AC * Small is positive and significant indicating that small firms with high AC produce more patents in the future. The coefficient estimate provided in column (4) indicates that in the year after a small firm achieves high AC, the number of patents increases by 50.7%. For the sub-sample of small firms with high AC, this increase represents around 1.59 additional patents. To put this change into perspective, we compare this number to the standard deviation of patents for this subsample. We find that this increase in patents represents 6.93% of the standard deviation of patents. The magnitude of this effect is large and economically significant.[15]

In columns (5) and (6), we use the total citations to all granted patents in the year. The dependent variable is the natural logarithm of (1 + citations). We find that firms with high absorptive capacity and small size also receive more citations on their patents, as compared to other firms. Using the coefficient estimate as in column (6), we estimate that citations increase by 49.6% in the consecutive year. For the sub-sample of small firms with high AC, this increase amounts to 2.54 additional citations, which represents around 9.31% of the standard deviation of citations for this sub-sample. Again, this magnitude is large and economically significant for these firms. Taken together, these results in columns (3)-(6) suggest that firms which are good at learning from their counterparts R&D are able to obtain tangible outcomes in the form of more patents and higher quality patents.

Table 6 confirms that our measure of AC is associated with the kind of real, measurable outcomes we would expect if a firm is learning from other firms' R&D. Firms with high AC go on to act *as if* they have directly invested in R&D: they are more likely to invest in their own R&D, they generate more accepted patent applications, and they generate more highly cited patents.

5 Is Absorptive Capacity Mis-priced?

In Section 4 we documented that firms with High AC earn higher future returns. These higher returns are primarily earned by firms in the smallest quintile of market value. Furthermore, we showed that these returns are not a repackaging of previously documented connections between returns and R&D expenditures, firm linkages, or firm characteristics.

To a first approximation, small firms with High AC appear to be underpriced. In the next subsection, we consider whether this apparent underpricing is due to high AC firms being riskier than low AC firms as suggested by Stoffman et. al. (2022). They conclude that small innovators are more risky than small non-innovators. In particular, we examine portfolio returns after accounting for standard risk factors and document the risk-adjusted

[15] The magnitude of the effect of country-level variables on firm patents has a wide variation. Atanassov and Liu (2019) document that a change in taxes at the state level has an impact of patents which represents 1.2% to 1.4% of the standard deviation of patents. Several papers document that the impact of banking deregulation in the US in the 1980s and 1990s on firm-level patenting varied between 9.7% and 23% (Chava et al. (2013), Amore, Schneider and Zaldokas (2013), Cornaggia, Tian, Wolfe (2013))

returns for a high AC/Small size portfolio. In the subsequent subsection we examine the correlation of our excess returns with several recently popularized short-horizon and long-horizon mispricing factors. Specifically, we compare portfolios returns during periods of high and low mis-pricing factor returns.

5.1 Risk Factors

In this subsection, we examine if the excess returns documented above are captured by the standard set of empirical asset pricing models including the single-factor CAPM, the Fama-French three-, four- , and five-factor models (Fama, and French (1993); Pastor and Stambaugh (2003); Fama and French (2014)), the Carhart (1997) 4-factor model, and the q^5 investment model (Hou et. al (2018)). Controlling for these factors, we can better understand whether the higher returns earned by High AC, Small firms are compensation for some form of risk captured by the standard risk-factor models. Table 7 Panel A reports the results for risk-adjusted returns for the portfolios which are in the lowest and the highest quintiles based on size.

In the first row, we report the excess returns for the 25-portfolios (as in Table 3). In the next row, we use the risk factors in the CAPM model, in the third row, the Fama and French (1993) 3-factor model, in the fourth row, the Carhart 4-factor model (Carhart (1997)), in the fifth row, Fama and French (1993) 3-factor model and liquidity risk factor (Pastor and Stambaugh 2003), in the subsequent row, the Fama-French 5-factor model (2015), and in the final row, the q^5 model (Hou et al 2018). The alphas for the High AC-Small portfolios are always significantly positive with large t-statistics. However, the risk-models are able to account for some of the large raw return alphas when AC is Low or when size is not Small.

In each row, the last column reports the High AC-Small minus High AC-Big spread. This spread measures the incremental High AC alpha due to small market capitalization. Column (7) reports the High AC-Small minus Low AC-Small spread. This spread measures the incremental Small alpha due to High AC. The spreads are significantly positive with large t-statistics for each of the risk-models and for both equal- and value-weighted portfolios (Panel A and Panel B, respectively). The spread results reinforce our earlier findings. Small, High AC firms earn higher future returns than either Big, High AC firms or Small, Low AC firms.

The above analysis does not entirely rule out risk based explanations. However, the results so far suggest that higher returns earned by High AC - Small firms cannot be explained by standard risk factors alone.

5.2 Mis-pricing Factors

Rather than pursue a potentially endless list of omitted risk factors, we directly employ mispricing factors to assess if there is a correlation between measures of market sentiment and the apparent undervaluation of small firms with High AC. Recently, three models have been introduced which develop factors designed to capture time-variation in systematic mispricing: the long and short horizon behavioral factors of Daniel, Hirshleifer and Sun (2020), the performance and management mispricing factors of Stambaugh and Yuan (2017), and the quality-minus-junk factor of Asness, Frazzini, and Pedersen (2019). We consider each of these mispricing factors separately to better understand whether the returns earned by High AC, Small firms are associated with periods of greater systematic mispricing.

The three papers create 5 mis-pricing factors. Three of the factors appear to capture long-horizon mis-pricing while the other two appear to capture short-horizon mis-pricing. Whether the apparent underpricing of AC is more likely to be a long-horizon or short-horizon phenomenon is an open question. As we argue in the introduction, AC is a substitute for a firms own R&D investment. As such, we would expect it to have long-horizon consequences like direct R&D spending. On the other hand, we would expect most mis-pricing to be short-horizon in nature. Therefore, the apparent underpricing of High AC-Small firms may be more closely correlated with the short-horizon behavioral factors.

We begin by considering the two short-horizon factors. In Table 8 we document the effect of short horizon or transient mis-pricing factors. Stambaugh and Yuan (2017) develop two mis-pricing factors loosely clustered around performance related anomalies (PERF) that dissipate quickly and management related anomalies (MGMT) that persist. We first divide the sample based on the short-horizon mis-pricing factor PERF. We denote a month as high (low) PERF if the value of the mis-pricing factor is above (below) the median. Columns (1) and (2) document the results. When the value of PERF is high, the average monthly return spread for high AC, small size firms is 40.5 basis points, and this spread is not statistically significant from zero. When PERF is low, the average monthly return spread is 61.1 basis points. The difference between the coefficients to *High AC * Small* in columns (1) and (2) is not statistically significant. An F-test for the equality of coefficients is unable to reject the null hypothesis. Similar to Stambaugh and Yuan (2017), Daniel, Hirshleifer and Sun (2020) propose both a short- and a long-horizon behavioral factor. FIN is intended to capture mis-pricing of a persistent nature while PEAD is formed to capture mis-pricing of a transient nature. For our second test, we divide the sample based on the PEAD factor. We denote a month as high (low) PEAD if the value of this mis-pricing factor is above (below) the median. Columns (3) and (4) document the results. When the value of PEAD is high,the average monthly return is 46.5 basis points for high AC, small size firms, and when PERF is low, this spread is 55.7 basis points. The difference between these coefficients is, also, not statistically different from zero. For both short-horizon factors, the coefficient on High AC*Small is significant and positive when the factor return is low. Moreover, although they are not significantly different, the point estimates when the factor return is low are actually greater than when they are high. We conclude that there is little evidence the higher returns earned by the High AC-Small portfolio are explained by short-horizon mispricing.

In Table 9 we report the results using the factors designed to capture long-horizon mispricing. Asness, Frazzini, and Pedersen (2019) create a quality-minus-junk factor, QMJ. They provide evidence that the factor is related to analysts' expectational errors and interpret quality-minus-junk as capturing time variation in systematic mispricing. We denote a month as high (low) QMJ if the QMJ factor in the month is above (below) median. Columns (1) and (2) report the results. When the mispricing factor is high, the coefficient on *High AC * Small* is 1.107 with a t-statistic of 4.64, indicating that the average monthly return spread of firms with high AC and small size is 110.7 basis points. On the other hand, when the mispricing factor is low, the average monthly returns spread of firms with high AC and small size is -5.5 basis points. Another notable result is that the difference in these coefficients is also statistically significant from zero. An F-test testing the restriction of equality in coefficients rejects the null at the 1% level. Next, we consider the long-horizon mis-pricing factor from Stambaugh and Yuan (2017), MGMT. We denote a month as high (low) MGMT if the the value of the factor in the month is above (below) median. Columns (3) and (4) document the results. When MGMT is high, the average monthly return spread of firms with high AC and small size is 109.1 basis points with a t-statistic of 5.02. When MGMT is low, the average return spread for the same category of firms is negative. This spread is not statistically different from zero. In the case of MGMT, the difference in coefficients for *High AC * Small* between columns (3) and (4) are statistically significant. Finally, we use the long-horizon mis-pricing factor from Daniel, Hirshleifer and Sun (2020), FIN. Columns (5) and (6) document the results. We divide our sample into high FIN and low FIN analogous to the procedure used for the other factors. When FIN is high, the average monthly return spread of firms with high AC and small size is 105.3 basis points with a t-statistic of 4.21.

Taken together, the results in Table 9 suggest that the apparent under-valuation of High AC, Small firms is related to longer-horizon mispricing in markets. On the other hand, the results in Table 8 suggest little relation between this under-pricing and short-horizon behavioral factors. We conclude that this evidence is consistent with the view that absorptive capacity is similar in nature to other R&D investments. Therefore it is likely to have long-term consequences and is also likely to be affected by managerial decisions which also appear to be related to long-horizon mis-pricing.

5.3 Mispricing around Earnings Announcements

In a previous section, we reported that well-known risk factors, such as the Fama-French five factors and the momentum factor cannot explain our main result. Nevertheless, it is still possible that unobserved risks could be driving our result. This would be the case if, for example, the high AC of small firms is a proxy for changes in the firm's discount rates, which would then lead to changes in the firm's expected returns. We carry out a test to examine this possibility.

We examine stock price reactions around earnings announcements. This approach has been widely used in the literature (LaPorta et al. (1997), Gleason and Lee(2003), Engelberg et al (2018) among others). The idea is the following: if an anomaly is associated with mispricing, then it will be stronger in the earnings announcement window, as the release of these earnings helps to correct prior misconceptions about the firm's expected cash flows. To conduct this test, we follow Engelberg et al (2018). Our unit of observation is firm-day and not firm-month. We regress daily stock return on *High AC * Small*, an earnings announcement time window ($EDAY$), and the interaction of these variables. We include a set of control variables, lagged values for each of the past ten days stock returns, stock returns squared, and trading volume (Lee et al. (2018)).

Table 10 reports the results. The earnings announcement window is defined as either the one-day window (columns (1) and (2)) or a three-day window (columns (3) and (4)) centered on the news release date. In all columns the coefficient is positive but significant only in columns (3) and (4). Given that there is significant lack of information around small firms, we would expect there to be some noise in the one-day estimation window. Consistent with a mispricing explanation, returns to the High AC, small firms are much larger during earnings announcement releases. In column (4), the coefficient for *High AC * Small * EDAY* is 0.220 and the coefficient for *High AC * Small* is 0.040. These results are very difficult to explain based on a standard risk model.

6 Underlying Mechanisms

The results presented thus far indicate that investors under-react to information related to the absorptive capacity of firms. A natural interpretation of underreaction is that investors are either unwilling or unable to devote sufficient attention to valuing all assets and are, therefore, slow to incorporate new information into prices. Alternatively, investors may be paying full attention but face high transaction costs, i.e., they face limits to arbitrage (D'Avolio, 2002; Asquith et. al., 2005; Stambaugh et. al., 2015). We investigate both under-reaction mechanisms: investor attention and limits to arbitrage. We recognize that there is ambiguity in interpreting some proxies as underreaction or limited attention. We will employ the most common categorizations in the analysis below.

We first examine whether high arbitrage costs are related to the relationship between absorptive capacity of small firms and future returns. We use idiosyncratic volatility (IVOL), firm age, and bid-ask spread as proxies for arbitrage costs. IVOL is the standard deviation of the residual from a regression of daily stock returns in excess of the risk-free rate on daily market returns in excess of the risk-free rate over the previous twelve months (Ang et al. (2006)). Age is the number of years listed on Compustat with non-missing price data. Bid-ask spread is measured as the difference between the bid and ask price divided by the midpoint of the two prices. The high and low groups are split by the median value of each respective measure (Bhardwaj and Brooks (1992), Lam and Wei (2011), and DeLisle, Ferguson, Kassa, and Zaynutdinova (2021)).

In columns (1) and (2) of Table 11, we divide our sample into two groups based on the median value of IVOL. The coefficient on the interaction term, *High AC * Small* is positive and significant in column (1), but the same coefficient is not significant in column (2). Note that high IVOL indicates higher arbitrage costs. Thus, the significant coefficient implies that the effect of absorptive capacity on firm returns is amplified by higher costs of arbitrage. Similarly, in columns (3) and (4), we divide our sample based on Age. The coefficient for the interaction term is positive and significant for young firms, firms which are below the median age in our sample. In columns (5) and (6), we divide our sample into two groups based on the median bid-ask spread. In this case we find that the coefficient for the interaction term is positive and significant for the group with high bid-ask spreads. Note that young firms and firms with higher bid-ask spreads face higher trading costs. Taken together, these results suggest that the under-valuation of absorptive capacity is amplified in the presence of larger arbitrage costs.

Next, we focus on the effect of limited investor attention in the cross-section of firms. Existing literature on limited attention argues that firm-specific information spreads slowly for stocks with greater information asymmetry such as those with lower analyst coverage, greater dispersion in forecasts by analysts, and lower institutional ownership (Hong and Stein (1999), Hirshleifer and Teoh (2003), Hong et al. (2007), Hou (2007), Cohen and Frazzini (2008)).

We test the limited attention channel by dividing our sample into groups based on the proxies for limited attention - number of analysts covering the stock, the standard deviation of the analyst estimates for the stock, and the percentage of institutional ownership. We use Institutional Brokers' Estimate System (I/B/E/S) to obtain data for the first two proxies.

Analyst coverage is calculated as the average of the monthly number of analysts providing fiscal year earnings forecasts for the stock in the previous year. Analyst dispersion is computed as the average of the monthly standard deviation of earnings estimates for the stock in the previous year, where the monthly standard deviation is the standard deviation divided by the absolute value of the mean of analyst estimate. We exclude from the sample stocks with zero dispersion, i.e. zero analyst or one analyst coverage. We use FactSet to obtain data for institutional ownership. Institutional ownership is calculated as the percentage of shareholding of the firm held by US funds, and reported in their 13-F filings. The high and low groups are split by the median value of each respective measure.

Table 12 presents the results. Columns (1) and (2) show the results for our main specification for stocks which have low and high analyst coverage respectively. The coefficient of the interaction variable, *High AC * Small* is positive and significant at the 5% level only for the sample with low analyst coverage. Note that low analyst coverage indicates limited investor attention. Columns (3) and (4) show the results for the subsamples with high and low forecast dispersion respectively. In column (3), the coefficient of interest is positive and significant. The coefficient of interest in column (4) is not significantly different from zero. High forecast dispersion indicates limited investor attention. Columns (5) and (6) show the results for the subsamples with high and low institutional ownership. The coefficient of interest is positive and significant in the case of low institutional ownership.

These results suggest that higher absorptive capacity can lead to higher returns for small firms which suffer from limited investor attention, such as those with low analyst coverage, high dispersion in analyst forecasts, and low institutional ownership. The results in Tables 11 and 12 indicate that both limited investor attention and limits to arbitrage contribute to the persistence of the underpricing of AC that we have identified.

7 Conclusion

Classically, what we typically think of as R&D investments (labs, market research, clinical trials, research scientists, etc.) can generate new knowledge, information, and techniques. These are investments made within the firm; but there is also an external dimension to R&D through which the firm assimilates existing information produced by other firms to generate new knowledge, information, and techniques. Just as firms vary in the degree to which they invest along the internal R&D dimension, they also vary in the degree to which they exploit the external dimension. This second aspect of R&D is relatively less researched and, therefore, less well understood.

We focus on this external dimension of R&D, what we refer to as the firm's absorptive capacity (AC): the ability to learn from other firms' R&D investments. We argue that absorptive capacity represents an important complement or, in some cases, simply an alternative to direct R&D investment. As such, we think AC should have two types of effects. First, within the firm, AC should produce future benefits akin to what we observe with internal R&D. Namely, greater innovative output, like new patents, techniques, products, etc. over a relatively long time horizon. Second, outside the firm, AC should be at least as difficult to value as internal R&D investments. Thus, we would expect AC to appear to be undervalued in much the same way that observed R&D investments appear to be undervalued.

We employ a new measure of AC based on total factor productivity (TFP) to study the impact of absorptive capacity on equity returns. One of the key advantages of our methodology is the fact that we control for the contribution of a firm's own R&D to its TFP. This allows us to differentiate between the impact of direct R&D investments and absorptive capacity. In other words, we are able to isolate the incremental contribution of a firm's ability to utilize external knowledge. To our knowledge we are the first to utilize such a measure in an asset pricing test.

The bulk of our analysis is focused on the external aspects of AC; that is, how does the market value a firm's absorptive capacity? We document return patterns that are consistent with the prediction that the market undervalues AC similarly to how the market undervalues direct R&D investment. Specifically, we find that stocks characterized by high AC in the past and that are also small earn positive excess returns after controlling for standard risk factors. However, the apparent underpricing of small, high AC firms is positively related to long-horizon behavioural factors. We further find that our main result is significantly stronger for firms subject to stricter limits to arbitrage and characterized by less investor attention. Overall, our results are consistent with the innovation returns literature that argues that innovation (and R&D in particular) is undervalued.

We also document real innovative outputs consistent with our prediction that absorptive capacity should have similar effects to traditional R&D. First, we find that small firms with high AC are more likely to invest in R&D in the future. More importantly, these firms generate significantly more patents; and, these patents are of higher quality as evidenced by the fact that they receive significantly more citations.

The real effects that we document have implications for R&D policy. The question of whether and how R&D incentives can improve firm productivity and real outcomes such as innovation is the continued focus of attention across several nations including the US. Policymakers are often concerned about the negative implications of R&D spillovers. In particular, the potential for reduced direct R&D investment if outside firms are also going to benefit from the firm's investments. However, our results show that it is important to also consider the positive real effects of R&D spillovers on other firms. Namely, the increases in future R&D investment and higher quality innovations that arise from the external dimension of R&D, absorptive capacity. These benefits, at least partially, offset the costs of reduced direct investment due to fears of R&D spillovers.

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Figure 1: Absorptive Capacity across Industries

The panel plots the median absorptive capacity (AC) across all firms in the industry for each year in our sample for two industries, Drugs and Textiles. The sample consists of non-financial and non-utility firms with at least one granted patent applied between years 1970 and 2006. The sample includes firms with returns from July 1986 to December 2006. The top line plots the median AC across all firms in the Drugs industry and the bottom line for the Textiles industry. Industry classification is based on Fama-French 17 industry classification.

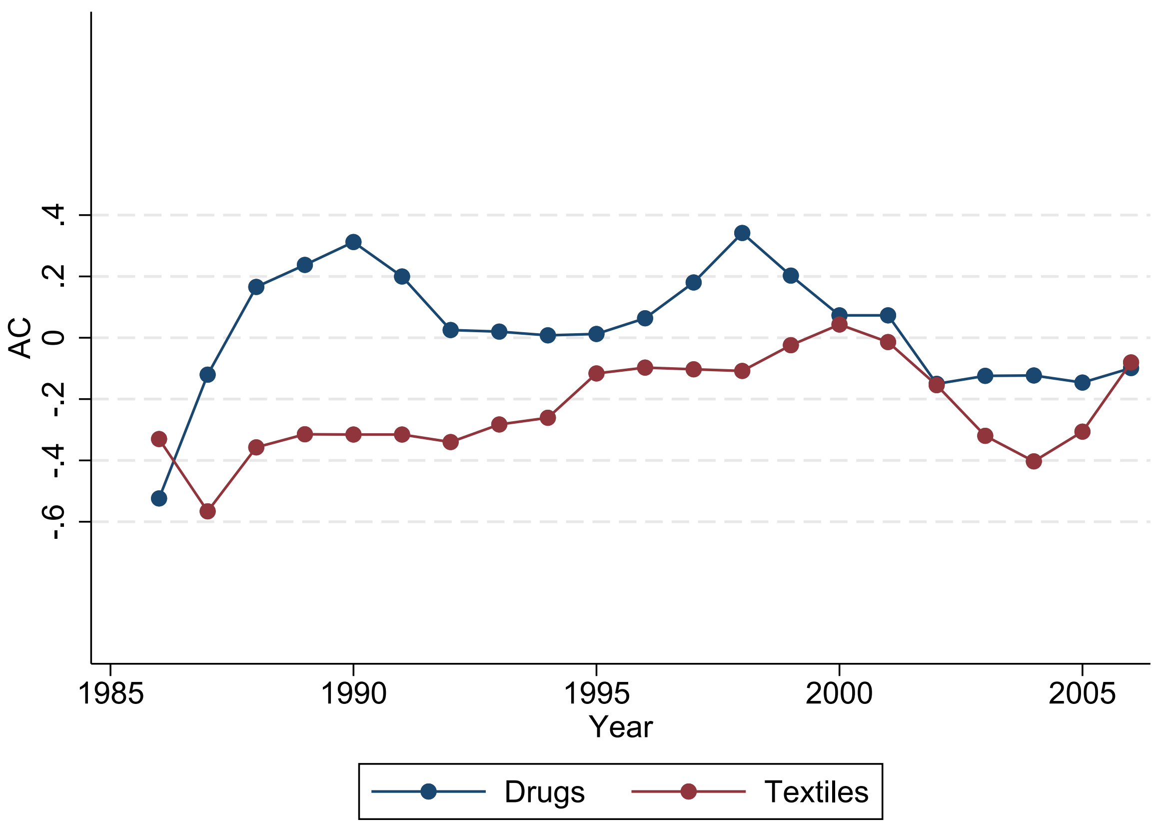

Table 1: Summary statistics

The sample consists of non-financial and non-utility firms with at least one granted patent with an application date between years 1970 and 2006. The sample includes firms with returns from July 1986 to December 2006. At the end of June of year t, we divide firms into five absorptive capacity (AC) groups based on AC twelve months ago by the 20th, 40th, 60th, and 80th percentiles. Panel A presents the summary statistics by the AC groups. AC is absorptive capacity, Ln(TFP) is the natural logarithm of total factor productivity, and Spilltech is technological spillover pool for each firm-year as defined in Section 3.1. Size is the natural logarithm of market capitalization of the firm in $ million. BM is the logarithm of the book-to-market ratio for fiscal year ending in calendar year t-1 divided by market equity at the end of December for t-1. RDME is R&D expenditure divided by year-end market equity. All other variables are as defined in Table A.1. Panel B reports the annual persistence in a firms AC quintile for lags of 1 to 5 years.

Panel A: Summary Statistics

	AC quintiles				
Variable	Low	2	3	4	High
Number of firms	183	184	184	184	184
Excess Return	0.99	0.96	0.90	0.89	1.07
AC	-4.45	-0.74	-0.11	0.51	4.09
Ln(TFP)	-0.24	-0.20	-0.12	-0.05	-0.05
Spilltech	0.59	0.59	0.61	0.63	0.61
Size	5.55	5.92	6.34	6.40	5.98
BM	-0.47	-0.48	-0.61	-0.68	-0.68
RDME	0.05	0.04	0.03	0.03	0.05
PATME	0.01	0.01	0.01	0.01	0.01
CAPXME	0.09	0.09	0.09	0.08	0.08
Reversal	1.29	1.25	1.25	1.24	1.32
Momentum	1.47	1.35	1.33	1.41	1.56
Illiquidity	0.09	0.07	0.05	0.05	0.06
IVOL	0.03	0.03	0.02	0.02	0.03
CAPXAT	0.06	0.06	0.06	0.07	0.06
PATAT	0.01	0.01	0.01	0.01	0.01
ROA	0.07	0.10	0.12	0.13	0.13
AG	0.07	0.08	0.10	0.14	0.16

Panel B: Mean Annual Persistence in Ability

Lag	Low	2	3	4	High
1	0.54	0.48	0.47	0.50	0.56
2	0.33	0.33	0.34	0.34	0.35
3	0.23	0.24	0.26	0.26	0.24
4	0.17	0.19	0.22	0.21	0.18
5	0.13	0.16	0.19	0.17	0.13

Table 2: AC and Spilltech by Industry

The sample consists of non-financial and non-utility firms with at least one granted patent with an application date between years 1970 and 2006. The sample includes firms with returns from July 1986 to December 2006. For each industry, Fama-French 17 industry classification, (column (1)), we report the median number of firm-years and summary statistics (columns (2) to (4)) for AC in the first row and for Spilltech in the second row.

Industry	N	25th percentile	Median	75th percentile
Food	862	-0.54	0.09	0.61
		0.15	0.23	0.36
Mining and Minerals	226	-1.54	-0.43	0.63
		0.14	0.26	0.59
Oil and Petroleum	786	-1.58	-0.36	0.91
		0.12	0.32	0.57
Textiles	682	-0.73	-0.24	0.25
		0.01	0.11	0.33
Consumer Durables	1103	-1.02	-0.15	0.79
		0.09	0.19	0.52
Chemicals	719	-1.04	-0.19	0.57
		0.37	0.77	1.10
Drugs	1030	-0.61	0.06	0.82
		0.43	0.75	1.26
Construction and Materials	926	-0.73	-0.14	0.52
		0.12	0.30	0.58
Steel Works	488	-1.11	-0.14	0.67
		0.16	0.42	0.70
Fabricated Products	435	-0.79	-0.12	0.55
		0.22	0.37	0.59
Machinery and Bus. Equipment	5435	-1.07	-0.14	0.92
		0.30	0.59	1.02
Automobiles	549	-0.65	-0.06	0.57
		0.34	0.63	0.98
Transportation	570	-0.87	-0.17	0.50
		0.12	0.54	1.07
Retail Stores	545	-0.42	-0.09	0.28
		0.05	0.13	0.37
Other	5318	-0.94	-0.13	0.71
		0.24	0.47	0.76

Table 3: Excess returns for equal- and value- weighted portfolios

This table reports the excess returns and adjusted returns for equal-weighted portfolios sorted on size and absorptive capacity. Panel A reports the average monthly portfolio return net of the one-month Treasury bill rate (excess return) for equal-weighted portfolios. Panel B presents the average monthly excess return for value-weighted portfolios. Spread (HML) is the difference in returns (or the long-short portfolio spread) between the high AC and low AC portfolios, within a Size group. Spread (SMB) is the difference in returns between the Small and Big portfolios, within an AC quintile. All standard errors are in parentheses and are calculated using Newey and West (1987) adjusted standard errors with twelve lags.

	AC quintile					
Size Quintile	Low	2	3	4	High	Spread (HML)
Panel A: Equal weighted portfolios						
Small	1.180***	1.594***	1.191***	1.319***	1.896***	0.715***
	(0.432)	(0.400)	(0.326)	(0.381)	(0.414)	(0.181)
2	1.122***	1.09***	1.203***	1.093***	0.847**	-0.275
	(0.35)	(0.359)	(0.298)	(0.337)	(0.345)	(0.202)
3	0.678**	0.728**	0.896***	0.771**	1.038***	0.360***
	(0.283)	(0.302)	(0.29)	(0.319)	(0.298)	(0.145)
4	0.949***	0.706***	0.797***	0.715**	1.024***	0.075
	(0.303)	(0.242)	(0.241)	(0.284)	(0.301)	(0.137)
Big	0.912***	0.806***	0.729***	0.685***	0.747**	-0.165
	(0.270)	(0.208)	(0.233)	(0.214)	(0.288)	(0.129)
Spread (SMB)	0.269	0.788***	0.462*	0.633**	1.148***	
	(0.396)	(0.326)	(0.359)	(0.315)	(0.386)	
Panel B: Value weighted portfolios						
Small	0.864**	1.652***	1.11***	1.157***	2.182***	1.317***
	(0.434)	(0.478)	(0.346)	(0.368)	(0.490)	(0.270)
2	1.081***	0.958***	1.309***	1.173***	0.869**	-0.212
	(0.346)	(0.362)	(0.276)	(0.380)	(0.414)	(0.281)
3	0.680**	0.615**	0.846***	0.686**	1.042***	0.361**
	(0.319)	(0.298)	(0.279)	(0.326)	(0.315)	(0.182)
4	0.900***	0.738***	0.632***	0.731***	0.887***	-0.013
	(0.300)	(0.232)	(0.237)	(0.272)	(0.330)	(0.181)
Big	0.700**	0.536**	0.562*	0.713***	0.783**	0.083
	(0.281)	(0.232)	(0.303)	(0.263)	(0.362)	(0.206)
Spread (SMB)	0.164	1.116***	0.548	0.445	1.400***	
	(0.437)	(0.437)	(0.480)	(0.379)	(0.582)	

Table 4: Fama-MacBeth Regressions

This table reports monthly Fama-Macbeth (1973) regressions of excess returns from July of year t to June of year t+1 on AC and Size. High AC is an indicator which takes the value one if the AC of the firm is in the highest quintile in year t-1, and zero otherwise. Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on Size, the market value of equity at the end of June of year t, and zero otherwise. All other variables are as defined in Table A.1. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). All continuous variables are Winsorized at the 1% and 99% levels and are normalized to have a mean of zero and standard deviation of 1. Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	Excess returns					
	(1)	(2)	(3)	(4)	(5)	(6)
High AC * Small	0.578***	0.724***	0.737***	0.591***	0.560***	0.523***
	(0.206)	(0.201)	(0.179)	(0.168)	(0.173)	(0.175)
High AC	0.041	0.000	-0.018	-0.080	-0.150	-0.104
	(0.112)	(0.109)	(0.096)	(0.099)	(0.098)	(0.097)
Small	0.468**					
	(0.191)					
Size		-0.188*	-0.152	-0.226**	-0.144	-0.118
		(0.106)	(0.094)	(0.095)	(0.112)	(0.106)
BM			0.09	0.008	0.015	0.038
			(0.080)	(0.088)	(0.084)	(0.088)
RDME				0.203**	0.179**	0.172**
				(0.100)	(0.087)	(0.084)
PATME				0.059	0.062	
				(0.044)	(0.041)	
CAPXME				-0.017	-0.013	
				(0.049)	(0.053)	
Reversal				-0.095	-0.106	-0.124
				(0.076)	(0.077)	(0.078)
Momentum				0.117	0.091	0.082
				(0.103)	(0.098)	(0.099)
Illiquidity					-0.055	-0.050
					(0.099)	(0.113)
IVOL					0.163	0.220*
					(0.128)	(0.125)
PATAT						0.026
						(0.057)
CAPXAT						0.072**
						(0.035)
ROA						0.099
						(0.062)
AG						-0.221***
						(0.040)
Industry FE	No	No	Yes	Yes	Yes	Yes
Observations	219,839	219,839	207,390	196,158	177,467	176,386
R-squared	0.014	0.019	0.064	0.090	0.103	0.112

Table 5: Fama-MacBeth Regressions: Controlling for alternative measures of firm linkages, and R&D effects

This table reports monthly Fama-Macbeth (1973) regressions of excess returns from July of year t to June of year t+1 on AC and Size controlling for other economic linkages, and other R&D effects. High AC is an indicator which takes the value one if the AC of the firm is in the highest quintile in year t-1, and zero otherwise. Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on Size, the market value of equity at the end of June of year t, and zero otherwise. Industry Return is the lagged monthly value-weighted average returns of an individual stock's 2-digit SIC industry (Moskowitz and Grinblatt (1999)). Customer Return is the lagged returns of a firm's portfolio of customers and Supplier Return is the lagged returns of a firm's portfolio of suppliers following Menzly and Ozbas (2010). Psuedo-conglomerate Return is the returns from a portfolio of pure play firms that collectively span an individual firm's lines of business, weighted by the industry segment's sales contribution to the focal firm (Cohen and Lou (2012)). Leader and Peer indicators are constructed following Jiang et al. (2016). Leader is an indicator variable which takes the value of one if a firm is an R&D leader that experiences R&D-to -sales and -assets greater tha 2%, within an industry year that experiences an aggregate R&D growth greater than 20%, and zero otherwise. Peer an indicator equal to one if a firm is not a leader within an industry that experiences an aggregate R&D growth during the current or the previous three years. $\Delta RDlarge_{t-1}$ ($\Delta RDlarge_{t-5}$) is an ndicator for large R&D increases, which takes the value one if R&D expenditure increased by 5%, R&D expenditure divided by lagged total assets is greater than 5% and if R&D change divided by lagged assets is greater than 5% last year. For t-5, if the conditions are met for the average values over the previous 5 years (Eberhart, Maxwell, and Siddique (2004)). Other controls refer to variables defined in Table 4. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). All continuous variables are Winsorized at the 1% and 99% levels and are normalized to have a mean of zero andstandard deviation of 1. Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	Excess returns					
	(1)	(2)	(3)	(4)	(5)	(6)
High AC * Small	0.520***	0.508***	0.518***	0.481***	0.498***	0.497***
	(0.175)	(0.176)	(0.173)	(0.170)	(0.170)	(0.171)
High AC	-0.084	-0.083	-0.081	-0.071	-0.089	-0.090
	(0.097)	(0.097)	(0.097)	(0.101)	(0.095)	(0.096)
Size	-0.087	-0.082	-0.081	-0.093	-0.117	-0.117
	(0.100)	(0.099)	(0.101)	(0.100)	(0.107)	(0.107)
Industry Return	0.070	0.059	0.056			
	(0.081)	(0.079)	(0.082)			
Customer Return		0.075				
		(0.049)				
Supplier Return		-0.003				
		(0.034)				
Pseudo-conglomerate Return			0.112**			
			(0.055)			
Leader				0.409		
				(0.473)		
Peer				0.121		
				(0.119)		
$\Delta RDlarge_{t-1}$					0.050	
					(0.079)	
$\Delta RDlarge_{t-5}$						-0.010
						(0.078)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes
Observations	173,476	173,476	173,476	173,476	173,079	173,079
R-squared	0.080	0.083	0.082	0.080	0.111	0.111

Table 6: Real Outcomes: Patents, Citations and R&D

This table reports annual Fama-Macbeth (1973) regressions of measures of innovation output on Absorptive capacity and size. High AC is an indicator which takes the value one if the AC of the firm is in the highest quintile and zero otherwise, Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on size, and zero otherwise. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). *Has R&D* is an indicator variable which takes the value one if the firm has non-zero, positive R&D expenses. *Ln(1+ Patents)* is the natural logarithm of one plus the number of granted patents applied for by the firm in the current year. *Ln(1+ Citations)* is the natural logarithm of one plus the number of citations received by granted patents applied for by the firm in the current year. Newey and West (1987) adjusted standard errors using one-month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	Has R&D		Ln(1+Patents)		Ln(1+Citations)	
	(1)	(2)	(3)	(4)	(5)	(6)
High AC * Small	0.051**	0.060***	0.367***	0.410***	0.361***	0.403***
	(0.023)	(0.019)	(0.063)	(0.051)	(0.088)	(0.067)
High AC	0.070***	0.035***	0.024	-0.045	0.118*	0.030
	-0.017	(0.015)	(0.043)	(0.040)	(0.057)	(0.057)
Size	-0.011*	0.010**	0.475***	0.524***	0.535***	0.601***
	(0.006)	(0.005)	(0.008)	(0.008)	(0.018)	(0.017)
BM	-0.099***	-0.056***	0.072	0.155***	-0.068	0.069
	(0.021)	(0.015)	(0.050)	(0.037)	(0.057)	(0.051)
Leverage	-0.082***	-0.054***	0.006	0.063***	-0.157***	-0.065**
	(0.007)	(0.004)	(0.021)	(0.017)	(0.030)	(0.023)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	16,694	16,694	16,694	16,694	16,687	16,687
R-squared	0.043	0.239	0.322	0.400	0.268	0.343

Table 7: Risk-adjusted portfolio returns

This table reports the risk-adjusted returns for portfolios based on size and absorptive capacity. Panel A reports the excess return and the alphas for CAPM, Fama and French (1993) three-factor model, Carhart model, Fama and French three-factor with liquidity factor (Pastor and Stambaugh 2003), Fama and French five-factor model (2014), and the q^5 model (Hou et al 2018). Excess return is the portfolio return minus risk-free. Panel B reports the excess returns and alphas for value-weighted portfolios. All standard errors in parentheses are Newey and West (1987) adjusted standard errors using twelve lags.

	Small size						High AC					
	AC Low	2	3	4	AC High	Spread (HML)	Size Small	2	3	4	Size Big	Spread (SMB)
Panel A: Equal-weighted portfolio												
Raw return	1.180***	1.594***	1.191***	1.319***	1.896***	0.715***	1.896***	0.847**	1.038***	1.024***	0.747**	1.148***
	(0.432)	(0.400)	(0.326)	(0.381)	(0.414)	(0.181)	(0.414)	(0.345)	(0.298)	(0.301)	(0.288)	(0.386)
CAPM Alpha	0.728*	1.133***	0.743*	0.783**	1.34***	0.611***	1.34***	0.186	0.316	0.237	0.01	1.330***
	(0.419)	(0.371)	(0.38)	(0.344)	(0.380)	(0.188)	(0.380)	(0.267)	(0.265)	(0.239)	(0.118)	(0.390)
3-factor Alpha	0.371	0.84***	0.537**	0.516**	1.177***	0.806***	1.177***	-0.008	0.141	0.213	0.156	1.021***
	(0.229)	(0.285)	(0.235)	(0.250)	(0.217)	(0.178)	(0.217)	(0.153)	(0.117)	(0.198)	(0.123)	(0.253)
4-factor Alpha	0.441*	1.02***	0.536**	0.643**	1.35***	0.909***	1.35***	0.16	0.297**	0.494**	0.355***	0.995***
	(0.237)	(0.295)	(0.242)	(0.263)	(0.234)	(0.177)	(0.234)	(0.170)	(0.123)	(0.210)	(0.136)	(0.255)
FF3 + Liq. Alpha	0.418*	0.901***	0.529**	0.528**	1.139***	0.722***	1.139***	-0.029	0.135	0.183	0.114	1.025***
	(0.234)	(0.286)	(0.236)	(0.257)	’(0.208)	(0.178)	(0.208)	(0.149)	(0.117)	(0.189)	(0.112)	(0.248)
5-factor Alpha	0.338	0.703**	0.481*	0.553**	1.153***	0.815***	1.153***	-0.058	0.111	0.186	0.291*	0.862***
	(0.238)	(0.282)	(0.251)	(0.250)	(0.232)	(0.208)	(0.232)	(0.181)	(0.130)	(0.224)	(0.169)	(0.223)
q^5 Alpha	0.361	0.723*	0.455	0.683*	1.236***	0.875***	1.236***	0.057	0.172	0.266	0.383*	0.853***
	(0.295)	(0.382)	(0.303)	(0.406)	(0.308)	(0.254)	(0.308)	(0.222)	(0.159)	(0.259)	(0.225)	(0.294)

Table 7 – Continued

	Small size						High AC					
	AC Low	2	3	4	AC High	Spread (HML)	Size Small	2	3	4	Size Big	Spread (SMB)
Panel B: Value-weighted portfolio												
Raw return	0.864**	1.652***	1.11***	1.157***	2.182***	1.317***	2.182***	0.869**	1.042***	0.887***	0.783**	1.400***
	(0.434)	(0.478)	(0.346)	(0.368)	(0.490)	(0.270)	(0.490)	(0.414)	(0.315)	(0.330)	(0.362)	(0.582)
CAPM Alpha	0.409	1.159**	0.672*	0.589*	1.61***	1.201***	1.61***	0.184	0.325	0.101	0.096	1.514***
	(0.429)	(0.469)	(0.404)	(0.331)	(0.504)	(0.286)	(0.504)	(0.348)	(0.235)	(0.217)	(0.180)	(0.600)
3-factor Alpha	0.062	0.962***	0.482*	0.386	1.468***	1.407***	1.468***	0.093	0.185	0.084	0.413***	1.055***
	(0.239)	(0.367)	(0.264)	(0.250)	(0.312)	(0.280)	’(0.312)	’(0.256)	’(0.135)	’(0.177)	’(0.109)	’(0.336)
4-factor Alpha	0.090	0.921***	0.403	0.386	1.461***	1.371***	1.461***	0.141	0.270*	0.235	0.456***	1.005***
	(0.252)	(0.342)	(0.276)	(0.263)	(0.291)	(0.267)	(0.291)	(0.274)	(0.149)	(0.176)	(0.148)	(0.324)
FF3 + Liq. Alpha	0.468**	1.397***	0.857***	0.775***	1.773***	1.304***	1.773***	0.46*	0.565***	0.443**	0.769***	1.004***
	(0.220)	(0.377)	(0.258)	(0.241)	(0.298)	(0.266)	(0.298)	(0.275)	(0.153)	(0.181)	(0.110)	(0.327)
5-factor Alpha	-0.025	0.775**	0.411	0.38	1.376***	1.402***	1.376***	0.075	0.153	0.055	0.584***	0.792***
	(0.250)	(0.345)	(0.280)	(0.255)	(0.293)	(0.297)	(0.293)	(0.243)	(0.145)	(0.177)	(0.131)	(0.302)
q^5 Alpha	-0.011	0.634*	0.424	0.502	1.242***	1.253***	1.242***	0.033	0.109	0.007	0.500***	0.742**
	(0.300)	(0.382)	(0.336)	(0.362)	(0.310)	(0.340)	(0.310)	(0.210)	(0.137)	(0.183)	(0.171)	(0.342)

Table 8: Short-Horizon Mispricing Factors

This table reports monthly Fama-Macbeth (1973) regressions of returns on absorptive capacity and size within subsamples divided into periods of high and low spreads between underpriced and overpriced stocks represented by the short-horizon mispricing factors. PERF is constructed by applying a 2 by 3 sorting procedure on size and the averaging rankings within a cluster of anomalies (distress, O-score, momentum, gross prfitability and return on assets), which are related more to performance and less controlled by management (Stambaugh and Yuan (2017)). Specifically, two size portfolios are sorted based on the NYSE median breakpoint each month and three portfolios are sorted based on the 20th and 80th percentiles of the average rank of the short-horizon anomaly cluster. Value-weighted portfolio returns are found for the four portfolios formed by the intersection of the two size categories with the top and bottom categories for the anomaly cluster. PERF is calculated as the simple average of the returns on the two low portfolios (underpriced stocks) minus the average of the returns on the high portfolios(overpriced stocks). PEAD is similarly constructed based on a 2 by 3 sorting on size and 4-day cumulative abnormal return around the most recent quarterly announcement date. Two size portfolios are sorted based on the NYSE median breakpoint each month and three portfolios are sorted based on the 20th and 80th percentiles of cumulative abnormal return for NYSE firms. Value-weighted portfolios returns are calculated for the portfolios formed on the intersection of small and big size groups and the high and low earnings surprise portfolios. PEAD is then calculated as the average return of the high earnings surprise portfolios minus the average of the low earnings portfolios. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). All continuous variables are winsorized at the 1% and 99% levels and normalized to have a mean of zero and standard deviation of 1 . Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	PERF		PEAD	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
High AC * Small	0.405	0.611**	0.465*	0.557*
	(0.314)	(0.280)	(0.252)	(0.301)
High AC	-0.259	-0.033	-0.090	-0.197
	(0.193)	(0.171)	(0.125)	(0.178)
Size	-0.217	-0.090	-0.229	-0.075
	(0.197)	(0.124)	(0.196)	(0.104)
BM	-0.049	0.073	-0.116	0.143**
	(0.133)	(0.092)	(0.136)	(0.070)
RDME	0.292**	0.080	0.364**	0.002
	(0.129)	(0.099)	(0.156)	(0.086)
PATME	0.070	0.056	0.060	0.066
	(0.053)	(0.048)	(0.042)	(0.054)
CAPXME	-0.178**	0.145**	-0.085	0.059
	(0.080)	(0.058)	(0.087)	(0.058)
Reversal	0.171***	-0.365**	0.110	-0.317**
	(0.059)	(0.149)	(0.076)	(0.147)
Momentum	0.568***	-0.362***	0.270*	-0.089
	(0.101)	(0.132)	(0.153)	(0.109)
Illiquidity	-0.087	-0.014	0.031	-0.130
	(0.127)	(0.125)	(0.134)	(0.173)
IVOL	-0.076	0.391*	0.226	0.101
	(0.246)	(0.210)	(0.203)	(0.142)
Industry FE	Yes	Yes	Yes	Yes
Observations	86,100	91,367	88,842	88,625
R-squared	0.104	0.102	0.101	0.105

Table 9: Long-Horizon Mispricing Factors

This table reports monthly Fama-Macbeth (1973) regressions of returns on absorptive capacity and size within subsamples divided into periods of high and low spreads represented by long-horizon mispricing factors. QMJ is constructed by sorting on size and quality, where quality is a composite score representing subcomponents of profitability, growth, and safety. At the end of each month, six value-weighted portfolios are formed by first sorting on size based on the median NYSE market equity and then on quality within size. QMJ is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. MGMT is constructed by applying a 2 by 3 sorting procedure on size and the averaging rankings within a cluster of anomalies (net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets), which reflect quantities that firms' management can affect (Stambaugh and Yuan (2017)). Specifically, two size portfolios are sorted based on the NYSE median breakpoint each month and three portfolios are sorted based on the 20th and 80th percentiles of the average rank of the long-horizon anomaly cluster. Value-weighted portfolio returns are found for the four portfolios formed by the intersection of the two size categories with the top and bottom categories for the anomaly cluster. MGMT is calculated as the simple average of the returns on the two low portfolios (underpriced stocks) minus the average of the returns on the high portfolios(overpriced stocks). FIN represents attempts by management to arbitrage misprcing via issuance/repurchase activities as represented by 1-year net share issuance (NSI) and 5-year composite share issuance (CSI) (Daniel, Hirshleifer, and Sun (2020)). If a firm belongs to high (low) NSI and/or CSI ranking it is defined as a high (low) financing group. High and low financing groups are interacted by size groups sorted on the median NYSE breakpoint at the end of June of year t. Value-weighted portfolio returns are calculated for each month from July of year t to June of year t+1. FIN is calculated each month as the average return of the low financing portflios minus average return of the high financing portfolios. All subsamples are divided by the respective factor each month as high (low) if it is above (below) median. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). All continuous variables are winsorized at the 1% and 99% levels and normalized to have a mean of zero and standard deviation of 1 . Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	QMJ		MGMT		FIN	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
High AC * Small	1.107***	-0.055	1.091***	-0.040	1.053***	-0.013
	(0.238)	(0.320)	(0.217)	(0.245)	(0.250)	(0.261)
High AC	-0.495***	0.191	-0.623***	0.313**	-0.630***	0.327**
	(0.186)	(0.147)	(0.179)	(0.123)	(0.206)	(0.152)
Size	-0.120	-0.182	-0.283	-0.027	-0.219	-0.087
	(0.227)	(0.141)	(0.187)	(0.134)	(0.189)	(0.151)
BM	0.083	-0.052	0.353***	-0.310***	0.346***	-0.308***
	(0.108)	(0.111)	(0.101)	(0.102)	(0.107)	(0.112)
RDME	-0.036	0.391***	-0.116	0.467***	-0.208**	0.561***
	(0.104)	(0.147)	(0.129)	(0.159)	(0.093)	(0.168)
PATME	0.042	0.083	0.075**	0.051	0.077	0.049
	(0.039)	(0.055)	(0.037)	(0.054)	(0.050)	(0.056)
CAPXME	-0.159***	0.126*	-0.060	0.032	-0.036	0.010
	(0.051)	(0.075)	(0.064)	(0.090)	(0.070)	(0.084)
Reversal	0.042	-0.242	0.012	-0.213	0.072	-0.273*
	(0.078)	(0.170)	(0.076)	(0.155)	(0.077)	(0.153)
Momentum	0.137	0.047	-0.129	0.299**	-0.072	0.248
	(0.127)	(0.160)	(0.103)	(0.139)	(0.101)	(0.199)
Illiquidity	0.228*	-0.313***	0.170	-0.258**	0.237*	-0.326***
	(0.133)	(0.117)	(0.135)	(0.127)	(0.134)	(0.114)
IVOL	-0.568***	0.858***	-0.430**	0.727***	-0.633***	0.933***
	(0.214)	(0.220)	(0.182)	(0.201)	(0.178)	(0.199)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86,629	90,838	86,625	90,842	87,317	90,150
R-squared	0.100	0.106	0.103	0.103	0.103	0.103

Table 10: Returns Around Earnings Announcement

This table reports regressions of announcement window daily returns (DLYRET) on day fixed effects, *High AC * Small*, earnings day indicator variables, and other lagged control variables. High AC is an indicator which takes the value one if the AC of the firm is in the highest quintile in year t-1, and zero otherwise. Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on Size, the market value of equity at the end of June of year t, and zero otherwise. EDAY is an indicator variable which takes the value one if the daily observation is during an announcement window and zero otherwise. Following Engelberg et al. (2018), we obtain earnings announcement dates from the Compustat database, examine the firm's trading volume scaled by market trading volume for the day before, the day of, and the day after the reported earnings annoucement date, and define the day with the highest volume as the earnings announcement day. Control variables include lagged values for each of the past ten days for stock returns, stock returns squared, and trading volume. Standard errors are clustered by date and shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	1-day window		3-day window	
	(1)	(2)	(3)	(4)
High AC * Small * EDAY	0.338	0.328	0.200**	0.220**
	(0.249)	(0.248)	(0.097)	(0.097)
High AC * Small	0.052***	0.046***	0.046***	0.040**
	(0.015)	(0.016)	(0.015)	(0.016)
EDAY	0.271***	0.269***	0.133***	0.137***
	(0.038)	(0.038)	(0.023)	(0.023)
High AC	-0.002	-0.004	-0.002	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Size	-0.022***	-0.012**	-0.023***	-0.012**
	(0.006)	(0.006)	(0.006)	(0.006)
Lagged controls	No	Yes	No	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	4,234,589	4,230,651	4,234,589	4,230,651
R-squared	0.001	0.010	0.001	0.010

Table 11: Limits to Arbitrage

This table reports monthly Fama-Macbeth (1973) regressions in subsets defined relative to the median value of idiosyncratic volatility, age, and bid-ask spread, respectively.IVOL is the standard deviation of the residual from a regression of daily stock returns in excess of the risk-free rate on daily market returns in excess of the risk-free rate over the previous twelve months ending in year t-1. Age is the number of years listed on Compustat at the end of year t-1. At June of each year, the average bid-ask spread is found over the previous 12 months, where the bid-ask spread is defined as the difference between the bid and ask price divided by the midpoint of the two prices. Fama-French (1997) 17 industry fixed effects are included. The independent variables are winsorized at the 1% and 99% levels and thereafter standardized to have a mean of zero and standard deviation of 1. Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	IVOL		Age		Bid-Ask spread	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
High AC * Small	0.516**	0.171	0.294	0.372**	0.637*	-0.868
	(0.221)	(0.526)	(0.907)	(0.187)	(0.325)	(0.968)
High AC	-0.198	0.048	0.381	-0.203*	-0.406	0.146
	(0.137)	(0.114)	(0.304)	(0.103)	(0.256)	(0.136)
Size	-0.354**	-0.157	-0.232	-0.177	-0.522**	0.091
	(0.152)	(0.109)	(0.213)	(0.118)	(0.251)	(0.234)
BM	-0.034	0.017	-0.020	0.015	-0.063	0.117
	(0.107)	(0.081)	(0.202)	(0.077)	(0.153)	(0.096)
RDME	0.222**	0.163*	0.252	0.219**	0.417*	0.288*
	(0.107)	(0.090)	(0.207)	(0.086)	(0.222)	(0.152)
PATME	0.060	0.081*	-0.064	0.074	0.195	0.142**
	(0.055)	(0.045)	(0.134)	(0.048)	(0.152)	(0.062)
CAPXME	0.176**	-0.090	-0.262	0.025	0.132	-0.146
	(0.080)	(0.067)	(0.258)	(0.061)	(0.088)	(0.149)
Reversal	-0.035	-0.274***	0.075	-0.119	-0.108	-0.365**
	(0.095)	(0.072)	(0.143)	(0.077)	(0.100)	(0.157)
Momentum	0.063	0.163	-0.054	0.091	0.142	-0.374***
	(0.112)	(0.109)	(0.161)	(0.100)	(0.155)	(0.139)
Illiquidity	0.011	-0.020	-0.282	-0.008	-0.102	3.003
	(0.098)	(0.260)	(0.232)	(0.113)	(0.127)	(6.301)
IVOL			0.172	0.200	0.015	0.171
			(0.255)	(0.128)	(0.255)	(0.302)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,890	90,040	23,654	151,276	59,969	57,355
R-squared	0.120	0.147	0.310	0.115	0.140	0.221

Table 12: Limited Attention

This table reports monthly Fama-Macbeth (1973) regressions of returns on Absorptive capacity and size within subsamples divided into high and low investor attention groups. High AC is an indicator which takes the value one if the AC of the firm is in the highest quintile and zero otherwise, Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on size, and zero otherwise. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). All continuous variables are winsorized at the 1% and 99% levels. Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	Analyst coverage		Forecast Dispersion		Institutional Ownership	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
High AC * Small	0.617	0.804**	1.648***	-0.203	-16.991	0.756*
	(0.582)	(0.347)	(0.506)	(0.666)	(11.442)	(0.450)
High AC	-0.145	-0.053	-0.062	-0.073	0.055	-0.381
	(0.088)	(0.105)	(0.114)	(0.079)	(0.380)	(0.260)
Size	-0.072	-0.253	-0.254*	-0.124	-0.945**	-0.388**
	(0.169)	(0.160)	(0.134)	(0.139)	(0.341)	(0.187)
BM	-0.035	0.052	0.047	0.084	0.135	-0.247
	(0.085)	(0.092)	(0.093)	(0.117)	(0.335)	(0.218)
RDME	0.220**	0.186*	0.173*	0.259*	1.749	0.405*
	(0.107)	(0.100)	(0.093)	(0.134)	(1.334)	(0.219)
PATME	0.176***	0.028	0.106	0.002	-1.003	0.155*
	(0.061)	(0.053)	(0.077)	(0.050)	(1.048)	(0.089)
CAPXME	-0.081	-0.112	-0.123*	-0.050	-1.257***	0.272
	(0.079)	(0.085)	(0.069)	(0.117)	(0.392)	(0.165)
Reversal	-0.112	-0.041	-0.128	-0.160	-0.833**	-0.297***
	(0.081)	(0.092)	(0.094)	(0.102)	(0.319)	(0.108)
Momentum	-0.005	0.139	0.063	0.122	0.104	-0.125
	(0.134)	(0.107)	(0.124)	(0.127)	(0.948)	(0.150)
Illiquidity	27.196	-0.259	-0.527	0.872	-3.891	-0.401
	(20.887)	(0.287)	(0.902)	(1.353)	(5.769)	(0.269)
IVOL	0.072	0.185	0.178	0.046	-0.389	0.175
	(0.239)	(0.134)	(0.166)	(0.214)	(0.646)	(0.296)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,426	75,552	62,258	62,184	11,421	52,484
R-squared	0.229	0.131	0.188	0.200	0.374	0.148

Appendix

Table A.1: Variable Definitions

This table shows a summary of all explanatory variables used in the analysis.

Variable name	Variable description
Ret	Monthly returns from Center for Research in Security Prices (CRSP)
Excess Ret	Monthly returns − risk-free rate
TFP	Firm-level productivity found using the Olley and Pakes (1996) method (İmrohoroğlu and & Tüzel (2014)). TFP is represented by ω_{it} from the production function $y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it}$. y is defined as the accounting value added (sales - material expense, where material expense is the difference between total expense (sales-oibdp) and labor expense (emp*wage)). k is capital stock calculated using the perpetual inventory method with depreciation of 8%.
AC	Measure of firm absorptive capacity, found as the average of the regression coefficients for technology spillover pools in rolling regressions of TFP on own R&D pool and technology spillover pools.
Small	An indicator variable which takes the value one if the firm is in the lowest quintile based on Size, the market value of equity at the end of June year t, and zero otherwise.
Spilltech	Firm-level technological spillover pool calculated as the weighted sum of the other firms' R&D expenditure, weighted by the uncentered correlation between firms' patent portfolios (Bloom, Shankerman, and Van Reenen (2013))
RD stock	Firm's own R&D stock calculated by the perpetual inventory method using R&D expenditure, assuming depreciation rate of 15%.
Size	Logarithm of market capitalization
BM	Logarithm of book to market ratio, the book equity for fiscal year ending in calendar year t-1 divided by market equity at the end of December for t-1. Book equity is shareholder's equity, plus balance-sheet deferred taxes and investment tax credit if available, minus the book value of preferred stock. Stockholders' equity, or common equity plus the carrying value of preferred stock, or total assets minus total liabilites in that order of availability is used as shareholders' equity. For the book value of preferred stock, redemption , liquidation or par value is used depending on availability. (Hou,Xue, and Zhang (2020))
RDME	R&D expenditure divided by year-end market equity.
PATME	Logarithm of one plus patent counts divided by year-end market equity (Hirshleifer, Hsu, and Li (2013))
CAPXME	Logarithm of one plus capital expenditure divided by year-end market equity.

(Continue)

Table A.1 – Continued

Variable name	Variable description
Reversal	Previous month's one-month raw return (Jagadeesh 1990).
Momentum	Cumulative raw return beginning twelve months ago through the month before last (Jagadeesh and Titman 1993)
Illiquidity	Absolute stock return in the previous month divided by trading volume in the same month (Amihud (2002))
Profitability	Profitability is defined as return on equity, ROE, measured as income before extraordinary items divided by 1-year-lagged book equity.
IVOL	Standard deviation of the residual from a regression of daily excess stock returns on daily excess market returns over the previous twelve months (Ang, Hodrick, Xing and Zhang (2006)).
CAPXAT	Capital expenditure divided by total assets.
PATAT	Patent counts divided by total assets.
ROA	Income before extraordinary items plus interest expenses scaled by lagged total assets.
AG	Asset growth is measured as the change in total assets divided by lagged total assets.
Industry Return	Lagged monthly value-weighted average returns of an individual stock's 2-digit SIC industry (Moskowitz and Grinblatt (1999)).
Customer Return	Lagged returns of a firm's portfolio of customer industries identified from BEA surveys. Specifically, portfolio returns are weighted by the share of sales to other industries. (Menzly and Ozbas (2010)).
Supplier Return	Lagged returns of a firm's portfolio of upplier industries identified from BEA surveys. Specifically, portfolio returns are weighted by the share of purchases from other industries. (Menzly and Ozbas (2010)).
Pseudo-conglomerate Return	Returns from a portfolio of pure play firms that collectively span an individual firm's lines of business, weighted by the industry segment's sales contribution to the focal firm (Cohen and Lou (2012)).

Table A.1 – Continued

Variable name	Variable description
Leader	An indicator variable which takes the value of one if a firm is a R&D leader that experiences R&D-to-sales and -assets greater than 2%, within an industry year that experiences an aggregate R&D growth greater than 20%, and zero otherwise (Jiang, Qian, and Yao (2016)).
Peer	An indicator equal to one if a firm is not a leader within an industry that experiences an aggregate R&D growth during the current or previous three years (Jiang, Qian, and Yao (2016)).
$\Delta RDlarge_{t-1}$ ($\Delta RDlarge_{t-5}$)	Indicator for large R&D increases, which takes the value one if R&D expenditure increased by 5%, R&D expenditure divided by lagged total assets is greater than 5% and if R&D change divided by lagged assets is greater than 5% last year. (if the conditions are met for the average values over the previous 5 years) (Eberhart, Maxwell, and Siddique (2004)).
Leverage	Logarithm of one plus total debt over book equity. Total debt is long-term debt plus debt in current liabilities. Book equity is shareholder's equity, plus balance-sheet deferred taxes and investment tax credit if available, minus the book value of preferred stock. Stockholders' equity, or common equity plus the carrying value of preferred stock, or total assets minus total liabilities in that order of availability is used as shareholders' equity. For the book value of preferred stock, redemption , liquidation or par value is used depending on availability.
EDAY	An indicator variable which takes the value one if the daily observation is during an earnings announcement date window and zero otherwise. Earnings announcement dates are from the Compustat database, and based upon calculations as specified in Engelberg, Mclean, and Pontiff (2018).

Olley and Pakes Method (1996)

Observations with missing values are dropped. Observations with SALE, AT, EMP, and PPENT less than 0.1 are dropped. Observations with CAPX missing and less than or equal to 0 are also dropped. Drop observations if materials <0.01 and if value added<0.01.

Olley and Pakes procedure:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it}$$

The basic idea is that labor(l) is an optimal decision made by firms at a point in time implying that it has no effects to the future, it is like a state variable. It is also the assumption that given the capital stock, investment is strictly increasing in the unknown firm productivity $i_t(k_{jt}, \omega_{jt})$. This in theory, implies that the inverse function of investment $h_t(k_{jt}, i_{jt}) = \omega_{jt})$ can identify firm productivity. In application, a polynomial function of capital stock and investment is used to approximate the sum of the polynomial terms for capital and investment as well as the TFP term: i.e. $\phi_t(k_{jt}, i_{jt}) = \beta_0 + \beta_k k_{jt} + \omega_{jt}$. TFP can be estimated given the parameters for capital stock and investment $\omega_{jt}(\beta_0, \beta_k) = \hat{\phi}_{jt} - \beta_0 - \beta_k k_{jt}$.

1. Define exit from Compustat and run probit regression on exit based on investment and lagged capital stock as well the second order polynomials and interaction term

2. Regress value added(y) on employment (l), investment(i) ,lagged capital stock(k) and the second order polynomials (i^2, k^2, ik) with industry specific year effects. In other words, the industry year effects are taken out from the TFP measure. From here, the coefficient for labor is estimated.

3. Define $y - \beta_l l$ by the estimated value by the results from step 2. for i, k, k^2, i^2, ik, and $residual$. Estimate nonlinear regression of $y - \beta_l l$ on constant, k, lagged $y - \beta_l l - \beta_k k$, and lagged exit probability. This gives the estimate for coefficient on capital.

4. lnTFP is computed by $y - \beta_l l - \beta_k k$ where $y - \beta_l l$ is from the first regression and $\beta_k k$ is from the second regression.

(Observations with less than 5 observations in the industry are dropped)

The calculation of the capital stock follows as closely as possible to the aggregation method as used in the spillover measure part.

Internet Appendix

This Appendix contains additional results to accompany the main results in the paper. First, we briefly describe the contents of each table and then report the tables.

1. In Table IA.1, we report Fama-Macbeth regression estimates for the effect of *High AC * Small* on monthly excess returns including the indicator variable, *Small* in place of the control variable, *Size*.

2. In Table IA.2, we report Fama-Macbeth regression estimates for the effect of *High AC * Small* on monthly excess returns using NYSE size deciles, and our main effect in sub-samples based on time-period. We use NYSE size decile as an alternative definition for small firms, where small firms are in the bottom 10 percentile of firms. In a separate specification, we divide the sample based on time period and report coefficients for these separate sub-samples. In one specification, we include months in the years 1986 to 1995, and in the second specification, we include months in the years 1996 to 2006.

3. In Table IA.3, we report Fama-Macbeth regression estimates for the effect of *High AC * Small* on monthly excess returns using alternative definitions for absorptive capacity.

   In this table, we check whether our main result is robust to alternative model specifications for AC. We estimate the following equation to calculate *AC avg*.

$$Ln(TFP_{it}) = a_{it} + b_{it} Ln(G_{it-1}) + c_{it} \mathbb{1}(G_{it-1} = 0)$$
$$+ d_{it} averageLn(Spilltech_{it}) + e_{it} \tag{7}$$
$$\tag{8}$$

where AC avg = d_{it} and *average* $Ln(Spilltech_{it})$ is the average of one to five year lags of *Ln(Spilltech)*.

We estimate the following equation to estimate *AC all*.

$$Ln(TFP_{it}) = a_{it} + b_{it} Ln(G_{it-1}) + c_{it} \mathbb{1}(G_{it-1} = 0)$$
$$+ \sum_{j=1}^{j=5} d_{it-j} Ln(Spilltech_{it-j}) + e_{it} \tag{9}$$
$$ACall_{it} = \frac{1}{5} \sum_{j=1}^{5} d_{it-j} \tag{10}$$

4. In Table IA.4, we report Fama-Macbeth regression estimates for the effect of *High AC * Small* on monthly excess returns using alternative industry classifications to create the industry-year fixed effects.

Table IA.1: Fama Macbeth Regressions: Controlling for Small Firms

This table reports monthly Fama-Macbeth (1973) regressions of excess returns from July of year t to June of year t+1 on AC and Size. High AC is an indicator which takes the value one if the AC of the firm is in the highest quintile in year t-1, and zero otherwise. Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on Size, the market value of equity at the end of June of year t, and zero otherwise. All other variables are as defined in Table A.1. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). All continuous variables are Winsorized at the 1% and 99% levels and are normalized to have a mean of zero and standard deviation of 1. Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	Excess Returns				
	(1)	(2)	(3)	(4)	(5)
High AC * Small	0.578***	0.661***	0.559***	0.543***	0.536***
	(0.206)	(0.186)	(0.170)	(0.173)	(0.172)
High AC	0.041	0.009	-0.052	-0.123	-0.088
	(0.112)	(0.096)	(0.099)	(0.095)	(0.096)
Small	0.468**	0.281*	0.315**	0.175	0.111
	(0.191)	(0.154)	(0.150)	(0.170)	-0.154
BM		0.135	0.085	0.068	0.088
		(0.086)	(0.095)	(0.097)	(0.099)
RDME			0.207**	0.172*	0.168*
			(0.101)	(0.088)	(0.086)
PATME			0.055	0.061	
			(0.043)	(0.041)	
CAPXME			-0.030	-0.026	
			(0.049)	(0.054)	
Reversal			-0.088	-0.100	-0.118
			(0.078)	(0.078)	(0.080)
Momentum			0.118	0.104	0.091
			(0.099)	(0.095)	(0.096)
Illiquidity				-0.047	-0.042
				(0.095)	(0.110)
IVOL				0.191	0.246*
				(0.129)	(0.129)
PATAT					0.023
					(0.057)
CAPXAT					0.072**
					(0.034)
ROA					0.116*
					(0.065)
AG					-0.224***
					(0.041)
Industry FE	No	Yes	Yes	Yes	Yes
Observations	219,839	204,101	192,969	174,557	173,476
R-squared	0.014	0.062	0.087	0.102	0.108

Table IA.2: Fama Macbeth Regressions: NYSE size deciles and different time sub-periods

This table reports monthly Fama-Macbeth (1973) regressions of excess returns from July of year t to June of year t+1 on AC and Size. High AC is an indicator which takes the value one if the AC of the firm is in the highest quintile in year t-1, and zero otherwise. Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on Size, the market value of equity at the end of June of year t, and zero otherwise. Small NYSE is an indicator variable which takes the value one if the firm is in the bottom 10 percentile based on NYSE size percentiles at the end of June of year t, and zero otherwise. All other variables are as defined in Table A.1. Columns (3) and (4) limit the sample to the time period 1986 to 1995, and columns (5) and (6) limit the sample to the time period 1996 to 2006. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). All continuous variables are Winsorized at the 1% and 99% levels and are normalized to have a mean of zero and standard deviation of 1. Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	Excess Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
High AC * Small NYSE	0.289*	0.304*				
	(0.155)	(0.155)				
High AC	0.096	-0.113	-0.119	-0.391**	0.083	-0.088
	(0.116)	(0.083)	(0.075)	(0.177)	(0.180)	(0.140)
Small NYSE	0.336**	0.236				
	(0.169)	(0.159)				
High AC * Small			0.794***	0.483*	0.764**	0.642**
			(0.221)	(0.277)	(0.320)	(0.262)
Small			-0.207	-0.162	-0.287**	-0.158
			(0.208)	(0.178)	(0.141)	(0.185)
BM		0.060		-0.153		0.094
		(0.094)		(0.183)		(0.073)
RDME		0.172*		0.401		0.175
		(0.089)		(0.270)		(0.133)
PATME		0.063		0.081		0.086
		(0.041)		(0.065)		(0.056)
CAPXME		-0.027		0.127		-0.098
		(0.054)		(0.247)		(0.113)
Reversal		-0.096		0.102		-0.204*
		(0.078)		(0.120)		(0.107)
Momentum		0.107		0.267**		-0.023
		(0.095)		(0.109)		(0.136)
Illiquidity		-0.031		-0.083		-0.131
		(0.090)		(0.187)		(0.154)
IVOL		0.184		0.106		0.253
		(0.130)		(0.131)		(0.194)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	204,101	174,557	100,019	78,028	118,920	95,801
R-squared	0.021	0.102	0.021	0.101	0.020	0.127

Table IA.3: Fama-Macbeth Regressions: Alternative specifications for AC

This table reports monthly Fama-Macbeth (1973) regressions of excess returns from July of year t to June of year t+1 on variations in AC and Size. High AC avg (all) is an indicator which takes the value one if the AC avg (all) of the firm is in the highest quintile in year t-1, and zero otherwise. AC avg is calculated in equation (5) in the main paper where *Ln(Spilltech)* is replaced by the average of one to five years lag in *Ln(Spilltech)*. AC all is calculated as the average of the coefficients of the one to five years lagged *Ln(Spilltech)* where all five lags are included simultaneously in equation (5) in the main paper. Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on Size, the market value of equity at the end of June of year t, and zero otherwise. RDC/Sale is the ratio of R&D stock to sales. All other variables are as defined in Table A.1. Some specifications include industry fixed effects using the 17-industry classification based on Fama and French (1997). All continuous variables are Winsorized at the 1% and 99% levels and are normalized to have a mean of zero and standard deviation of 1. Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	Excess Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
High AC avg * Small	0.703***	0.613***				
	(0.223)	(0.209)				
High AC avg	0.027	-0.097				
	(0.115)	(0.087)				
High AC all * Small			0.675***	0.528***		
			(0.215)	(0.187)		
High AC all			-0.028	-0.158*		
			(0.117)	(0.095)		
High AC * Small					0.831***	0.559**
					(0.278)	(0.244)
High AC					-0.036	-0.043
					(0.109)	(0.151)
RDC/Sale					1.194	-1.250
					(1.144)	(1.071)
Size	-0.206*	-0.156	-0.209*	-0.163	-0.210**	-0.110
	(0.108)	(0.116)	(0.111)	-0.117	(0.094)	(0.110)
Other controls	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Observations	239,777	180,603	220,481	180,603	176,111	158,455
R-squared	0.018	0.102	0.061	0.101	0.084	0.124

Table IA.4: Fama-Macbeth Regressions: Alternative industry fixed effects

This table reports monthly Fama-Macbeth (1973) regressions of excess returns from July of year t to June of year t+1 on variations in AC and Size. High AC is an indicator which takes the value one if the AC of the firm is in the highest quintile in year t-1, and zero otherwise. Small is an indicator variable which takes the value one if the firm is in the lowest quintile based on Size, the market value of equity at the end of June of year t, and zero otherwise. All other variables are as defined in Table A.1. Columns (1) and (2) include fixed effects based on Fama-French 30 industry classification, columns (3) and(4) based on Fama-French 12 industry classification, and columns (5) and (6) based on SIC 2-digit industry classifications=. All continuous variables are Winsorized at the 1% and 99% levels and are normalized to have a mean of zero and standard deviation of 1. Newey and West (1987) adjusted standard errors using twelve month lags are shown in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *.

	Excess Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
High AC * Small	0.686***	0.534***	0.724***	0.558***	0.705***	0.500***
	(0.186)	(0.172)	(0.173)	(0.169)	(0.176)	(0.168)
High AC	-0.066	-0.145	-0.039	-0.142	-0.029	-0.126
	(0.092)	(0.103)	(0.094)	(0.101)	(0.100)	(0.103)
Small	-0.192*	-0.112	-0.115	-0.112	-0.122	-0.123
	(0.104)	(0.106)	(0.089)	(0.105)	(0.093)	(0.103)
BM		0.029	0.099	0.015	0.096	-0.013
		(0.078)	(0.077)	(0.081)	(0.082)	(0.088)
RDME		0.181**		0.176**		0.187**
		(0.070)		(0.073)		(0.085)
PATME		0.051		0.052		0.058
		(0.040)		(0.041)		(0.040)
CAPXME		-0.010		-0.016		0.003
		(0.051)		(0.051)		(0.053)
Reversal		-0.112		-0.102		-0.116
		(0.078)		(0.078)		(0.076)
Momentum		0.082		0.074		0.082
		(0.096)		(0.096)		(0.093)
Illiquidity		-0.016		-0.047		-0.027
		(0.095)		(0.096)		(0.102)
IVOL		0.137		0.153		0.155
		(0.118)		(0.118)		(0.121)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	219,839	174,557	204,101	174,557	204,101	174,557
R-squared	0.079	0.120	0.060	0.096	0.116	0.142

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